Retina Vessels Detection Algorithm for Biomedical Symptoms Diagnosis

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ABSTRACT
This paper presents a method for blood vessel detection in digital retinal images. The method uses fuzzy logic approach with block wise gridding. It uses an adaptive approach for vessel detection. The segmentation is produced by classifying each pixel of the image as *vessel* or *nonvessel*. The performance of the proposed methodology is evaluated on the publicly available DRIVE database. It also contains manually labeled images by experts. Performance of this method on set of test images shows significant improvement than other solutions present in the literature. The method proves especially accurate results for vessel detection in DRIVE images. The method is simple and has fast implementation. It shows effectiveness and robustness with different image conditions. The vessel detection performance has a sensitivity of 0.8653 with specificity 0.9833. The accuracy of the method is 0.9728 for Drive database. This blood vessel detection and segmentation technique can play a useful clinical role in an automated retinopathy analysis system.

Keywords
Diabetic retinopathy, block wise gridding, retinal image, vessels segmentation.

1. INTRODUCTION
Diabetes is one of the most rapidly increasing health threat worldwide. The most common complication caused by diabetes is Diabetic Retinopathy (DR). It is the result of long-standing diabetes. It occurs when blood vessels in the retina change. It damages the small blood vessel of the retina. Sometimes these vessels swell and leak fluid or even close off completely. In other cases, abnormal new blood vessels grow on the surface of the retina. Diabetic retinopathy usually affects both eyes. People who have diabetic retinopathy often don't notice changes in their vision in the disease's early stages. But as it progresses, diabetic retinopathy usually causes vision loss that in many cases cannot be reversed. Diabetic Retinopathy can be of different types. These are not different diseases but they are different stages of the same condition. It is also possible to have more than one type at the same time.

The diagnosis of diabetic retinopathy is based on clinical eye examination and eye fundus imaging. Automatic segmentation of retinal vessels of fundus images is the first step in the development of an automatic retinal screening system. The segmentation and analysis of retinal vasculature is of main interest in diagnosing and treating diabetic retinopathy that directly affect the morphology of the retinal vessel tree.

The retinal vasculature mainly consists of arteries and veins that are visible within the retinal image. As compared to the other anatomical structures, retinal vessels have a lower reflectance and thus they appear darker relative to the background in the color retinal images. Typically in a color image with RGB channels, the red channel is oversaturated and the blue channel contains almost no information, while the bulk of the relevant data is contained within the green channel. Therefore, the blood vessels appear most contrasted in the green channel and it is used for automatic segmentation of vessels.

2. RELATED WORK
Many different approaches for automated vessel segmentation have been reported in the literature. These can be divided into two groups: Unsupervised methods and supervised methods. First group i.e. unsupervised methods includes Vessel tracking methods, Matched filtering techniques, Mathematical morphology, Deformable models and Model based locally adaptive thresholding. Supervised methods include pixel classification based on some classifier.

Regarding unsupervised methods, Vessel tracking method [1] obtains vasculature structure using vessel center lines. These are traced using local information while trying to find the path that matches best to a vessel profile model. In matched filtering technique [2], a 2-D linear structural element with Gaussian cross-profile section is used. It is rotated in 3-D to get vessel cross-profile identification. It uses different orientations to fit vessels of different configuration. A threshold value is used to filter the vessels from background. Mathematical morphology [3] uses piecewise linear probing. The vasculature of final segmentation is extracted from background by using morphological operations. Deformable or snake models [4] are also exploited for retinal vessel segmentation. A snake once placed on the image near the contour of interest, evolved to fit into the shape of the desired structure using iterative steps. Model based locally adaptive thresholding [5] is verification based multithreshold probing scheme. It includes relevant information related to retinal vessels into verification process.

Supervised methods are based on pixel classification. Each pixel is classified as vessel or non-vessel. These methods utilize manually-labeled images for classification. Staal et al. [7] presented a ridge based method in which ridges are used as primitives to form line elements. Each pixel is assigned to nearest line element and image is partitioned into patches. Feature vector for each pixel is computed based on properties of patches and line elements. These feature vectors make use of kNN-classifier and sequential forward feature selection for classification. Soares et al. [8] extracted feature vectors which are composed of pixel's intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales tuning to specific frequencies. It uses a Bayesian classifier with class-conditional probability density functions described as Gaussian mixtures for pixel classification. Ricci and Pefetti [9] proposed a vessel segmentation method based on line operators. They used two orthogonal line detectors along with the gray-level of the target pixel to construct the feature vector with use of support vector machine (SVM) for pixel classification as vessel or nonvessel. Marin et al. [10] used a five layer feed forward neural network scheme for pixel classification. A 7-D feature vector is computed which composed of gray-level and moment invariants-based features for pixel representation. Finally Fraz et al. [11] proposed a method based on ensemble system of bagged and boosted decision trees and utilizes a feature vector based on gradient orientation analysis (GOA), morphological transformation with linear structuring element, line strength measures and the Gabor filter response which encodes information to successfully handle images.

In this study, we presented a retinal vessel detection technique for biomedical symptoms diagnosis, based on fuzzy logic with block wise gridding. This method includes feature vector calculation based on intensity of pixel.

3. PROPOSED METHOD

A method is proposed to automatically detect and segment blood vessels in eye fundus images. As manually labeling of blood vessels is very tedious and time consuming job, so automatic detection and segmentation is of prime concern. More vessels are present in the green part of RGB image of retina, so our algorithm for vessel detection is implemented with green extraction of RGB image. MATLAB based Graphic User Interface (GUI) tool is developed to be used by the ophthalmologist for marking vessels in fundus images. The marked images are to be used for the development of DR grading and database system. The detection of retinal vessels can contribute to the mass screening of the diabetic retinopathy. In this work, we outline an automated approach for detection of blood vessels in fundus eye image based on fuzzy logic with block wise gridding. This is an adaptive method which selects the threshold values range separately for each sub-block. Figure-1 shows the block diagram of proposed work.

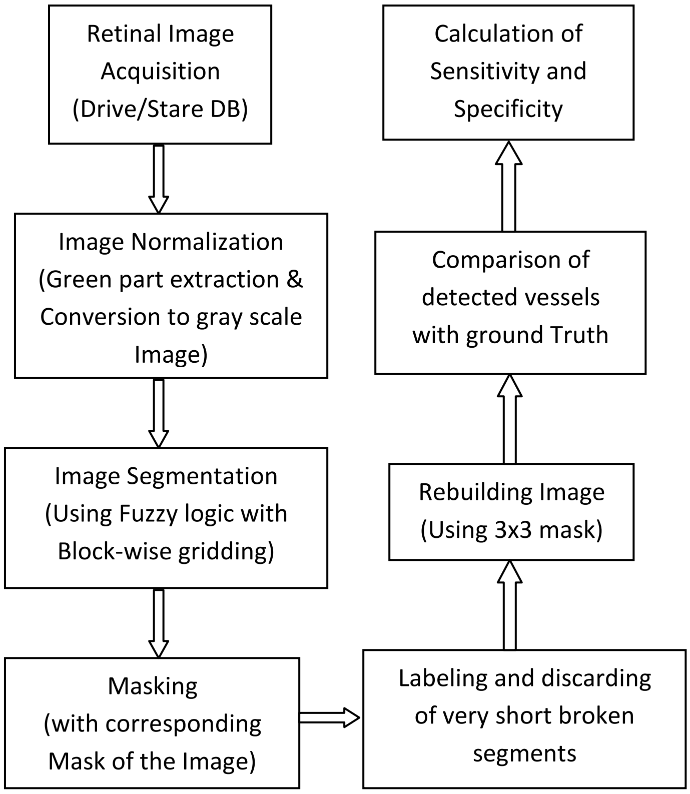

Figure: 1 Block Diagram of Proposed Method

The images and masks used are taken from DRIVE database. The image is normalized and green part is extracted. The green extracted image is then converted to gray scale image. On this gray scale image, segmentation is applied based on fuzzy logic. Image is first split into sub-blocks. Each block is picked and fuzzy logic based thresholding is applied on each block. The output is segmented based on a threshold value, which may be different for each block. Evaluation of the algorithm is done by comparing it with the corresponding manually segmented image by human observer as shown below in figure-2. And finally the analysis parameters are calculated.

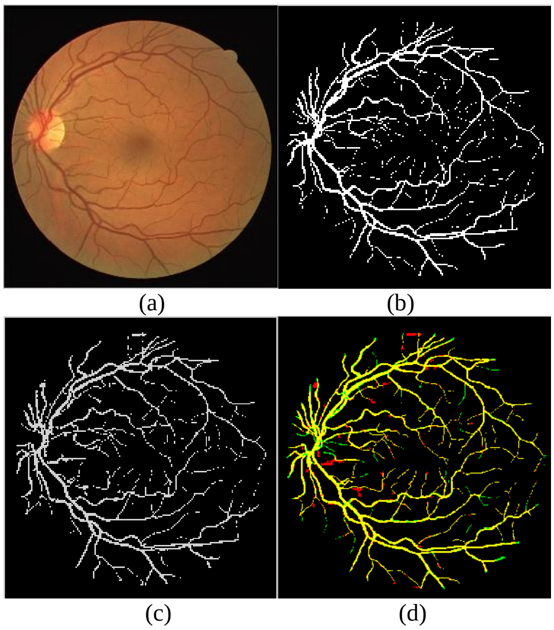

Figure 2: Vessel segmentation on image from DRIVE database; (a) Input image; (b) Manual segmentation by expert; (c) Automatic Segmentation by the method, (d) Comparison with ground truth. **Red** shows output from proposed method, **Green** shows output from manual observation, **yellow** shows vessels present in final output and manual observation.

3.1 Image Acquisition

GUI Interface is used for loading image, corresponding mask and manual segmentation in tif or gif format. It is shown below in figure-3. The images and their corresponding masks are from DRIVE database.

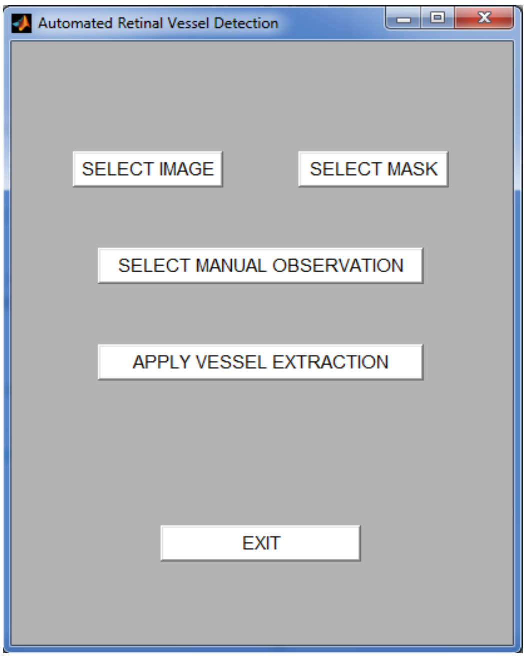

Figure 3: GUI for Automated retinal vessel detection

3.2 Image Normalization

As more vessels are present in the green part of RGB image of retina, So green part is extracted. As extraction is done in 2D form, so it is converted into gray scale image. Moreover all morphological functions are also applicable to 2D images only.

3.3 Image Segmentation and Masking with mask

The image is subdivided into blocks of 8x8 pixels. Each block is picked and fuzzy logic is applied on it. A range of threshold values is selected based on the intensity values present in each block. The image is segmented based on this range of threshold values, which may be different for each block. The threshold values range used for segmentation is selected based on some set of rules.

Following are the rules for selecting the threshold values range:

1. Find the Maximum(max), minimum(min) and mean value of intensity of pixels for each 8x8 pixel block. Also find the maximum value of intensity(max_img) of pixels for whole image.
2. If (max > max_img -5 || min < 20) then either it is disc area or dark background, so discard the area.
3. If (max-mean > 90) then this may be at disc boundary, so discard the area.
4. If(max-min > 6) then
   a. If (mean-min) > 10
   b. Then maximum value of threshold(th_max) = min + ((abs(min-max)/2) * .9)
   c. And minimum value of threshold(th_min) = min
5. If(max-min <= 6) then discard the area.
6. Th_max and th_min gives the final range of threshold value.

A final segmented image is produced using these threshold values.

Logical “AND” operation is performed between segmented image and mask of the image to find the final image of detected vessels.

3.4 Discarding short Segments

A few very small disjoint segments are found in the above output image. These are discarded after labeling them. They are discarded based on their size i.e area, length and width. The segments which have area less than 100 are taken, and if their length or width is less than 15 then they are discarded, because this much small disjoint segment could not be part of the vessel tree.

3.5 Rebuilding image using 3x3 mask

It is found that there are few blank pixels found in the extracted vessels. They are filled using 3x3 masking i.e. for every 3x3 matrix of pixels, if among eight neighbors, 4 are present then activate the middle pixel also. Finally the output is smoothened and the result is shown in figure-4.

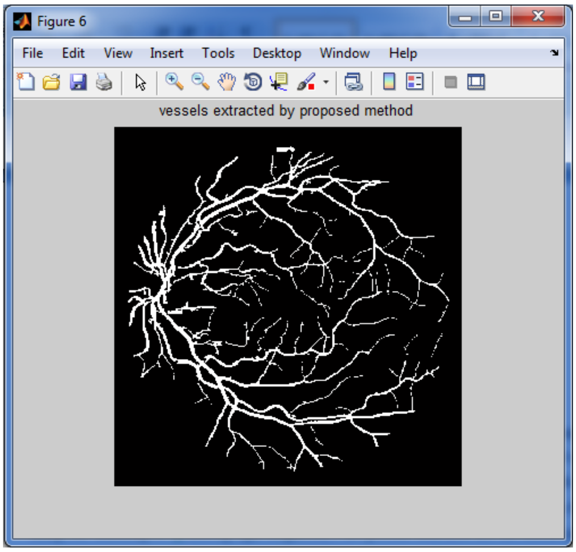

Figure 4: Image showing segmented retinal vessels

3.6 Comparison with Ground Truth

Evaluation of this algorithm is done by comparing the output image with the corresponding manually segmented image. Different color scheme is used for that. In figure-5 shown below, Red color shows the vessels extracted by proposed method. Green color shows the vessels shown in ground truth. Yellow color shows the vessels which are present in output of proposed method and same present in the ground truth.

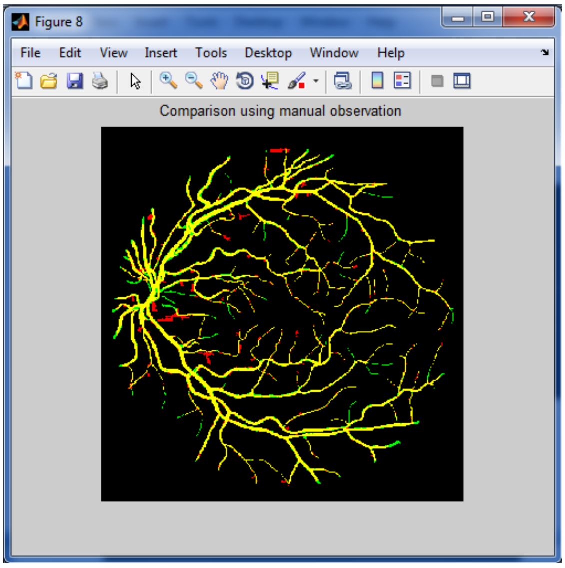

Figure 5: Image showing comparison with ground truth

3.7 Calculating SN, SP and Acc

In the final step, Analysis parameters such as Sensitivity(SN), Specificity(SP) and Accuracy(acc) of this algorithm are calculated. Sensitivity gives the percentage of pixels correctly classified as vessels by the method. Specificity gives the percentage of non-vessels pixels correctly classified as non-vessels by the method. Accuracy gives the percentage of the overall accuracy of the method. These parameters are describes as -

$$Sensitivity = \frac{Tp}{Tp + Fn}$$

$$Specificity = \frac{Tn}{Tn + Fp}$$

$$Accuracy = \frac{Tp + Tn}{Tp + Fn + Tn + Fp}$$

where Tp is true positive, Tn is true negative, Fp is false positive and Fn is false negative at each pixel. True positives(Tp) are pixels marked as vessel in both the segmentation given by a method and the manual segmentation used as ground truth. False positives(Fp) are pixels marked as vessel by the method, but that are actually negatives in the ground truth. True negatives(Tn) are pixels marked as background in both images. And false negatives(Fn) are pixels marked as background by the method, but actually are vessel pixels.

4. RESULTS

This method is evaluated on DRIVE database. 20 Images from Drive database are taken and their average for analysis parameters is taken. The Performance of method on DRIVE database Images is shown below in Table 1.

Table 1. Performance of method on DRIVE database Images

Image	SN	SP	Acc
1	0.8851	0.9909	0.9815
2	0.8268	0.9829	0.9669
3	0.8703	0.9881	0.9763
4	0.8078	0.9748	0.9594
5	0.8512	0.9935	0.9802
6	0.8386	0.9879	0.9734
7	0.8362	0.9784	0.9654
8	0.8768	0.973	0.9647
9	0.8649	0.9911	0.9808
10	0.8778	0.9888	0.9797
11	0.8242	0.974	0.9606
12	0.8816	0.9841	0.9752
13	0.8344	0.9864	0.9715
14	0.8819	0.9783	0.9705
15	0.7707	0.9682	0.9541
16	0.8859	0.9889	0.9796
17	0.8962	0.9807	0.9736
18	0.9212	0.981	0.9763
19	0.9383	0.9843	0.9805
20	0.9366	0.9902	0.9862
Average	**0.8653**	**0.9833**	**0.9728**

The average sensitivity of this method is **0.8653**. The average specificity of this method is **0.9833**. The average accuracy of this method is **0.9728** for drive Database. Our proposed method gives significantly improved results as compared to other methods present in the literature. Performance of DRIVE database is measured on the test set using the manual observation of first observer as ground truth.

In order to compare the results with other retinal vessel segmentation techniques, same analysis parameters are used. As shown below table-2, show the comparison of results with previous papers for DRIVE database.

Table 2. Performance comparison of vessel segmentation methods (DRIVE Images)

S.No.	Methods	Year	SN	SP	Acc
1	Staal	2004	N.A.	N.A.	0.9441
2	Soares	2006	0.7332	0.9782	0.9461
3	Ricci	2007	N.A.	N.A.	0.9595
4	Lupascu	2010	0.7201	N.A.	0.9597
5	Marin	2011	0.7067	0.9801	0.9452
6	Fraz (Base Paper)	2012	0.7406	0.9807	0.948
7	**Proposed Method**	**2013**	**0.8653**	**0.9833**	**0.9728**
N.A. - Not Available					

5. CONCLUSION AND FUTURE SCOPE

Automatic detection and segmentation of blood vessels in eye fundus images is done based on fuzzy logic method with block-wise gridding. This is an adaptive method which segments the retinal vessels based on the threshold value calculated separately for each sub-block. The images and masks are taken from DRIVE as well as STARE database. The final segmented image is applied with mask. The results are compared with manually detected retinal vessels of image. The sensitivity and specificity calculated is more than the methods present previously. For Future scope, this method can be applied to categorize the disease of Diabetic retinopathy.

6. REFERENCES

[1] O. Chutatape, L. Zheng, and S. Krishman, “Retinal blood vessel detection and tracking by matched Gaussian and Kalman filters,” IEEE Proceedings of International Conference in Medicine and Biology Society, 1998, vol. 20, pp. 3144–3149.

[2] A. Hoover, V. Kouznetsova, and M. Goldbaum, “Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response,” IEEE Transactions on Medical Imaging, vol. 19, no. 3, pp. 203–210, Mar. 2000.

[3] A. M. Mendonça and A. Campilho, “Segmentation of retinal blood vessels by combining the detection of centerlines and morphological reconstruction,” IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp. 1200–1213, Sep. 2006.

[4] L. Espona, M. J. Carreira, M. Ortega, and M. G. Penedo, “A snake for retinal vessel segmentation,” Pattern Recognition and Image Analysis, vol. 4478, Lecture Notes Comput. Sci., pp. 178–185, 2007.

[5] X. Jiang and D. Mojon, “Adaptive local thresholding by verification based multithreshold probing with application to vessel detection in retinal images,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 1, pp. 131–137, Jan. 2003.

[6] B. S. Y. Lam and H. Yan, “A novel vessel segmentation algorithm for pathological retina images based on the divergence of vector fields,” IEEE Transactions on Medical Imaging, vol. 27, no. 2, pp. 237–246, Feb. 2008.

[7] J. Staal, M. D. Abràmoff, M. Niemeijer, M. A. Viergever, and B. v. Ginneken, “Ridge based vessel segmentation in color images of the retina,” IEEE Transactions on Medical Imaging, vol. 23, no. 4, pp. 501–509, Apr. 2004.

[8] J. V. B. Soares, J. J. G. Leandro, R. M. Cesar, Jr., H. F. Jelinek, and M. J. Cree, “Retinal vessel segmentation using the 2D Gabor wavelet and supervised classification,” IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp. 1214–1222, Sep. 2006.

[9] E. Ricci and R. Perfetti, “Retinal blood vessel segmentation using line operators and support vector classification,” IEEE Transactions on Medical Imaging, vol. 26, no. 10, pp. 1357–1365, Oct. 2007.

[10] D. Mar´ın, A. Aquino, M. E. Geg´undez-Arias, and J. M. Bravo, “A new supervised method for blood vessel segmentation in retinal images by using gray-level and moment invariants-based features,” IEEE Transactions on Medical Imaging, vol. 30, no. 1, pp. 146–158, Jan. 2011.

[11] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka, and C.G. Owen, and S. A. Barman, “An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation,” IEEE Transactions Biomedical Engineering, vol. 59, no. 9, pp. 2538-2548, Sep. 2012.

[12] K. Sai Deepak and Jayanthi Sivaswamy, “Automatic Assessment of Macular Edema From Color Retinal Images”, IEEE Transactions on Medical Imaging, vol. 31, no. 3, pp. 766-776, March 2012.

[13] Zafer Yavuz, Cemal Köse, “Retinal Blood Vessel Segmentation Using Gabor Filter And Tophat Transform”, IEEE Conference on Signal Processing and Communications Applications, pp. 546-549, November 2011.

[14] Maryam Mubbashar, Anam Usman and M. Usman Akram, “Automated System for Macula Detection in Digital Retinal Images”, IEEE International Conference on Information and Communication Technologies, 2011.

[15] S. You, E. Bas, D. Erdogmus and J. Kalpathy-Cramer, “Principal Curve Based Retinal Vessel Segmentation Towards Diagnosis of Retinal Diseases”, IEEE International Conference on Healthcare Informatics, Imaging and Systems Biology, pp. 331-337, June 2011.

[16] M. Usman Akram, Ibaa Jamal, Anam Tariq and Junaid Imtiaz, “Automated Segmentation of Blood Vessels for Detection of Proliferative Diabetic Retinopathy”, IEEE International Conference on Biomedical and Health

Informatics, Hong Kong and Shenzhen, China, pp. 232-235, January 2012.

[17] Shilpa Joshi, Dr P.T. Karule, "Retinal Blood Vessel Segmentation", International Journal of Engineering and Innovative Technology (IJEIT), Volume 1, Issue 3, pp. 175-178, March 2012.

[18] Xiayu Xu, Meindert Niemeijer, Qi Song, Milan Sonka, Mona K. Garvin, Joseph M. Reinhardt and Michael D. Abràmoff, "Vessel Boundary Delineation on Fundus Images Using Graph-Based Approach", IEEE Transactions on Medical Imaging, vol. 30, no. 6, pp. 1184-1191, June 2011.

[19] Ahmad Zikri Rozlan, Nor Syazwani Mohd Ali, Hadzli Hashim, "GUI System for Enhancing Blood Vessels Segmentation in Digital Fundus Images", IEEE Control and System Graduate Research Colloquium on Communication, Networking & Broadcasting, pp. 55-59, 2012.

[20] Faraz Oloumi, Rangaraj M. Rangayyan, Anna L. Ells, "A Graphical User Interface for Measurement of the Openness of the Retinal Temporal Arcade", IEEE International Symposium on Medical Measurements and Applications Proceedings, March 2012.

[21] Gwénolé Quellec, Stephen R. Russell, and Michael D. Abràmoff, "Optimal Filter Framework for Automated, Instantaneous Detection of Lesions in Retinal Images", IEEE Transactions on Medical Imaging, vol. 30, no. 2, pp. 523 - 533, February 2011.

[22] Keith A. Goatman, Alan D. Fleming, Sam Philip, Graeme J. Williams, John A. Olson, and Peter F. Sharp, "Detection of New Vessels on the Optic Disc Using Retinal Photographs", IEEE Transactions on Medical Imaging, vol. 30, no. 4, pp. 972 - 979, April 2011.

[23] Xiayu Xu, Meindert Niemeijer, Qi Song, Milan Sonka, Mona K. Garvin, Joseph M. Reinhard and Michael D. Abràmoff, "Vessel Boundary Delineation on Fundus Images Using Graph-Based Approach", IEEE Transactions on Medical Imaging, vol. 30, no. 6, pp. 1184 - 1191, 2011.