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SEGMENTATION OF RETINAL BLOOD VESSELS BY TOP-HAT MULTI-SCALE DETECTION FOR OPTIC DISC REMOVAL

Ain Nazari[a,b], Mohd Marzuki Mustafa[a], Mohd Asyraf Zulkifley[a*]

[a]Department of Electric, Electronic & Systems Engineering, Faculty of Engineering & Built Environment, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.
[b]Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia.

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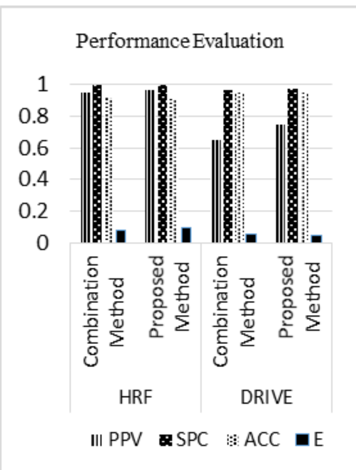
*Corresponding author
asyraf.zulkifley@ukm.edu.my

Graphical abstract



Abstract

Nowadays, an automatic retinal vessels segmentation is important component in computer assisted system to detect numerous eye abnormalities. There are various sizes of the retinal blood vessels captured from fundus image modality, which can be detected by using multi-scale approach. However, the main limitation of the current multi-scale approaches is the inability to remove the optic disc from the detected blood vessels. In this paper, a hybrid of multi-scale detection with pre-processing approach is proposed so that clearer vessel segmentation can be obtained. The proposed method embedded with a pre-processing phase that includes four series of processes that include Top-hat transformation as the main part. This technique will reduce the influence of the structure of optic disc and enhance the contrast of the vessel from the background. Then, the result from the pre-processing phase will be fed to the multi-scale detection to perform the segmentation. The proposed method is evaluated on two publicly available online databases: HRF and DRIVE. On HRF database, the best obtained precision and specificity values are 0.9689 and 0.9989, respectively. Meanwhile, for DRIVE database, the system performs well in all performance measures: precision, specificity, accuracy and error with the best values of 0.7541, 0.9739, 0.9510 and 0.0490, respectively. In conclusion, the proposed method is able to filter the unwanted optical disc from the fundus image effectively. Thus, retinal blood vessel image can be used for further analysis process and beneficial for pre-screening system development.

Keywords: Retinal image, segmentation, multi-scale line detection

Abstrak

Pada masa kini, segmentasi salur darah retina secara automatik ialah langkah yang penting dalam sistem berbantu komputer untuk mengesan pelbagai keabnormalan pada mata. Terdapat pelbagai saiz pada salur darah dapat digambarkan oleh modus imej fundus, di mana ia boleh dikesan dengan menggunakan pendekatan pelbagai-skala. Walau bagaimanapun, masalah utama bagi pendekatan pelbagai-skala terdapat pada masa kini ialah ia tidak mampu membuang kawasan lingkaran optik yang dapat dikesan pada salur darah. Dalam kajian ini, gabungan antara garis pengesanan pelbagai skala dengan pra-pemprosesan diperkenalkan bagi mendapatkan segmentasi salur darah yang lebih jelas. Kaedah yang dicadangkan melibatkan empat siri proses pra-pemprosesan, di mana trasnformasi 'Top-hat' merupakan bahagian utama dalam kajian ini. Teknik ini akan membuang kawasan yang mempengaruhi lingkaran optik dan meningkatkan perbandingan kontra di antara salur darah dengan latar belakang. Seterusnya, hasil daripada fasa pra-pemprosesan akan dimasukkan kepada garis pengesanan pelbagai skala untuk melakukan proses segmentasi. Kaedah yang dicadangkan dinilai dengan menggunakan dua pangkalan data dalam talian: HRF dan DRIVE. Bagi pangkalan data HRF, nilai yang terbaik untuk kejituan dan kekhusuan ialah 0.9689 dan 0.9989. Manakala bagi pangkalan data DRIVE, sistem ini menunjukkan prestasi yang baik bagi kesemua ukuran prestasi: kejituan, kekhusuan, ketepatan dan ralat dengan nilai bacaan terbaik iaitu 0.7541, 0.9739, 0.9510 dan 0.0490. Kesimpulannya, kaedah yang dicadangkan boleh menapis lingkaran optik yang tidak diperlukan dalam imej fundus secara efisien. Justeru, imej salur darah retina boleh digunakan untuk proses analisis seterusnya dan bermanfaat kepada pembangunan sistem pra-penyaringan.

Kata kunci: Imej retina, segmentasi, garis pengesanan pelbagai-skala

1.0 INTRODUCTION

The features extracted from retinal blood vessels such as length, width, tortuosity and branching patterns can be utilized for early stage detection, screening, treatment and evaluation of numerous diseases such as diabetes, hypertension, cardiovascular disease and stroke. Therefore, an automatic detection based on fundus image is necessary and important for the detection of blood vessels. On the other hand, manual segmentation of the retinal blood vessels is a time consuming process that requires experience due to the complexity of the vascular network [1]. In medical society, an automatic detection of retinal images is an important preliminary step in the development of computer-aided analysis for the abnormalities detection [2]. Thus, effective methods to segment the vessels in retinal images are crucial due to improved accuracy and consistency as well as reducing the time taken, even by the medical experts.

Currently, there are numerous works have been done on segmenting the blood vessels in retinal images. Methods in [1], [3], and [4] summarized the extensive surveys and reviews of the related issues. The method proposed by Ricci and Perfetti [5] segmented the retinal blood vessels just using basic line detector. This method efficiently detects the vessels within the central reflex. However, it tends to merge two identical size of vessels which are closely positioned. To overcome the drawback, the generalized multi-scale line detection is proposed by Nguyen et al. [6], which introduced the variable length compared to the fixed length scale. Even though the longer line has the same disadvantage like the basic line detector but the shorter line is able to counter the merging by removing the background noise to improve the segmented image. Moreover, to encounter the weakness of the individual line detection, combination method is introduced in [6], which combine all line responses at different scale with the same weight in order to get the vessel responses. By using the different scales, the longer length line is able to detect more vessels response compared to the shorter one. As a result, it gives a false response to the optic disc area and also the pathologies structures. On the other hand, Yanli [7] also proposed a method to improve the multi-scale line detection using top-hat transformation by replacing the inverted green channel with the enhanced intensity in the combination method.

The aforementioned methods perform well to detect the main parts of blood vessel but it does not able to remove unwanted optic disc. In the retinal image, optic disc is the brightest area with a circular shaped [8]. Some simple methods to remove the optic disc can be found in [9] and [10]. To address the above problem, an automated segmentation of the retinal image based on the pre-processing phase approach merge with the multi-scale detection is proposed. Firstly, in the pre-processing phase, there are four steps need to be done to obtain better contrast and non-optical disc image of vessels. Next, the resultant image from pre-processing phase will be processed with multi-scale detection to get the fine vessels. An overview of the approach is depicted in Figure 1 and each of the stage is further discussed in next sections.

2.0 EXPERIMENTAL

The two important parts of the proposed algorithm which are the pre-processing phase and also multi-scale detection as illustrated in Figure 1. In the pre-processing phase, there are four steps: (1) the color conversion, (2) adaptive histogram, (3) homogenized image and (4) Top-hat transformation. Thereafter, the multi-scale detection is performed to extract the blood vessels. The comprehensive explanation of each stage will be discussed as below.

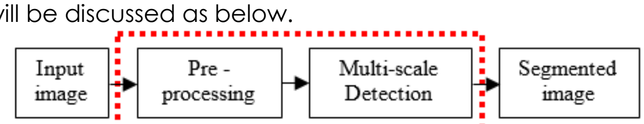
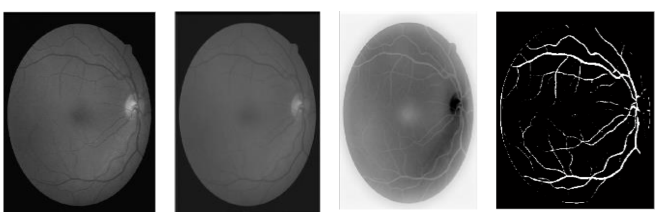


Figure 1 Block diagram for the overall proposed system.

2.1 Pre-Processing

Color fundus image is frequently associated with noise, low contrast and uneven illumination. Thus, the pre-processing step is required to improve the drawback of image. Unfortunately, the important data or information of image might be lost if improper pre-processing technique is applied. Therefore, in this proposed algorithm, the original RGB color image is converted to the intensity channel of the HSI color space as shown in Figure 2(a) to distinguish the shadows and to increase the intensity of the blood vessel in the color image compare to the RGB color channel [11]. Besides, HSI model is more robust to lighting change as shown in [12]. Intensity channel is holding an important information required for the blood vessels detection and the intensity itself alone is able to disassociate from the other two components which are hue and saturation channels. Referring to [13], hue channel is not stable for the low saturation and unreliable for the segmentation technique. Whereas, the intensity channel retains the relevant information from the red and blue channels since the intensity channel from HSI color space is defined as the average from the red, blue and green channel. Other than that, the intensity component capable to smooth out and reduce the noise in the image [14]. Subsequently, the resultant image is accomplished with adaptive histogram intended for the contrast enhancement as shown in Figure 2(b).

To decrease the influence of the background in fundus image, the homogenized process is applied as shown in Figure 2(c). In order to obtain the homogenized image, a 3×3 mean filter is convolved with Gaussian parameters of m×m = 9×9 with mean μ=0, variance σ^2= 1.82, which is able to reduce the noise efficiently [15]. Then, a 59×59 filter is applied to the image to reproduce background image. Finally, the homogenized image is acquired from the difference between the Gaussian image and the background image.



(a) (b) (c) (d)

Figure 2 Pre-processed images (a) Intensity of HSI (b) The result from adaptive histogram (c) Homogenized image (d) Enhanced vessels image

Furthermore, the morphological operator using structuring element are applied to enrich the vessel divergence from the homogenized image. This morphological erosion operation is done followed by dilation. It serves as a shape filter by erasing the object in the image that smaller from the size of the structuring element. In addition, morphological opening by linear structuring element oriented at the specific angle will eliminate a vessel or part of it when the structuring element cannot be contained within the vessels. The elimination will success with two conditions: (1) vessel and the structuring elements have orthogonal directions and (2) structuring element is longer than the vessel width. On the other hand, the detected vessels will be maintained when the vessel is parallel with the orientation of the structuring element [16]. The Top-hat transformation is expressed as the following equation:

$$I_{th}^{\theta} = \mathrm{I} - (\mathrm{I}_o S^{\theta}) \tag{1}$$

Where I_{th}^{θ} represents the Top-hat transformed image with the I is the image to be processed, θ represents the angular rotation of the structuring element and S referring to the structuring elements for morphological opening. Noted that, by considering the opening along a class of linear structuring elements, the sum of Top-hats along each direction will brighten the vessels. Regardless of the direction the length of the structuring elements is large enough to extract the vessels with the widest diameter. The morphological of Top-hat transformation is set with a length of 21 pixels and the rotation of angle at 22.5° for each set of line structuring elements. This size is selected due to the diameter range of the widest vessel of retinal images. Then, the sum of the Top-hat transformation is evaluated as:

$$I_{th} = \Sigma_{\theta \in A} I_{th}^{\theta} \tag{2}$$

Where I_{th} represents the sum of the top hat transformation implemented with θ degrees of the structuring element. The set A indicated by {x|≤x≤180, x mod (22.5) = 0}. So that, the bright retinal area and the isolated round of the optic disc will be removed since the diameter is less than the length of the structuring elements pixels. Hence, the sum of Top-hat on the filtered image will improve all vessels detection, involving small and tortuous vessel in any directions. The final complete pre-processing phase image (I_{ppp}) is presented in Figure 2(d).

2.2 Multi-Scale Detection

The proposed method is originated from the combination method of multi-scale line detection proposed by Nguyen et al. [6]. The main weakness of this method is it generates strong false vessel detection, especially in the optic disc region. Thus, the possibility of detecting incorrect vessel is high. The combination equation is stated in equation (3):

$$R_{combined} = \frac{1}{\eta_L}\left(\sum_L R_W^L + I_{igc}\right) \tag{3}$$

Where the η_L is the number of scales, R_W^L is the line responses of the line detector of scale L and W is the sub-window, and I_{igc} is the inverted green channel value at the corresponding pixel. The limitation of the method is demonstrated in Figure 3(a).

Conversely, the proposed method is based on the merging of the multi-scale line detection and the pre-processing phase. The end result from the pre-processing phase is fed into the association method. The proposed equation is defined in equation (4):

$$R_{enhanced} = \frac{1}{\eta_L}\left(\sum_L L * R_W^L + I_{igc} + I_{ppp}\right) \quad (4)$$

Where R_W^L is the line responses of the line detector at eight scales (L= 1, 3, 5, 7, 9, 11, 13 and 15) and η_L is the number of scales. In addition, each line response is set to the different weight according to the length of the line detection. This different weight will affect the vessel response due to the less background noise with shorter line detection. Meanwhile, I_{ppp} is the pre-processing phase output merges with the I_{igc} at each the corresponding pixel. This pre-processing phase produces enhanced input image that provides more blood vessels information. Then, this pre-processing is also good in reducing false vessel responses at the optic disc region. Figure 3 exhibits two samples of each database: HRF and DRIVE. It clearly shows that the proposed method is able to reduce the detection of false positive in the optic disc region. Row 1 and row 2 exhibit the healthy and glaucoma cases from HRF database. Meanwhile, row 3 and row 4 are the tested and trained images from DRIVE database.

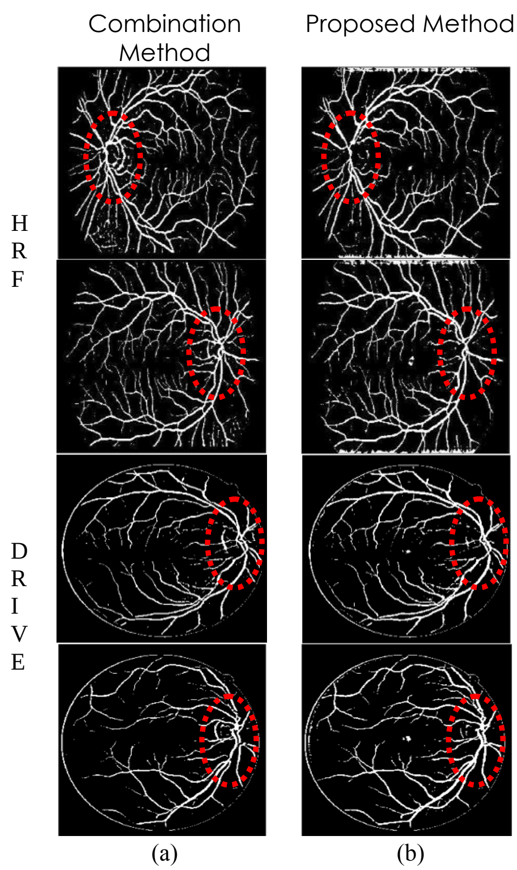


Figure 3 The visual comparison on treated images for HRF and DRIVE database (a) Segmented blood vessels images using combination method by Nguyen et al.'s method (b) Segmented using proposed method

3.0 RESULTS AND DISCUSSION

The performance of the proposed algorithm is evaluated based on two online databases of retinal images which are High-Resolution Fundus (HRF) [17] and Digital Retinal Images for Vessel Extraction (DRIVE) [18]. There are 45 images in HRF database that consists of healthy, diabetic retinopathy, and glaucoma cases. The ground truth images in HRF databases are produced by three experts in retinal image and the ophthalmology. Due to the hardware limitation, the size of images from HRF database will be reduced by 20 percent from the original size, which is from 2336×3504 to 468×701 pixels. While, for DRIVE database, there are 40 color images divided into two sets: test set and training set with 20 images of each set with the size of 584x565 pixels. Similar to the HRF database, the DRIVE database have three observers that manually segmented the ground truth images. In addition, both databases provided mask images that represent the field of view (FOV), where the images are automatically masked with background data is removed precisely. A total of 85 images were tested to validate the performance of the proposed algorithm.

Figure 4 displays samples of segmented blood vessels evaluated on HRF database while Figure 5 shows the segmented image based on DRIVE database. From both figures, it is clear that the proposed algorithm proficient in reducing the false detection in the optic disc region. However, one of the drawback of the proposed method is the detection of macula at the fundus image center. The macula can be clearly observed in Figure 4 at row 1 and Figure 5 at the same row. Meanwhile, for the quantitative evaluation, four performance measurements are selected, which are precision (PPV), specificity (SPC), accuracy (ACC), and error (E) as shown in Table 1. The TP, FP, TN and FN represent the true positive, false positive, true negative, and false negative, respectively.

Figure 6 displays the performance comparison between the proposed algorithm and the combination method for HRF and DRIVE databases. For HRF database, the highest performance value in terms of precision and specificity for the proposed method are 0.9689 and 0.9989, respectively. However, the accuracy and error need to be improved. Unlike HRF database, the proposed system obtained better performance form DRIVE database. In fact, the DRIVE database returns better performance measures of the segmentation output where the image occupied from the database is covered with the high pixel intensity. The performance measures of fundus images from DRIVE database produced average precision, specificity, accuracy, and error values of 0.7541, 0.9739, 0.9510, and 0.0490, respectively.

Table 1 Performance measures for retinal blood vessels segmentation.

Measure	Description
Precision (PPV)	TP / (TP + FP)
Specificity (SPC)	TN / (FP + TN)
Accuracy (ACC)	(TP+ TN) / (TP+TN+FP+FN)
Error (E)	(FP+FN) / (TP+TN+FP+FN)

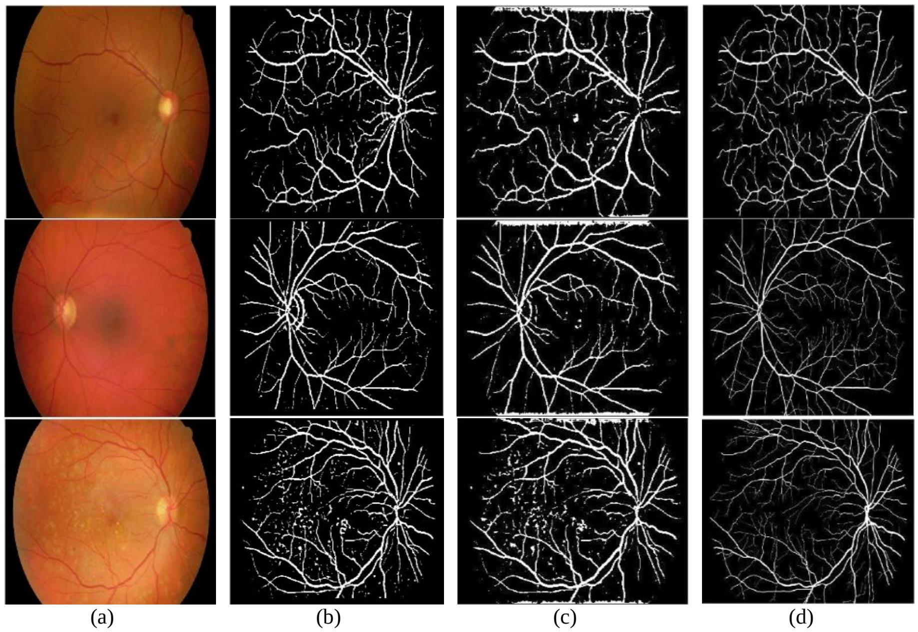


Figure 4 An examples of segmented image from HRF database: (a) Input image (b) Nguyen et al.'s method (c) Proposed method (b) Ground truth image

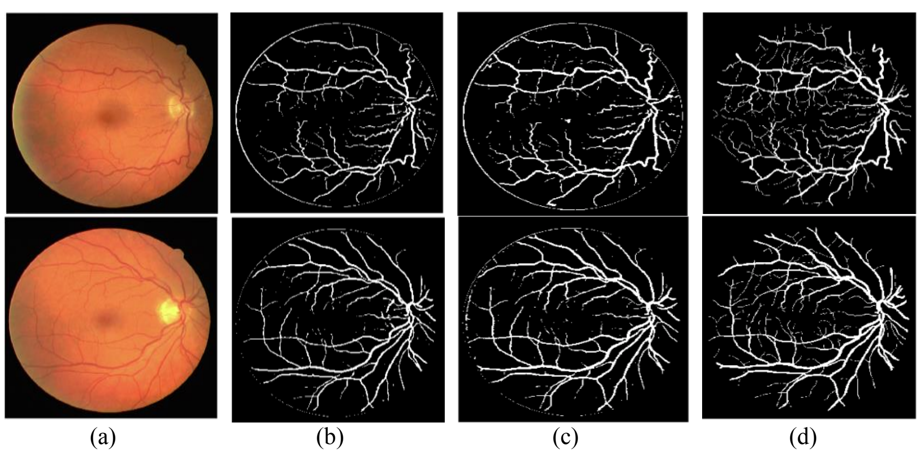


Figure 5 An examples of segmented image from DRIVE database: (a) Input image (b) Nguyen et al.'s method (c) Proposed method (b) Ground truth image

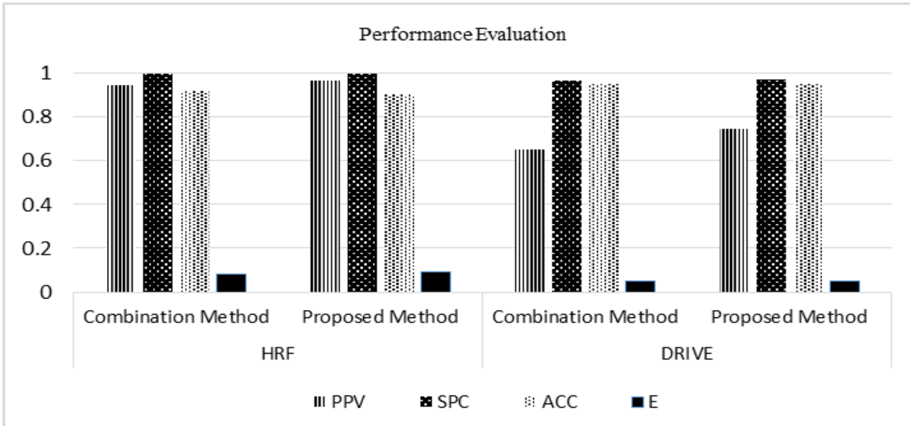


Figure 6 The performance evaluation for HRF and DRIVE databas

4.0 CONCLUSION

An efficient segmentation of blood vessels with optic disc removal method has been proposed for the fundus image. Two well-known publicly available databases, which are HRF and DRIVE have been used to validate and verify the performance of the proposed algorithm. The multi-scale detection and Top-hat are able to reduce and remove the optic disc region, which directly improve the vessel detection performance. The proposed algorithm successfully provides higher performance measures for the both databases. However, one of the restrictions that need to be improved is the false detection of the macula. Another limitation is the inclusion of noise in the optic cup region, due to the brightness feature which decreases the performance measures. For future work, the proposed algorithm will be improved in order to remove the unwanted macula and optic cup components.

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References

[1] Fraz, M. M., Barman, S. A., Remagnino, P., Hoppe, A., Basit, A., Uyyanonvara, B., Rudnicka, A. R. et al. 2012. An Approach To Localize The Retinal Blood Vessels Using Bit Planes And Centerline Detection. *Computer Methods and Programs in Biomedicin.* 108(2): 600–616.

[2] Fathi, A., Naghsh-Nilchi, A. R. & Mohammadi, F. A. 2013. Automatic Vessel Network Features Quantification Using Local Vessel Pattern Operator. *Computers In Biology And Medicine.* 43(5): 587–93.

[3] Kirbas, C. & Quek, F. K. H. 2003. Vessel Extraction Techniques And Algorithms: A Survey. Bioinformatics And Bioengineering, 2003. Proceedings. *Third IEEE Symposium.* 238–245.

[4] Fraz, M. M., Remagnino, P., Hoppe, a, Uyyanonvara, B., Rudnicka, a R., Owen, C. G. & Barman, S. a. 2012, October. Blood Vessel Segmentation Methodologies In Retinal Images--A Survey. *Computer Methods And Programs In Biomedicine.*

[5] Ricci, E. & Perfetti, R. 2007. Retinal Blood Vessel Segmentation Using Line Operators And Support Vector Classification. *Medical Imaging, IEEE Transactions* on. 26(10): 1357–1365.

[6] Nguyen, U. T. V, Bhuiyan, A., Park, L. A. F. & Ramamohanarao, K. 2013. An Effective Retinal Blood Vessel Segmentation Method Using Multi-Scale Line Detection. *Pattern Recognition.* 46(3): 703–715.

[7] Hou, Y. 2014. Automatic Segmentation of Retinal Blood Vessels Based on Improved Multiscale Line Detection. *8*(2): 119–128.

[8] Qureshi, R. J., Kovacs, L., Harangi, B., Nagy, B., Peto, T. & Hajdu, A. 2012. Combining Algorithms For Automatic Detection Of Optic Disc And Macula In Fundus Images. *Computer Vision and Image Understanding.* 116(1): 138–145.

[9] Khadijah, S., Zaki, M., Zulkifley, M. A. & Nazari, A. 2014. Tracing of Retinal Blood Vessels through Edge Information (November). 28–30.

[10] Salazar-Gonzalez, A., Kaba, D., Li, Y. & Liu, X. 2014. Segmentation of Blood Vessels and Optic Disc in Retinal Images. *IEEE Journal of Biomedical and Health Informatics.* 2194(c): 1–1.

[11] Jin, H., Miska, M., Chung, E., Li, M. & Feng, Y. 2004. Road Feature Extraction from High Resolution Aerial Images Upon Rural Regions Based on Multi-Resolution Image Analysis and Gabor Filters.

[12] Zulkifley, M. A. & Moran, B. 2010. Enhancement Of Robust Foreground Detection Through Masked Greyworld And Color Co-Occurrence Approach. *Proceedings - 2010 3rd IEEE International Conference on Computer Science and Information Technology, ICCSIT 2010.* 4: 131–136.

[13] Harangi, B. & Hajdu, A. 2014. Automatic Exudate Detection By Fusing Multiple Active Contours And Regionwise Classi Fi Cation. 54: 156–171.

[14] Winder, R. J., Morrow, P. J., McRitchie, I. N., Bailie, J. R. & Hart, P. M. 2009. Algorithms For Digital Image Processing In Diabetic Retinopathy. Computerized Medical Imaging And Graphics : *The Official Journal Of The Computerized Medical Imaging Society*. 33(8): 608–22.

[15] Diego Marín, Arturo Aquino*, Manuel Emilio Gegúndez-Arias, and J. M. B. 2011. A New Supervised Method For Blood Vessel Segmentatio In Retinal Images By Using Gray-Level And Moment Invariants-Based Features. *IEEE Transactions On Medical Imaging.* 30(1): 146–158.

[16] Fraz, M. M., Basit, a & Barman, S. a. 2013. Application Of Morphological Bit Planes In Retinal Blood Vessel Extraction. *Journal Of Digital Imaging*. 26(2): 274–86.

[17] Yin, Y., Adel, M. & Bourennane, S. 2012. Retinal Vessel Segmentation Using A Probabilistic Tracking Method. *Pattern Recognition.* 45(4): 1235–1244.

[18] Staal, J., Abràmoff, M. D., Niemeijer, M., Viergever, M. A. & van Ginneken, B. 2004. Ridge-Based Vessel Segmentation In Color Images Of The Retina. *Medical Imaging, IEEE Transactions* on. 23(4): 501–509.