A Review on Blood Vessel Segmentation Algorithms

Aravindh Sharma[1] Vignesh[2] Dileeban[3]
[1,2,3]Department of Information Technology
[1,2,3]SASTRA University, Thanjavur, India

Abstract— Retinal vessel segmentation algorithms are important factor in ophthalmological diagnosis systems. This work examines the blood vessel segmentation methodologies in two dimensional retinal images and a survey of techniques is presented. The aim of this paper is to review, analyse and categorize the retinal vessel extraction algorithms, techniques and methodologies, giving a brief description. We intend to give the reader a structure for the existing methods to introduce the range of retinal vessel segmentation algorithms to discuss the current trends and future directions and summarize the open problems.

Keywords: Blood Vessel Segmentation Algorithms

I. Introduction

The retinal vasculature has been acknowledged as an indispensable in both ophthalmological and cardiovascular disease diagnosis such as glaucoma and diabetic retinopathy. The attributes of retinal blood vessels including length, width, tortuosity, branching pattern, and angles will contribute to the diagnostic result. However, manual segmentation of retinal blood vessels, although possible, is a time consuming and repetitive work, and it also requires professional skills. To assist ophthalmologists with this complex and tedious work, the demand for the fast automated analysis of the retinal blood vessel images arises.

However, fully automated the analysis and make it work for real – life diagnosis is a harsh risk. First, we find the thin blood vessels because it contributes to the differential diagnosis list, the extraction of blood vessels is required to be extremely accurate so as to help with the diagnosis. Automatic extraction of the retinal vasculature can assist the doctors in the implementation of screening programs for retinopathies. The measure of the state of retinal vessels network allows doing other characterizations for each kind of pathology. The examination of the retina encloses a fundus exam, generally do it with high definition ophthalmology camera, for example, RetCam. Though, there are hospitals or complete populations where they do not have this kind of sophisticated equipment. They should diagnosis with a bad quality image or video. Some algorithms have been designed and tested for that kind of images too.

The input for algorithms are fundus color images and the requirement is to be able to classify each pixel as vessel or non- vessel and give an output image with the blood vessels network. For doing this complex task, researchers use and improve many algorithms like Gaussian and Gabor filter, histogram equalization, clustering, binarization, motion contrast, matched filter, combined corner/edge detector, multi-scale line operator, neural network, ant, genetic, morphological operators. Combined algorithms create one method to obtain successful results. In this paper, we have presented a survey of algorithms particularly focusing on the extraction of blood vessels using various image processing techniques.

Such as the morphological operation based and produced by thresholding make contain the noise, and its used to removing noise and removing imperfection from the retinal blood vessels segmentation system. This operation follows perform Dilation, Erosion, Opening, Closing, and Gradient of an image. The Dilation methods are used to distribute the given blood vessels, to convert the small elements vessels too big elements of the object. Erosion is a method used to sharpen the edges in the retinal blood vessels and reduce the pixel size.

Opening, erosion followed by dilation. Closing, the dilation followed by erosion. Gradient an image. It is used to directional changing color. Top-hat-transform is an operation that extracts small elements and details form the retinal images. They are two types of transform, white top hat and Blacktop hat transform. White top-hat is the difference between the input image opening by some structuring element of the blood vessels. Black top-hat transform is the difference between closing an input image. The various process is feature extraction, Background equalization, and image enhancement. Note: [In this method to remove the larger bright object for selecting structuring element from the retinal blood vessels segmentation. That between remove object and object of interest in the vessels. Segmentation method is used to split the image from the retinal image. It is used in the method of dilation and erosion.

For instance, Roychowdhury and Parhi [1] presented about Retinal Vessel Segmentation by Major Vessel Extraction and Sub-Image Classification. Segmentation methods like matched filtering are used in studies like [2] [3] [13] [38] & [39]. Elisa Ricci and Renzo Perfetti [4] discussed retinal Vessel Segmentation Using Line Operators and Support Vector Classification. Studies of [5] [23] emphasis on centreline highlighting. Tolias and panas [6] discussed fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering. [3] & [7] discussed detection of retinal vessels using Gaussian filter. Shen & Turer [8] presented rapid automated tracing and feature extraction. Zhao and Rada [10] & Al-Diri [11] discussed regarding Infinite Perimeter Active Contour Model. Liu & Sun [9] presented about Recursive Tracking of Vascular Networks in Angiograms Based on the detection-deletion scheme.

Xiaoyi Jiang [12] & Temitope[20] discussed Adaptive Thresholding techniques. Joes and Michael presented about Ridge-Based Vessel Segmentation in Color Images of the Retina. Ghaderi and Hassanpour [15] presented about Retinal Vessel Segmentation Using the 2-D Morlet Wavelet and Neural Network. Frédéric Zana and Jean presented on Segmentation of Vessel Like Patterns Using Mathematical Morphology and Curvature Evaluation. Qiaoliang li discussed a Cross-modality Learning Approach. Paweł Liskowski, Krzysztof Krawiec [18] emphasized on Deep neural networks. Ana Salazar [21] discussed segmentation of optic discs in retinal images. Furdato and

All rights reserved by www.ijsrd.com

Travassos discussed regarding density clustering in diabetic retinopathy.

Bandara [24] presented about Retinal Image Enhancement Technique for Blood Vessel Segmentation Algorithm. Benzon and Gao [26] focused their studies on Regularization-Based Multiconcavity Modeling. Shabana and Deepa [27] discussed EM algorithm. Soumya Sree and Rafega [29] presented a paper on diagnosis for Diabetic Patients based on BP and SVM.Fraz and Andres [33] presented an Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation. Wendeson, Joyce [34] discussed an unsupervised Retinal Vessel Segmentation Using Combined Filters.

Joao and Jorge [35] presented Retinal Vessel Segmentation Using the 2-D Gabor Wavelet and Supervised Classification. Sauitra and haussian [36] presented about automated Retinal Blood Vessels Extraction Using Optimized Gabor Filter. Dash and bhoi [40] discussed Detection of Retinal Blood Vessels from Ophthalmoscope Images Using Morphological Approach. Franklin and Rajan [41] presented Retinal vessel segmentation employing ANN technique by Gabor and moment invariants-based features.

From the survey we have studied that Image processing techniques such as Morphological Operations, Gaussian mixture model(GMM), Two-dimensional matched filtering, Matched gaussian Kalman filtering, Morphological operations, Edge detection, Fuzzy clustering, Amplitude modified second order Gaussian filtering, thresholding, adaptive tracking algorithm in recursive procedure, Infinite perimeter active contour model, implicit neural cost function, Adaptive local thresholding, threshold probing, Ridge-based vessel segmentation, KNN classifier, sequential forward feature selection, Multilayer feedforward neural network, linear filtering, Cross-modality learning approach, global contrast normalization, zero-phase whitening, gamma corrections, Adaptive histogram equalization, pruning, distance transform, Two steps density-based clustering, vascular tree removal. The difference of Gaussian filter(DoG), Adaptive contrast enhancement, SUACE algorithm, Tyler Coye algorithm, Multiconcavity modeling, perceptive transform, regularization, Curvelet Transform, thinning operation, multi-layered thresholding, image histogram, SVM classifier, parallel environment, and parallel algorithm are the methodologies which were used.

Methods have been tested in databases with more than 20 images. Some of the databases are available freely, for example DRIVE and STARE [2] and REVIEW [3]. Results have been quantified in terms of sensitivity (True Positive) and graph under ROC curve [4]. The goal of this review is to provide comprehensive information for the understanding of existing vessel segmentation algorithms by summarizing their methodology and efficiency. Each segmentation approach is first analysed in the general.

II. IMAGE PROCESSING TECHNIQUES AND METHODOLOGIES

A. *Retinal Photography:*

Retinal photography requires the use of a complex optical system, called a fundus camera. It is a specialized low power microscope with an attached camera, capable of simultaneously illuminating and imaging the retina. It is designed to image the interior surface of the eye, which includes the retina, optic disc, macula, and posterior pole. The fundus camera normally operates in three modes. In Color photography the retina is examined in full color under the illumination of white light. In Red-free photography, the vessels and other structures are improved in contrast and the imaging light is filtered to remove the red colors. The fluorescent angiograms are acquired using the dye tracing method. A sodium fluorescein or indocyanine green is injected into the blood, and then the angiogram is obtained by photographing the fluorescence emitted after illumination of the retina with blue light at a wavelength of 490 nanometers.

B. *Retinal vessel segmentation*

The retinal vasculature is composed of arteries and veins appearing as elongated features, with their tributaries visible within the retinal image. There is a wide range of vessel widths ranging from one pixel to twenty pixels, depending on both the width of the vessel and the image resolution. Other structures appearing in ocular fundus images include the retina boundary, the optic disc, and pathologies in the form of cotton wool spots, bright and dark lesions and exudates. The vessel cross-sectional intensity pro- files approximate a Gaussian shape or a mixture of Gaussians in the case where a central vessel reflex is present. The orientation and grey level of a vessel does not change abruptly, they are locally linear and gradually change in intensity along their lengths. The vessels can be expected to be connected and, in the retina, form a binary treelike structure. However, the shape, size and local grey level of blood vessels can vary hugely and some background features may have similar attributes to vessels as illustrated.

Vessel crossing and branching can further complicate the profile model. As with the processing of most medical images, signal noise, drift in image intensity and lack of image contrast pose significant challenges to the extraction of blood vessels. Retinal vessels also show an evidence of a strong reflection along their centerline known as a central vessel reflex, which is more apparent in arteries than veins, is stronger at images taken at longer wavelengths, and typically found in the retinal images of younger patients.

C. *Retinal image databases*

A summary of all the publicly available retinal image databases known to us is given in this section. Most of the retinal vessel segmentation methodologies are evaluated on two databases (DRIVE and STARE).

1) *DRIVE database*

The DRIVE (Digital Retinal Images for Vessel Extraction) is a publicly available database, consisting of a total of 40 color fundus photographs. The photographs were obtained from a diabetic retinopathy screening program in the Netherlands. The screening population consisted of 453 subjects between 31 and 86 years of age. Each image has been JPEG compressed, which is common practice in screening programs. Of the 40 images in the database, 7 contain pathology, namely exudates, hemorrhages and pigment epithelium changes. The images were acquired using a Canon CR5 non-mydriatic 3-CCD camera with a 45° field of view (FOV). Each image is captured using 8bits per color plane at 768×584pixels. The FOV of each image is circular with a

All rights reserved by *www.ijsrd.com*

diameter of approximately 540 pixels. The set of 40 images was divided into a test and training set both containing 20 images. Three observers, the first and second author and a computer science student manually segmented a number of images. All observers were trained by an experienced ophthalmologist (the last author). The first observer segmented 14 images of the training set while the second observer segmented the other 6 images. The test set was segmented twice resulting in a set X and Y. Set X was segmented by both the first and second observer (13 and 7 images, respectively) while set Y was completely segmented by the third observer. The performance of the vessel segmentation algorithms is measured on the test set. In set X the observers marked 577,649pixels as vessel and 3,960,494 as background (12.7% vessel). In set Y 556,532 pixels are marked as vessel and 3,981,611 as background (12.3% vessel).

2) *STARE Database*

The STARE database contains 20 images for blood ves- sel segmentation; ten of these contain pathology.The digitized slides are captured by a TopCon TRV-50 fundus camera at 35° field of view. The slides were digitized to 605 × 700 pixels, 8 bits per color channel. The approximate diameter of the FOV is 650×500pixels. Two observers manually segmented all the images. The first observer segmented 10.4% of pixels as vessel, against 14.9% vessels for the second observer. The difference in segmentation between the two observers is due to the fact that the second observer segmented many more of the thinner vessels than the first one. Performance is computed with the segmentation of the first observer as the ground truth.

III. RETINAL VESSEL SEGMENTATION APPROACHES

A common categorization of algorithms for segmentation of vessel like structures in medical images includes image driven techniques, such as edge-based and region-based approaches; pattern recognition techniques, model-based approaches, tracking-based approaches and neural network-based approaches. In this review, we are dealing with vessel segmentation explicitly in two dimensional retinal images therefore, following the convention; the papers are cate- gorized according to the image processing methodologies employed and the algorithms used. We have divided the retinal vessel segmentation algorithms into six main categories; (1) pattern recognition techniques, (2) matched filtering, (3) vessel tracking/tracing, (4) mathematical morphology, (5) multiscale approaches, (6) model based approaches and (7) parallel/hardware based approaches.

AUTHOR	YEAR	IMAGE PROCESSING TECHNIQUE	INPUT IMAGE	PRE-PROCESSING	RESULT ACCURACY
Roychowdhury et al.	2016	Morphological Operations, gaussian mixture model(GMM)	2D	Yes	Accuracy DRIVE:95.2% Accuracy STARE: 95.15% Accuracy CHASE DB1: 95.3%
Chaudhuri et al.	1989	Two-dimensional matched filtering	2D	No	-
Chutatape et al.	1998	Matched gaussian kalman filtering	2D	Yes	-
Elisa Ricci et al.	2007	Morphological operations, matched Ffltering	2D	Yes	Accuracy DRIVE:96.46% Accuracy STARE: 95.95%
Mendonca et al.	2006	Edge detection, morphological operations	2D	Yes	Accuracy DRIVE:94.52% Accuracy STARE: 95.40%
Tolias et al.	1998	Fuzzy clustering	2D	Yes	Accuracy: 82.35%
L. Gang et al.	2002	Amplitude modified second order gaussian filtering	2D	Yes	Accuracy: 85.5%
H. Shen et al.	1999	thresholding, edge detection, morphological processing	2D	No	-
Liu and Sun	1993	Matched filtering, adaptive tracking algorithm inrecursive procedure.	2D	No	-
Zhao et al.	2015	Infinite perimeter active contour model	2D	Yes	Accuracy DRIVE:95.4%
Al-Diri et al.	2009	Morphological operations, implicit neural cost function	2D	Yes	Accuracy: 95%
Jiang et al.	2003	Adaptive local thresholding, threshold probing	2D	Yes	Accuracy: 89.5%
Hoover et al.	2000	Adaptive thresholding, matched filter	2D	Yes	Accuracy: 80%
Staal et al.	2004	Ridge-based vessel segmentation, KNN classifier, sequential forward feature selection.	2D	Yes	Accuracy: 94.55%

Soares et al.	2006	Multilayer feed forward neural network	2D	Yes	Accuracy: 94.9%
Fredric Zana et al.	2001	Morphological operations and matched filtering, linear filtering.	2D	Yes	Accuracy DRIVE:94.8% Accuracy STARE: 95.4% Accuracy CHASE DB1: 94.2%
Qiaoliang et al.	2016	Cross modality learning approach	2D	No	Accuracy DRIVE:95.27% Accuracy STARE:96.28% Accuracy CHASE DB1: 95.81%
Paweł et al.	2016	global contrast normalization, zero-phase whitening, gamma corrections	2D	Yes	Accuracy DRIVE:94.79% Accuracy STARE:95.59%
Chanwimaluang et al.	2003	Morphological operations and local thresholding approach.	2D	Yes	Sensitivity: 92.15% Specificity: 84.46%
Temitope et al.	2015	Adaptive thresholding technique	2D	Yes	Accuracy DRIVE:94.7% Accuracy STARE:95.1%
Ana et al.	2014	Adaptive histogram equilization, pruning, distance transform	2D	Yes	Accuracy DRIVE:94.12% Accuracy STARE:94.41%
Furtado et al.	2017	Two steps density based clustering, vascular tree removal	2D	Yes	Accuracy: 94%
Mendonca et al.	2006	Morphological operations, difference of guassian filter(DoG)	2D	Yes	Accuracy DRIVE:94.73% Accuracy STARE:94.42%
Bandara et al.	2017	Adaptive contrast enhancement, SUACE algorithm, Tyler Coye algorithm	2D	Yes	Accuracy DRIVE:94.11% Accuracy STARE:94.89%
Ambaji et al.	2018	Morphological operations, gaussian filter, adaptive thresholding	2D	Yes	Accuracy DRIVE:92.3% Accuracy STARE:82.6%
Lam et al.	2010	Multiconcavity modeling, perceptive transform, regularization.	2D	Yes	Accuracy DRIVE:94.72% Accuracy STARE:95.67%
Shabana et al.	2015	Matched filtering, morphological processing, adaptive thresholding	2D	Yes	Accuracy: 95.13
Chandani et al.	2013	Curvelet Transform, thinning operation, multi-layered thresholding, image histogram	2D	Yes	Accuracy DRIVE:97.23% Accuracy STARE:98.83%
Soumya et al.	2015	Histogram Equalization, Gaussian Filter, SVM classifier	2D	Yes	-

Minal et al.	2016	Morphological operations, histogram equalization, SVM classifier	2D	Yes	-
Benadict et al.	2011	parallel environment and parallel algorithm	2D	Yes	Accuracy: 92.60%
Lili Xu et al.	2010	Adaptive local thresholding, SVM classifier	2D	Yes	Accuracy: 93.20%
Muhammad et al.	2012	gradient vector field, morphological operations, gabor filter	2D	Yes	Accuracy DRIVE:96.15% Accuracy STARE:97.63% Accuracy CHASE DB1: 97.12%
Wendeson et al.	2016	Combined matched filters, frangi's filter, gabor filter, simple thresholding	2D	Yes	Accuracy DRIVE:94.64% Accuracy STARE:95.32%
Soares et al.	2006	Gabor wavelet transform, GMM classifier	2D	Yes	Accuracy DRIVE:96.14% Accuracy STARE:96.71%
Kumar et at.	2014	Optimized Gabor filter, histogram equalization. Image format conversion.	2D	Yes	Accuracy: 99.72
Felipe-Riveron et al.	2006	Morphological operators, reconstruction by dilation, threshold by hysteresis.	2D	Yes	-
Al-rawi et al.	2007	Genetic algorithms - Gaussian matched filter. Image format conversion.	2D	Yes	MAA DRIVE: 94.22% AUC DRIVE: 95.82%
Odstrcilik et al.	2013	Matched filter, BS plane illumination correction, contrast equalization, thresholding.	2D	Yes	Accuracy: 95.39%
Gökhan et al.	2009	Ant, Matched filter. Image format conversion.	2D	Yes	-
Mohammadi et al.	2014	Back propagation neural network, Gaussian and Gabor filters.	2D	Yes	True Positive: 99% False Positive: 50%

Table 1: Summary of Proposals

IV. DISCUSSION

To perform this work, we made a systematic review exploring in different journals. First, the results have been filtered by a previous year and ordered by relevance. Next, we read the abstract of each article and we performed a selection of the best works for the full reading. Finally, we proceed to decide whether to include or discard the article from the survey.

Typical edge detection techniques, such as Sobel operator, Canny border detector, and Prewiit operator are not appropriate for vessel detection. We have revised several combination of algorithm (matched filtering, mathematical morphology) for the retinal vessels extraction. So, we can say that it is necessary more than one processing algorithm to acquire acceptable results, and before to segment the image it is convenient to do pre-processing tasks. In comparison with the manual labelled and segmentation, in manual process experts do not need pre-processing but it is a harder task. In order to test automatic methods there are some databases with labelled images.

Most methods detect vessels in normal retina images well, but they do not have any procedure to cope with lesions on images of abnormal retinas. In order to resolve it, more pre-processing tasks are required.

One common pre-processing task, is to obtain grayscale image from the green channel. Generally, blood vessels are darker than the background, although there are areas where the vascular network is not visible because its level is similar to the background. Several studies showed green channel save the best pixel information. Contrast enhanced is another of the most common pre-processing task, is did it in both healthy and pathological retinal images.

About the results, true positive cases are over 90%, but we note three points: in medicine we need to achieve 100% in both true positives and false negatives cases, and that they must work in bad quality images well.

All rights reserved by *www.ijsrd.com*

V. CONCLUSION

The set of algorithms studied reveals that to improve automatic segmentation of retinal vessels it is necessary to pre-process images and create segmentation methods by combination. This requirement has been a venue of research by itself in the last decade.

Pre-processing tasks are required before applying segmentation algorithms. The most common ones are contrast enhanced, extraction of green channel and convert to grayscale image. Also, since most cases algorithms working on grayscale intensity, users can convert to color image again after the process.

Best results are obtained in healthy retinal image. It seems that more research is needed over pathological retinal images and bad quality images. On the one hand, improving results on pathological retinal image is a mandatory goal for supporting medical diagnosis. On the other hand, improving results in bad quality images is an objective to achieve for populations where neither expensive nor sophisticated ophthalmology cameras are available.

In order to share the latest findings and help to real diagnosis this kind of algorithms could be part of a telemedicine system. Also, it could be available on the internet cloud.

REFERENCES

[1] S. Roychowdhury, D. D. Koozekanani, and K. K. Parhi , Blood Vessel Segmentation of Fundus Images by Major Vessel Extraction and Sub-Image Classification , IEEE Journal of Biomedical and Health Informatics , VOL. 19, Pages 1118-1028, 2016.

[2] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson and M. Goldbaum, Detection of blood vessels in retinal images using two-dimensional matched filters, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 8, NO. 3, SEPTEMBER 1989.

[3] O. Chutatape, Liu Zheng and S. M. Krishnan, Retinal blood vessel detection and tracking by matched Gaussian and Kalman filters, dings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 20, Pages 2538-2548, No 6,1998.

[4] Elisa Ricci and Renzo Perfetti, Retinal Blood Vessel Segmentation Using Line Operators and Support Vector Classification, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 26, NO. 10, OCTOBER 2007.

[5] A. M. Mendonca 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, SEPTEMBER 2006.

[6] Y. A. Tolias and S. M. Panas, A fuzzy vessel tracking algorithm for retinal images based on fuzzy clustering, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 17, NO. 2, APRIL 1998

[7] L. Gang, O. Chutatape and S. M. Krishnan, Detection and measurement of retinal vessels in fundus images using amplitude modified second-order Gaussian filter, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 49, NO. 2, FEBRUARY 2002.

[8] H. Shen, J. N. Turner, H. L. Tanenbaum, and B. Roysam, Rapid automated tracing and feature extraction from retinal fundus images using direct exploratory algorithms, IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE, VOL. 3, NO. 2, JUNE 1999.

[9] I. Liu and Y. Sun, Recursive Tracking of Vascular Networks in Angiograms Based on the detection-deletion scheme, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 12, NO. 2, JUNE 1993.

[10] Y. Zhao, L. Rada, K. Chen, S. P. Harding, and Y. Zheng, Automated Vessel Segmentation Using Infinite Perimeter Active Contour Model with Hybrid Region Information with Application to Retinal Images , IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 34, NO. 9, SEPTEMBER 2015

[11] B. Al-Diri, A. Hunter, and D. Steel, An Active Contour Model for Segmenting and Measuring Retinal Vessels, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 28, NO. 9, SEPTEMBER 2009.

[12] Xiaoyi Jiang, Member, IEEE Computer Society, and Daniel 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, JANUARY 2003.

[13] Adam Hoover*, Valentina Kouznetsova, and Michael 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, MARCH 2000.

[14] Joes Staal , Michael D. Abràmoff , Meindert Niemeijer, Max A. Viergeve , and Bram van Ginneken , Ridge-Based Vessel Segmentation in Color Images of the Retina , IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 23, NO. 4, APRIL 2004.

[15] R.Ghaderi H.Hassanpour M.Shahiri , Retinal Vessel Segmentation Using the 2-D Morlet Wavelet and Neural Network , International Conference on Intelligent and Advanced Systems ,2007 .

[16] Frédéric Zana and Jean-Claude Klein , Segmentation of Vessel Like Patterns Using MathematicalMorphology and Curvature Evaluation , IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 10, NO.7, JULY 2001 .

[17] Qiaoliang Li, Member, IEEE, Bowei Feng, LinPei Xie, Ping Liang*, Huisheng Zhang and Tianfu Wang , A Cross-modality Learning Approach for Vessel Segmentation in Retinal Images , IEEE Transactions on Medical Imaging ,PP- 0278-0062 (c) 2015 IEEE .

[18] Paweł Liskowski, Krzysztof Krawiec, Segmenting Retinal Blood Vessels with Deep Neural Networks IEEE TRANSACTIONS ON MEDICAL IMAGING, PP-0278-0062 (c) 2015.

[19] T. Chanwimaluang and Guoliang Fan, An Efficient Blood Vessel detection Algorithm for Retinal Images, Circuits and Systems, 2003. ISCAS '03. Proceedings of the 2003 International Symposium, 2003.

[20] Temitope Mapayi, Serestina Viriri, and Jules-Raymond Tapamo, Adaptive Thresholding Technique for Retinal Vessel Segmentation Based on GLCM-Energy

All rights reserved by *www.ijsrd.com*

Information, Computational and Mathematical Methods in Medicine, Volume 2015, Article ID 597475, 11 pages , 2015.
[21] Ana Salazar-Gonzalez, Djibril Kaba, Yongmin Li, and Xiaohui Liu,Segmentation of the Blood Vessels and Optic Disk in Retinal Images, IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 18, NO. 6, NOVEMBER 2014.
[22] P. Furtado, C. Travassos, R. Monteiro, S. Oliveira, C. Baptista, F. Carrilho [1]Serviço Endocrinologia, Segmentation of Eye Fundus Images by Density Clustering in Diabetic Retinopathy , PP- 978-1-5090-4179-4/17/$31.00 ©2017 IEEE ,2017.
[23] Ana Maria Mendonça, *Senior Member*, and Aurélio Campilho , Segmentation of Retinal Blood Vessels by Combining the Detection of Centerlines and Morphological Reconstruction, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 25, NO. 9, SEPTEMBER 006.
[24] A. M. R. R. Bandara and P. W. G. R. M. P. B. Giragama Base Hospital Kebithigollawa Kebithigollawa , A Retinal Image Enhancement Technique for Blood Vessel Segmentation Algorithm, ICIIS'2017 1570379063, PP- 978-1-5386-1676-5/17/$31.00 ©2017 IEEE .
[25] Ambaji S. Jadhav and Pushpa B. Patil, Detection of Blood vessels in Retinal images for diagnosis of Diabetics , Proceedings of the Second International Conference on Inventive Systems and Control (ICISC 2018) IEEE Xplore Compliant - Part Number:CFP18J06-ART, ISBN:978-1-5386-0807-4; DVD Part Number:CFP18J06DVD, ISBN:978-1-5386-0806-7 , 2018.
[26] Benson S. Y. Lam , Yongsheng Gao and Alan Wee-Chung Liew , General Retinal Vessel Segmentation Using Regularization-Based Multiconcavity Modeling, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 29, NO. 7, JULY 2010.
[27] Shabana Mol S, Prof. Deepa Thomas, Dr.Jubilant J Kizhakkethottam, Segmentation of the Blood Vessel and Optic Disc in Retinal Images Using EM Algorithm, IOSR Journal of Computer Engineering (IOSR-JCE)e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 17, Issue 6, Ver. V (Nov – Dec. 2015), PP 102-112 .
[28] Chandani Nayak, Lakhwinder Kaur , Retinal Blood Vessel Segmentation for Diabetic Retinopathy Using Multilayered Thresholding , International Journal of Science and Research (IJSR) , Volume 4 Issue 6, June 2015 .
[29] Soumya Sree M, Asst. Prof. A Rafega Beham, Automated Diagnosis of Retina Images for Diabetic Patients based on BP and SVM , International Journal of Computer Science and Mobile Computing , IJCSMC, Vol. 4, Issue. 2, February 2015, pg.299 – 306.
[30] Minal B. Wankhade, Dr. A. A. Gurjar, Detection of Retinal Blood Vessels for Disease Diagnosis, International Journal of Engineering Science and Computing , Vol.6, DOI 10.4010/2016.547, March 2016.
[31] J.Benadict Raja, C.G.Ravichandran, Blood Vessel Segmentation For High Resolution Retinal Images, IJCSI International Journal of Computer Science Issues, Vol. 8, Issue 6, No 2, November 2011.
[32] Lili Xu, Shuqian Luo , A novel method for blood vessel detection from retinal images , Xu and Luo BioMedical Engineering OnLine 2010 .
[33] Muhammad Moazam Fraz, Paolo Remagnino, Andreas Hoppe, Bunyarit Uyyanonvara, Alicja R. Rudnicka, Christopher G. Owen, and Sarah A. Barman , An Ensemble Classification-Based Approach Applied to Retinal Blood Vessel Segmentation, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 59, NO. 9, SEPTEMBER 2012.
[34] Wendeson S. Oliveira, Joyce Vitor Teixeira, Tsang Ing Ren, George D. C. Cavalcanti, Jan Sijbers, Unsupervised Retinal Vessel Segmentation Using Combined Filters, PLOS ONE | DOI:10.1371/journal.pone.0149943 February 26, 2016 .
[35] João V. B. Soares, Jorge J. G. Leandro, Roberto M. Cesar Jr., Herbert F. Jelinek, and Michael J. Cree , Retinal Vessel Segmentation Using the 2-D Gabor Wavelet and Supervised Classification, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 25, NO. 9, SEPTEMBER 2006.
[36] Saumitra Kumar Kuri, Md. Rabiul Hossain, Automated Retinal Blood Vessels Extraction Using Optimized Gabor Filter, INTERNATIONAL CONFERENCE ON INFORMATICS, ELECTRONICS & VISION 2014, 978-1-4799-5180-2/14/$31.00 , 2014.
[37] Edgardo Felipe-Riveron[1] and Noel Garcia-Guimeras , Extraction of Blood Vessels in Ophthalmic Color Images of Human Retinas, J.F. Martínez-Trinidad et al. (Eds.): CIARP 2006, LNCS 4225, pp. 118 – 126, 2006. © Springer-Verlag Berlin Heidelberg, 2006.
[38] *Mohammed Al-Rawi*, *Huda Karajeh*, Genetic algorithm matched filter optimization for automated detection of blood vessels from digital retinal images, computer methods and programs in biomedicine, May 2007.
[39] Jan Odstrcilik, Radim Kolar, Attila Budai, Joachim Hornegger, Jiri Jan, Jiri Gazarek, Tomas Kubena, Pavel Cernosek, Ondrej Svoboda, Elli Angelopoulou, Retinal vessel segmentation by improved matched filtering: evaluation on a new high-resolution fundus image database, The Institution of Engineering and Technology, Vol. 7, Iss. 4, pp. 373–383, February 2013.
[40] Jyotiprava Dash and Nilamani Bhoi , Detection of Retinal Blood Vessels from Ophthalmoscope Images Using Morphological Approach, Electronic Letter on Computer Vision and Image Analysis 16(1):1-14, 2017.
[41] S. Wilfred Franklin and S. Edward Rajan , Retinal vessel segmentation employing ANN technique by Gabor and moment invariants-based features, S.W. Franklin, S.E. Rajan / Applied Soft Computing 22 (2014) 94–100 , April 2014.

All rights reserved by *www.ijsrd.com*