Significance Of Image Matting For Fundus Images

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Abstract— In this paper, a hierarchical image matting model is proposed to extract blood vessels from fundus images. More specifically, a hierarchical strategy is integrated into the image matting model for blood vessel segmentation. Normally the matting models require a user specified tri map, which separates the input image into three regions: the foreground, background and other regions. However, creating a user specified tri map is laborious for vessel segmentation tasks. In this paper, we propose a method that first generates tri map automatically by utilizing region features of blood vessels, then applies a hierarchical image matting model to extract the vessel pixels from the unknown regions. The proposed method has low calculation time and outperforms many other state-of-art supervised and unsupervised methods.

I.INTRODUCTION

Blood vessels can be conceptualized anatomically as an intricate network, or tree-like structure (or vasculature), of hollow tubes of different sizes and compositions including arteries, arterioles, capillaries, venules, and veins. Their continuing integrity is vital to nurture life: any damage to them could lead to profound complications, including stroke, diabetes, arteriosclerosis, cardiovascular diseases and hypertension, to name only the most obvious. Vascular diseases are often life-critical for individuals, and present a challenging public health problem for society. The drive for better understanding and management of these conditions naturally motivates the need for improved imaging techniques. The detection and analysis of the vessels in medical images is a fundamental task in many clinical applications to support early detection, diagnosis and optimal

treatment. In line with the proliferation of imaging modalities, there is an ever-increasing demand for automated vessel analysis systems for which where blood vessel segmentation is the first and most important step. As blood vessels can be seen as linear structures distributed at different orientations and scales in an image, various kernels (or enhancement filters) have been proposed to enhance them in order to ease the segmentation problem. In particular, a local phase based filter recently introduced by Lathen et al seems to be superior to intensity based filters as it is immune to intensity inhomogeneity and is capable of faithfully enhancing vessels of different widths.

It is worth noting that morphological filters such as path opening in combination with multiscale Gaussian filters. The main disadvantage of morphological methods is that they do not consider the known vessel cross-sectional shape information, and the use of an overly long structuring element may cause difficulty in detecting highly tortuous vessels.

II. EXISTING DESIGN

The distribution of vessel orientations around an image point is quantified using the new concept of entropy of vascular directions. The robustness of the method for OD localization is improved by constraining the search for maximal values of entropy to image areas with high intensities. This method produces segmentations by classifying each image pixel as vessel or non vessel, based on the pixel's feature vector. Feature vectors are composed of the pixel's intensity and two-dimensional Gabor wavelet transform responses taken at multiple scales. The probability distributions are estimated based on a training set of labeled pixels obtained from manual segmentations.

Disadvantages Of Existing Design

1.It only takes into account information local to each pixel through image filters, ignoring useful information from shapes and structures present in the image.

2. This method did not perform well for very large variations in lighting throughout an image, but this occurred for only one image out of the 40 tested from both databases.

3. It is possible to use only the skeleton of the segmentations for the extraction of shape.

III. PROPOSED DESIGN

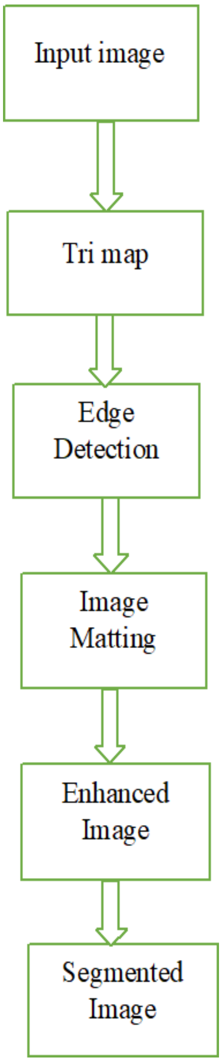

Figure 1: Block Diagram of the Proposed design

The input image is converted into the Gray scale image. From Gray scale image it is Categorized into three regions. The background region, foreground region and unknown region. This is called Tri-map. These regions are extracted from gray scale image. The image matting is done for regions. The output of image matting undergoes the enhanced technique and display the Segmented image.

TRI MAP

Region features of blood vessels have been used for blood vessel segmentation and performed well on segmentation accuracy and computational efficiency. In this paper, the tri map of an input fundus image is generated automatically by utilizing region features of blood vessels.

1. Area indicates the number of pixels in the region.
2. Bounding Box specifies the smallest rectangle in corporating the region.
3. Extent represents the region proportion in the bounding box.
4. V Ratio represents the ratio of the length to the width of the bounding box.
5. Convex Hull means the smallest convex polygon in corporating the region.
6. Solidity represents the region proportion in the convexhull.

The CV model was initially proposed by Chan and Vese to solve the piecewise constant segmentation problem. It has been widely used and extended to address a wide range of segmentation problems. Without loss of generality, here we choose the 2- dimensional (2D) segmentation problem as an example. Denoting a given image by u0(x), x = (x1; x2), the CV model can be formulated as the energy minimization problem below:

Vessel Skeleton Extraction aims to further distinguish the unknown regions and provide more information on blood vessels. In Section V(B)" Vessel Segmentation Performance", the effectiveness of vessel skeleton extraction will be presented.

IMAGE MATTING:

Hierarchical image matting model is proposed to label the pixels in the unknown regions as vessels or background in an incremental way. Specifically, after stratifying the pixels in unknown regions (called unknown pixels) into m hierarchies by a hierarchical strategy.

ENHANCED IMAGE:

Image enhancement is the procedure of improving the quality and information content of original data before processing. Common practices include contrast enhancement, spatial filtering, density slicing, and FCC.

SEGMENTED IMAGE:

Image segmentation is a method in which a digital image is broken down into various subgroups called Image segments which helps in reducing the complexity of the image to make further processing or analysis of the image simpler. Segmentation in easy words is assigning labels to pixels.

IV. RESULTS

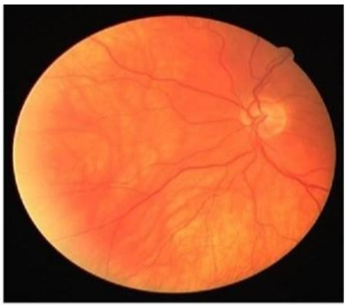

Figure 2: Input Image

The Input Image is Converted in to Gray Scale image.

Figure 3 : Gray Scale Image

Extraction of gray scale image to foreground region

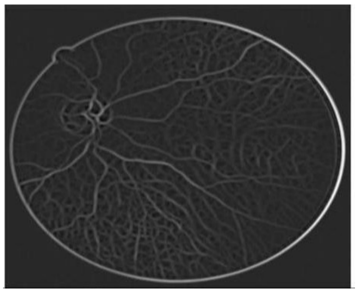

Figure 4: Foreground Region
Extraction of gray scale image to other region

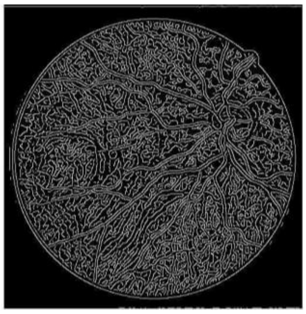

Figure 5: Other Region
Extraction of gray scale image to unknown region

Figure 6: Local Enhancement

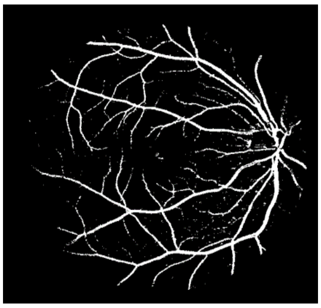

Figure 7: Output Image

IV. CONCLUSION

Image matting means precisely segmenting the foreground from an image, which is crucial in many important applications. However, to the best of our knowledge, image matting has rarely been employed previously to extract blood vessels from fundus image. The major reason may be that generating a user specified tri map for vessel segmentationis an extremely laborious and time-consuming task. In addition, a proper image matting model needs to be designed carefully to improve the vessel segmentation performance. In order to address these issues, region features of blood vessels are first employed to generate the tri map automatically.

Then a hierarchical image matting model is proposed to extract the vessel pixels from the unknown regions. More specifically, a hierarchical strategy is integrated into the image matting model for blood vessel segmentation. The proposed model is very efficient and effective in blood vessel segmentation, which achieves a segmentation accuracy of 96:0%, 95:7% and 95:1% on three public available datasets with an average time of 10:72s, 15:74s and 50:71s, respectively. The experimental results show that it is a very competitive model compared with many other segmentation approaches.

V. REFERENCES

[1] S. Abbasi-Sureshjani, M. Favali, G. Citti, A. Sarti, and B. M. T. H.Romeny, "Curvature integration in a 5d kernel for extracting vessel connections in retinal images," IEEE Transactions on Image Processing, vol. PP, no. 99, pp. 1–1, 2017.

[2] J. J. Kanski and B. Bowling, Clinical Ophthalmology: A Systematic Approach. Elsevier Health Sciences, 2011.

[3] M. W. Law and A. C. Chung, "Segmentation of intracranial vessels and aneurysms in phase contrast magnetic resonance angiography using multirange filters and local variances," IEEE Transactions on image processing, vol. 22, no. 3, pp. 845–859, 2013.

[4] Y. Cheng, X. Hu, J. Wang, Y. Wang, and S. Tamura, "Accurate vessel segmentation with constrained b-snake," IEEE Transactions on Image Processing, vol. 24, no. 8, pp. 2440–2455, 2015.1

[5] M. M. Fraz, P. Remagnino, A. Hoppe, B. Uyyanonvara, A. R. Rudnicka,C. G. Owen, and S. A. Barman, "Blood vessel segmentation methodologiesin retinal images–a survey," Computer Methods and Programs In Biomedicine, vol. 108, no. 1, pp. 407–433, 2012.

[6] J. Staal, M. D. Abr`amoff, M. Niemeijer, M. A. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of theretina," IEEE Transactions on Medical Imaging, vol. 23, no. 4, pp. 501–509, 2004.

[7] J. V. Soares, J. J. Leandro, R. M. Cesar, H. F. Jelinek, and M. J. Cree,"Retinal vessel segmentation using the 2-d gabor wavelet and supervised classification," IEEE Transactions on Medical Imaging, vol. 25, no. 9,pp. 1214–1222, 2006.

[8] C. A. Lupascu, D. Tegolo, and E. Trucco, "Fabc: Retinal vessel segmentation using adaboost," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 5, pp. 1267–1274, 2010.

[9] D. Mar´ın, A. Aquino, M. E. Geg´undez-Arias, and J. M. Bravo, "A newsupervised method for blood vessel segmentation in retinal images byusing gray-level and momentinvariants-based features," IEEE Transactionson Medical Imaging, vol. 30, no. 1, pp. 146– 158, 2011.

[10] P. Liskowski and K. Krawiec, "Segmenting retinal blood vessels with deep neural networks," IEEE Transactions on Medical Imaging, vol. 35,pp. 1–1, 2016.

[11] O. S. Daniele Cortinovis, "Retina blood vessel segmentation with a convolution neural network (u-net),"orobix/retina-unet, 2016.

[12] O. Ronneberger, P. Fischer, and T. Brox,"U-net: Convolutional networks for biomedicalimage segmentation," in International Conference on Medical image computing and computer- assisted intervention. Springer,2015, pp. 234– 241.

[13] A. F. Frangi, W. J. Niessen, K. L. Vincken, and M. A. Viergever, "Multiscale vessel enhancement filtering," in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 1998, pp. 130–137.

[14] 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, 2000.

[15] F. K. Quek and C. Kirbas, "Vessel extraction in medical images by wave propagation and traceback," IEEE Transactions on Medical Imaging, vol. 20, no. 2, pp. 117–131, 2001.

[16] K. Sun and S. Jiang, "Local morphology fitting active contour for automatic vascular segmentation," IEEE Trans. Biomed. Eng., vol. 59,pp. 464–473, 2012.

[17] J. Staal, M. Abramoff, M. Niemeijer, M. Viergever, and B. van Ginneken, "Ridge-based vessel segmentation in color images of the retina," IEEE Trans. Med. Imag., vol. 23, pp.

501–509, 2004.

[18] X. You, Q. Peng, Y. Yuan, Y. Cheung, and J. Lei, “Segmentation of retinal blood vessels using the radial projection and semi-supervised approach,” Pattern Recogn., vol. 44, pp. 2314–2324, 2011.

[19] E. Ricci and R. Perfetti, “Retinal blood vessel segmentation using lineoperators and support vector classification,” IEEE Trans. Med. Imag. ,vol. 26, pp. 1357–1365, 2007.

[20] C. Sinthanayothin, J. Boyce, H. Cook, and T. Williamson, “Automatedl ocalisation of the optic disc, fovea, and retinal blood vessels from digital colour fundus images,” Brit. J. Ophthal., vol. 83, pp. 902–910, 1999.

[21] D. Marin, A. Aquino, M. Gegundez-Arias, and J. Bravo, “A new supervised method for blood vessel segmentation in retinal images byusing gray-level and moment invariants-based features,” IEEE Trans.Med. Imag., vol. 30, pp. 146–158, 2011.

[22] H. Li, W. Hsu, M. Lee, and T. Wong, “Automatic grading of retinal vessel caliber,” IEEE Trans. Biomed. Eng., vol. 52, pp. 1352–1355, 2005.

[23] S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, and M. Goldbaum,“Detection of blood vessels in retinal images using two-dimensional matched filters,” IEEE Trans. Med. Imag., vol. 25, pp. 203–210, 1989.