Received Date: 02/05/2020 Acceptance Date: 15/05/2020 Publication Date: 31/05/2020

Wavelet based Image Matting model for Blood vessel Segmentation from Fundus Images

[1]Vadla Jagan Mohanachari, [2]Kommu Vineeth, [3]Cherukuru Uneesha, [4]Gujjala Mohan Kumar, [5]Talari VijayKumar, [6]V.V Satyanarayana Tallapragada

[1, 2, 3, 4, 5] Student-B.Tech Final Year, [6]Associate Professor,
[1, 2] Department of Electronics and Communication Engineering,
Sree Vidyanikethan Institute of Engineering and Technology, Tirupathi, India.
Email - [1]chary14021@gmail.com, [2]king.nani037@gmail.com, [3]uneesha2001@gmail.com,
[4]mohang3151999@gmail.com, [5]talarivijay40@gmail.com

Abstract: *The recent trend of segmenting blood vessels from retinal image is the need of the hour for ophthalmologists. In this paper, wavelet based method for blood vessels segmentation is proposed using a novel hierarchical image matting model that helps to get more precise results compared to the state of art techniques. Two techniques such as hierarchical strategy of selection and image matting model are combined. Such a model converts the input to final region by separating the foreground and background. In this paper, the trimap is generated using wavelet transformation and a scaling factor is applied to the wavelet transformation based on experimentations. Proposed method outperforms existing techniques in terms of performance, having very low time complexity and better accuracy.*

Key Words: *Blood vessels segmentation, region feature extraction, Image matting model, tirmap, wavelet.*

1. INTRODUCTION:

Retinal diseases have erupted and are evolving into the humans at a faster pace as the immunity levels decrease due to aging, hereditary and many other causes. To identify retinal diseases the structure of the retina need to be identified and properly extracted. Retinal blood vessels usually are a hard and found to be twine mesh like form or tree like structure [1]. This structural property seems to aid in the detection of various ailments that are having interrelation with ocular diseases viz., strokes, occlusions of veins etc[2-4]. Early stage detection of these diseases is possible only when the features that are extracted from the retina or eye image are of proper and conducive manner, hence, developing a way for the detection or identification of the disease at an early stage. Hence, these morphological features are imperative in the detection of the ailment.

Diseases such as ocular sicknesses and angiocardiopathy will be having a serious impact, hence, retinal analysis and further having the blood vessel analysis will result in having information regarding the ailments which are unknown and have not got diagnosed. Blood vessel segmentation has become an important parameter which has become imperative in the decision making[5]. The techniques that are existing for such vessel segmentation are of two types broadly. Supervised ad unsupervised, wherein the former extracts the vessel information using specific predefined functions and later uses unknown. In general, both are heuristic and it is a well known fact that supervised algorithms or techniques provide better accuracy when compared to the unsupervised algorithms.

Ridge profiles in the retinal images are used to extract features and extracted nearly 27 features which are further classified using KNN classifier[6]. Such a combination has resulted in better segmentation. Automatic segmentation of vasculature in retinal images using Bayesian classifier with Gaussian mixtures is carried out[7]. A seven dimensional characteristic vector is formed by the use of wavelet transform which uses Gabor as the basis function. Segmenting the blood vessels automatically by using AdaBoost in retinal images is done and has achieved better accuracy with forty one dimensional feature vector that is used for encoding the information[8]. This is also used for extracting the special properties from the image that is classified. Various classifiers exist and Neural network is one among them which is used for blood vessel segmentation in retinal images[9]. Pixels are classified using seven dimensional vector which consists of variour features viz., gray level and moment invariant features. These features are observed to be having a better representation of the image. Sohini Roychowdhury et al.[10] proposed a method to extract vessels and sub image classification using Gaussian Mixture Model (GMM) and proven to have less time complexity and observed to have 95.3% accuracy. Paweł Liskowski, Krzysztof Krawiec[11] proposed a supervised segmentation technique to segment the retinal blood vessels using deep neural networks and achieved an accuracy of upto 97%. Experiments were done to improve the performance based on averaging multiple prediction using CNN. This system is observed to outperform the existing systems[12]. Information increase is done dependent on the accessible examples utilizing profound systems. This kind of engineering catches setting and symmetric way which limits the information[13]. Upgrade of veins is a significant factor for examination of the retinal pictures. The multiscale neighborhood structure is utilized for improvement. Such a picture is called Hessian which is tried on 2-D DSA and 3D aortoiliac and cerebral MRA information [14]. A.D. Hoover et al.[15] has proposed a computerized technique for finding and outlining veins in the pictures from the visual fundus. Nearby and worldwide vessel highlights are utilized combined to portion the vessel arrange. An exactness of 90% is accomplished utilizing such a system [15].

This paper is organized as follows: Section II clearly describes the image matting model used in this work. Section III describes wavelet based image matting that can effectively extract the veinal structural from the retinal image. Section IV provides details on the methodology followed. Section V elaborates the results. Section VI gives the conclusions.

2. IMAGE MATTING:

For proper segmentation of the image the background and foreground need to be separated accurately. Hence, Image Matting is considered for such purpose. Such a matting aims to extract the foreground given a trimap of a picture. Concretely, the input image I are often considered as a linear aggregation of a foreground image F and a background image B:

$$I = a_z F + (1 - a_z) B \qquad (1)$$

where α_z indicates probability of foreground ranging between 0 to 1. Bayesian framework is used to solve matting problem. Maximum Likelihood is used for estimating the α value. A closed form solution is proposed which is shown to be an effective objective function that is derived from color smooth hypothesis for determining the optimal value for α. Local and global methods are analysed for α estimation[18]. A novel method is used to solve the large kernel matting[20-27] Laplacian and it will gives faster results[19]

3. WAVELET BASED IMAGE MATTING:

Wavelets are used for image enhancement before it passes to the proposed model. Image matting based on wavelet is novel technique for blood vessels segmentation which helps us to get more improved results under different circumstances.

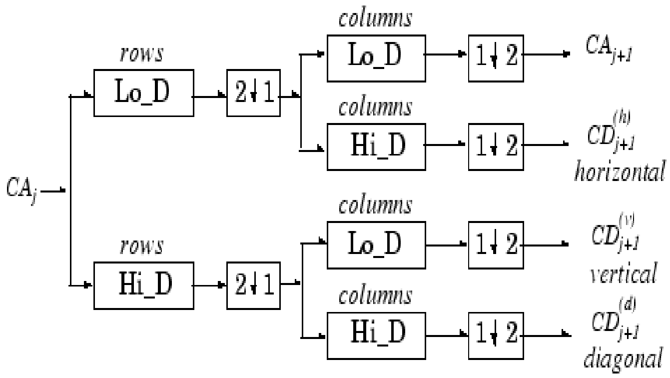

Fig. 1 Basic Wavelet Decomposition for Image Enhancement

Figure 1 shows that wavelet is used for decomposition and after decomposition is useful for analyzing the data in frequency domain and this work is related to frequency domain enhancement.

4. METHODOLOGY:

This section details about the process undergone in this proposed scheme. The trimap is generated using the matting function by the taking the fundus image as the input.

District highlights of veins have been utilized for vein division and performed well on division precision and computational effectiveness[28]. In this paper, automatically the trimap is generated for the fundus image based on the region features of the blood vessels. There exists various region based features. They are shown in Fig. 2.

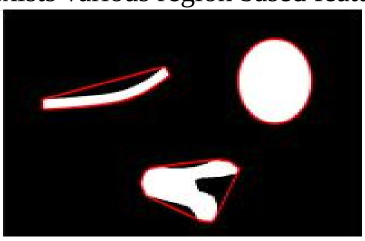

Fig. 2. Convex hull generated based on region features and thresholding[30].

The image for the illustration of convex hull. Trimap creation involves two main steps:
1) Segmentation and
2) Extraction of skeleton.

The process of trimap generation is shown in Fig.3. Foreground is separated using segmentation[29].

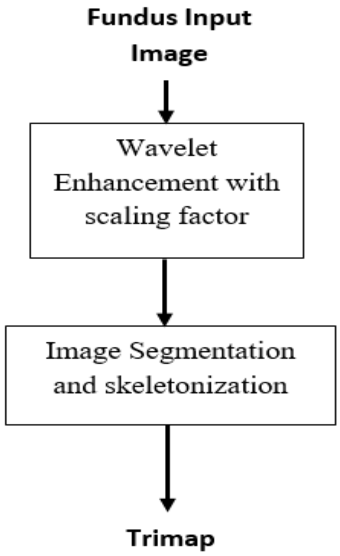

Fig. 3. The process of trimap generation in the proposed technique.

Right now, obscure pixels are stratified into various progressive systems. For the ith obscure pixel in U, its Euclidean separations with all vessel pixels in V are determined first. At that point the nearest separation di is picked and doled out to the ith obscure pixel. From that point onward, the obscure pixels are stratified into various pecking orders as indicated by the nearest separates. The primary chain of importance has the most minimal estimation of the nearest separation while the last order has the most elevated estimation of the nearest separation. The obscure pixels that live in low chain of command propose that they are near veins; The obscure pixels remain in high progression shows that they are far away from veins. which gives a praiseworthy procedure of stratifying the obscure pixels. Further, after post processing, the non vessel regions are removed and only vessel regions remain.

5. RESULTS:

This section clearly discusses the results based on the experiments performed on the publicly available datasets viz., DRIVE[6], which consists of 40 fundus images. The segmentation algorithms provide the segmented results which are further classified and compared with the ground truth images which provide accurate results. Hence, accuracy of the proposed technique is computed based on the metrics that are available. Accuracy, Sensitivity and Specificity are the three measures which are used for result analysis. Sensitivity is defined as the ratio of true positives to the total of true positives and false negatives. In contrast to sensitivity, specificity is the ratio of true negatives to the total of true negatives and false positives. Accuracy on the other hand, is defined as the ratio of sum of true positives and true negatives to all true values and negatives. Sensitivity (Se) and Specificity (Sp) reflect the algorithm's ability to detect vessel pixels and background pixels. Accuracy (Acc) is a global measure of classification performance combing both Se and Sp. The performance of the vessel segmentation method is also measured by the area under a receiver operating characteristic (ROC) curve (AUC). Here, the input retinal image is selected from DRIVE database. Because there is huge complexity in color image we selected to operate on green plane which is having better contrast than remaining two planes. Wavelet is frequency domain analysis and in our project we used it for image enhancement. Wavelet based image enhancement improves the quality of an input image to great extent compared to state of art techniques. A Hierarchical model is used to differentiate the input image into different three regions as foreground, background and unknown region. This is the unknown region obtained after some mdifications such as morphological processing.To calculate the neighberhood distance we used distance formula. We added the skeleton and segmented blood vessels to get the final results of blood vessel segmentation. These is groundtruth image provided by experts and collected from the DRIVE database.

Objective Analysis for given Image
Acc = 0.9972, Sp =0.9439, Se = 0.6882

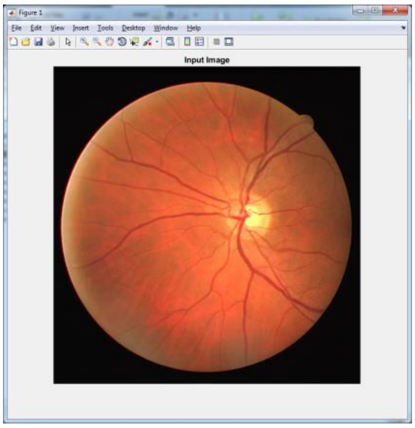

Fig.4 Input Image

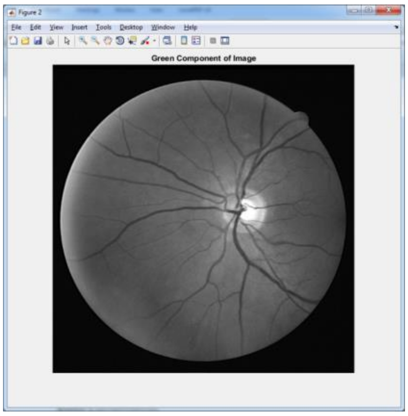

Fig.5 Green plane selected

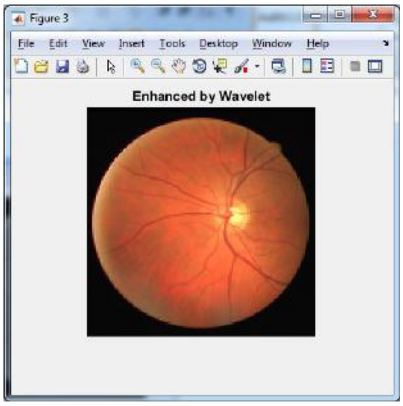

Fig.6 Wavelet Based Enhancement

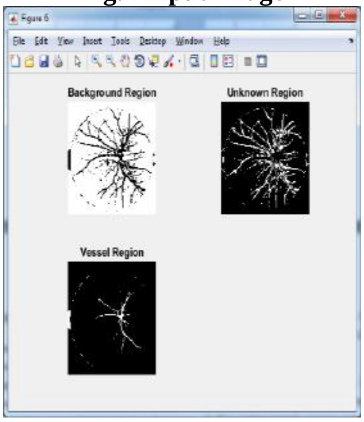

Fig.7 Segmentation results

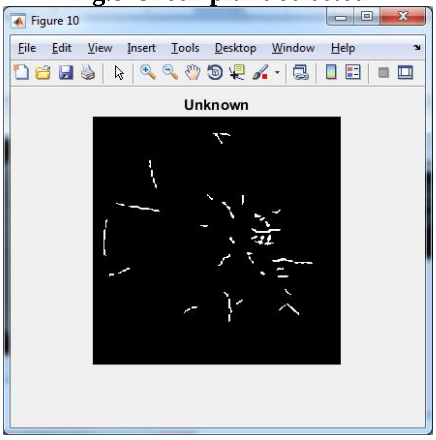

Fig.8 Unknown Region

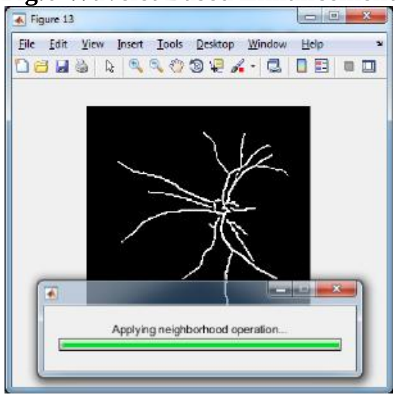

Fig.9 Applying neighberhood processing

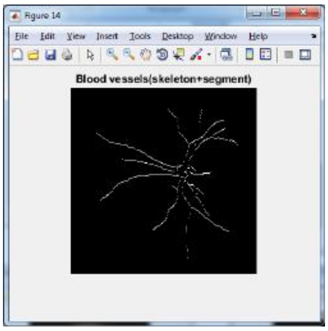

Fig.10 Blood vessel segmentation

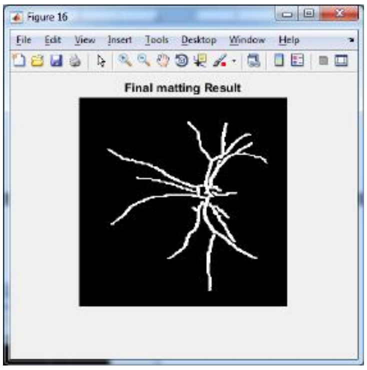

Fig.11 Final Matting results provided by experts

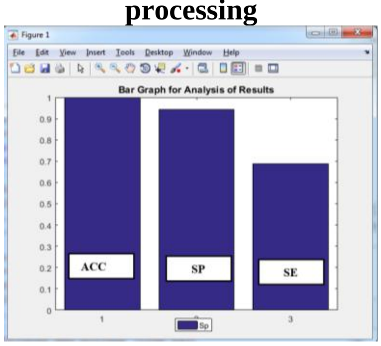

Fig.12 Bar graph for analysis of results

6. CONCLUSION:

Retinal blood vessels segmentation is crucial in many applications. In this implementation we successfully applied hierarchical strategy for segmenting an image into three regions like foreground, background and the final region is unknown pixels region. Image matting model further differentiates image into foreground and background region. Region features are used for image segmentation and this segmentation method is having very low computational complexity there is use of DRIVE database image samples which provides results better than all the state of art technique.

REFERENCES:

1. S. Abbasi-Sureshjani, M. Favali, G. Citti, A. Sarti, and B. M. terHaarRomeny, “Curvature integration in a 5D kernel for extracting vessel connections in retinal images,” IEEE Trans. Image Process., vol. 27, no. 2, pp. 606–621, Feb. 2018.
2. J. J. Kanski and B. Bowling, Clinical Ophthalmology: A Systematic Approach. London, U.K.: Elsevier Health Sciences, 2011.
3. M. W. K. Law and A. C. S. Chung, “Segmentation of intracranial vessels and aneurysms in phase contrast magnetic resonance angiography using multirange filters and local variances,” IEEE Trans. Image Process., vol. 22, no. 3, pp. 845–859, Mar. 2013.

4. Y. Cheng, X. Hu, J. Wang, Y. Wang, and S. Tamura, "Accurate vessel segmentation with constrained B-snake," IEEE Trans. Image Process., vol. 24, no. 8, pp. 2440–2455, Aug. 2015.
5. M. M. Fraz et al., "Blood vessel segmentation methodologies in retinal images—A survey," Comput. Methods Programs Biomed., vol. 108, no. 1, pp. 407–433, 2012.
6. J. Staal, M. D. Abramoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of the retina," IEEE Trans. Med. Imag., vol. 23, no. 4, pp. 501–509, Apr. 2004.
7. J. V. B. Soares, J. J. G. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree, "Retinal vessel segmentation using the 2-D Gabor wavelet and supervised classification," IEEE Trans. Med. Imag., vol. 25, no. 9, pp. 1214–1222, Sep. 2006.
8. C. A. Lupas, D. Tegolo, and E. Trucco, "FABC: Retinal vessel segmentation using AdaBoost," IEEE Trans. Inf. Technol. Biomed., vol. 14, no. 5, pp. 1267–1274, Sep. 2010.
9. D. Marín, A. Aquino, M. E. Gegúndez-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 Trans. Med. Imag., vol. 30, no. 1, pp. 146–158, Jan. 2011.
10. S. Roychowdhury, D. D. Koozekanani, and K. K. Parhi, "Blood vessel segmentation of fundus images by major vessel extraction and subimage classification," IEEE J. Biomed. Health Inform., vol. 19, no. 3, pp. 1118–1128, May 2015.
11. P. Liskowski and K. Krawiec, "Segmenting retinal blood vessels with deep neural networks," IEEE Trans. Med. Imag., vol. 35, no. 11, pp. 2369–2380, Nov. 2016.
12. D. Cortinovis and O. Srl. (2016). Retina Blood Vessel Segmentation With a Convolution Neural Network (U-Net). [Online]. Available: https:// github.com/orobix/retina-unet
13. O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.(Lecture Notes in Computer Science). Berlin, Germany: Springer, 2015, pp. 234–241.
14. A. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," in Proc. Int. Conf. Med. Image Comput.Comput.-Assist. Intervent. Berlin, Germany: Springer, 1998, pp. 130–137.
15. A. D. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," IEEE Trans. Med. Imag., vol. 19, no. 3, pp. 203–210, Mar. 2000.
16. Y.-Y. Chuang, B. Curless, D. H. Salesin, and R. Szeliski, "A Bayesian approach to digital matting," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), vol. 2, Dec. 2001, p. 264.
17. A. Levin, D. Lischinski, and Y. Weiss, "A closed-form solution to natural image matting," IEEE Trans. Pattern Anal. Mach. Intell., vol. 30, no. 2, pp. 228–242, Feb. 2008.
18. K. Heet, J. Sun, and X. Tang, "Fast matting using large kernel matting Laplacian matrices," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2010, pp. 2165–2172.
19. Y. Zheng and C. Kambhamettu, "Learning based digital matting," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Sep./Oct. 2009, pp. 889–896.
20. E. S. Varnousfaderani and D. Rajan, "Weighted color and texture sample selection for image matting," IEEE Trans. Image Process., vol. 22, no. 11, pp. 4260–4270, Nov. 2013.
21. Q. Chen, D. Li, and C.-K. Tang, "KNN matting," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2012, pp. 869–876.
22. E. Shahrian, D. Rajan, B. Price, and S. Cohen, "Improving image matting using comprehensive sampling sets," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2013, pp. 636–643.
23. D. Cho, S. Kim, and Y.-W. Tai, "Consistent matting for light field images," in Proc. Eur. Conf. Comput. Vis. Zurich, Switzerland: Springer, 2014, pp. 90–104.
24. L. Karacan, A. Erdem, and E. Erdem, "Image matting with KLdivergence based sparse sampling," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Dec. 2015, pp. 424–432.
25. D. Cho, Y.-W. Tai, and I. Kweon, "Natural image matting using deep convolutional neural networks," in Proc. Eur. Conf. Comput. Vis. Zurich, Switzerland: Springer, 2016, pp. 626–643.
26. C. Li, P. Wang, X. Zhu, and H. Pi, "Three-layer graph framework with the sumd feature for alpha matting," Comput. Vis. Image Understand., vol. 162, pp. 34–45, Sep. 2017.
27. Y. Aksoy, T. O. Aydin, and M. Pollefeys, "Designing effective interpixel information flow for natural image matting," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Apr. 2017, pp. 228–236.
28. Y. Lee and S. Yang, "Parallel block sequential closed-form matting with fan-shaped partitions," IEEE Trans. Image Process., vol. 27, no. 2, pp. 594–605, Feb. 2018.
29. M. M. Fraz et al., "An ensemble classification-based approach applied to retinal blood vessel segmentation," IEEE Trans. Biomed. Eng., vol. 59, no. 9, pp. 2538–2548, Sep. 2012.
30. Zhun Fan , Senior Member, IEEE, Jiewei Lu , Caimin Wei, Han Huang, Xinye Cai , and Xinjian Chen, Senior Member, IEEE" A Hierarchical Image Matting Model for Blood Vessel Segmentation in Fundus Images".IEEE VOL. 28, NO. 5, MAY 2019.