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# Research Article
# Automatic Segmentation of Retinal Blood Vessels of Diabetic Retinopathy Patients using Dempster-shafer Edge Based Detector

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## Abstract

**Background and Objective:** Diabetic Retinopathy (DR) is a micro-vascular complication of diabetes which results in the alteration or total damage of retinal blood vessels. This is responsible for most partial loss of sight and blindness among diabetic patients across nations of the world. Early examination of retinal blood vessels could help in the detection and diagnosis of the symptoms of DR thereby curtailing its effects. **Methodology:** Dempster-shafer edge based detector was used to segment retinal blood vessels from retinal images sourced from Digital Retinal Image for Vessel Extraction (DRIVE). Prior to the segmentation, median filter, Contrast Limited Adaptive Histogram Equalization (CLAHE) and mahalanobis distance algorithms were used to preprocess the raw retinal images so that accurate blood vessels detection and segmentation will be achieved. **Results:** A segmentation accuracy of 0.9765 was recorded when receiver operating characteristics of the technique was computed. This showed that an acceptable degree of blood vessel segmentation was achieved. Furthermore, the segmented blood vessels are publicly available for academic and research purposes. **Conclusion:** Dempster-shafer edge based detector has been further shown to be an effective algorithm for blood vessels segmentation in healthy as well as DR retinal images.

Key words: Blood vessels, diabetes, diabetic retinopathy, DRIVE, retina, segmentation

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Data Availability: All relevant data are within the paper and its supporting information files.

## INTRODUCTION

Diabetes remains a prevalent disease across nations of the world. An average of 387 million people worldwide is diabetic, of these, 22 million are in sub-Saharan Africa while Nigeria hosts 4 million diabetic individual[1,2]. Diabetic Retinopathy (DR) has been revealed to be a micro vascular complication of diabetes which causes the gradual and eventual damage of retinal blood vessels. This is responsible for most cases of blindness among working class people of 20-74 years[3]. At the early stage of DR, its symptoms may not be noticeable, however, they become visible at the late stages when it might have wrecked irreversible damage that will make its treatment difficult or nearly impossible[2]. Therefore, early and accurate detection of the symptoms of DR could help reduce its havoc across the world[4,5].

The first noticeable sign of DR is the gradual swelling up of the retina blood vessel which later cause its expansion and the spilling of blood on the surface of the retina. This results in lesions like exudates (soft and hard), micro-aneurysms, cotton wool spots, hemorrhages etc. However, if diabetic patient could subject themselves to regular scanning of their retina, the symptoms of DR could be promptly detected and treated. Prior to the detection of DR symptoms, retinal blood vessels must be detected and extracted from retinal images, this itself is an hectic task for ophthalmologist. Manual approach to blood vessel segmentation is known to be tedious, time consuming, requires high level of expertise and prone to human errors[6-8]. This has made the automatic approach to blood vessel segmentation a valuable area of research. Yet, retinal blood vessel segmentation is a hectic task which becomes more tasking when the retinal images begin to show symptoms of these diseases[3,9]. Though several techniques have been proposed in literature for retinal blood vessel segmentation, accuracy of these techniques still remain a major issue of concern. Therefore, this article reports an automatic blood vessels detection and segmentation technique in DR retinal images using Dempster-shafer edge based detector.

Due to the complexity of blood vessels detection and removal from retinal images with symptoms of DR, a lot of techniques have been proposed in the literature. This includes blood vessels segmentation technique carried out by Zhao *et al.*[10]. Graph cut segmentation technique with retinex-based image inhomogeneity correction and local phase-based vessel enhancement was introduced. An AUC value of 0:953 was recorded when DRIVE dataset was used to evaluate the performance of the technique.

Similarly, directional response vector similarity and region growing method was used for retinal blood vessel segmentation by Lazar and Hajdu[11]. Other techniques that employed summed responses of a pixel for vessel segmentation suffer from false high responses. This was overcome using symmetry constrained multiscale matched filtering technique. DRIVE dataset was used to validate the technique and a AUC value less than 0.8 was achieved. Region based Otsu Thresholding was employed for retinal blood vessel segmentation by Khan *et al.*[12]. The CLAHE was employed to enhance the retinal images prior to segmentation. The performance of the technique was tested on DRIVE dataset and a AUC value of 0.882 was achieved. Deep convolutional neural network was proposed for retinal blood vessel segmentation by Vengalil *et al.*[13]. Convolutional neural network was integrated into deep learning framework for blood vessel segmentation. An AUC value of 0.8940 was achieved when the technique was evaluated on DRIVE dataset.

Furthermore, matched filtering and AdaBoost classifier were employed for retinal blood vessel segmentation by Memari *et al.*[14]. Prior to segmentation, the retinal image was enhanced using morphological operations while the contrast was increased using CLAHE. An AUC of 0.9795 was recorded when DRIVE was used to evaluate the performance of the segmentation technique. Fan *et al.*[15] introduced a hierarchical image matting model for retinal blood vessel segmentation. The continuous and extendible characteristics of retinal blood vessels were incorporated into the image matting model. The performance of the technique was carried out on DRIVE datasets and an accuracy of 0.881 was obtained.

An intelligent blood vessel segmentation technique that could track vessels in the presence of occlusion was presented by Hassan *et al.*[16]. The technique used hidden markov model for the vessel segmentation. When evaluated on DRIVE dataset, an AUC of 0.9 was achieved. In the same vein, convolutional neural network was employed for retinal blood vessel segmentation by Guleryuz and Ulusoy[17]. When the performance was carried out on DRIVE dataset using ROC curve, an accuracy of 0.9802 was achieved. Luo *et al.*[18] used condition random field to reduce the number of encoders and decoders used by U-Net for a more improved retinal blood vessel segmentation. The improved segmentation technique was validated on DRIVE dataset while ROC curve was used for the performance evaluation. A segmentation accuracy of 0.9748 was achieved. Modified U-Net called CDNet segmentation technique was employed for blood vessel segmentation by Peng *et al.*[19]. Here, segmentation task is seen as a set of convolution and deconvolution layers with down-sampling and up-sampling parts. An AUC value of 0.9841 was achieved when the technique was tested on DRIVE dataset. This article presents a Dempster-shafer edge based detector for retinal blood vessel segmentation. The performance of the technique was evaluated using sensitivity, specificity and AUC.

## MATERIALS AND METHODS

The steps employed in segmenting blood vessels from the raw retinal images are discussed in this section.

**Data acquisition:** Publicly available retinal images sourced from DRIVE[20]. The database contains 40 retinal images obtained at 45° Field of View (FOV) using a Canon CR5 non-mydriatic 3-CCD camera. The images were divided into 20 testing and training sets each, the 20 testing sets were used to validate the proposed technique. All the images have a resolution of 768×584 pixels with 8 bits per color plane. Also, 7 of the images contains pathological signs such as exudates and hemorrhages.

**Preprocessing:** Due to the invasive nature of retina capturing procedure, instances where users do not fully cooperate for proper data capturing may be experienced. Users may have tears covering their eyes which could blur the view of the retina. Also, some users may find it difficult to hold their eye still during the imaging process therefore causing the retinal images to be unevenly illuminated whereby some sections of the image becomes brighter or darker or in worst scenario some sections become washed out with a significant or total loss of contrast, this is called shading[21]. This unwanted information in images leads to the distortion of its pixels, preprocessing task helps to obtain a high quality image that has a uniform pixel distribution.

The preprocessing task was carried out to suppress unwanted information while enhancing the needed information. The retinal images acquired were coloured images that are made up of Red (R), Green (G) and Blue (B) components, however, red and blue components are very noisy and have low vessel-background contrast[9,22].

Therefore, the red and green components of the input retinal image were removed using Eq. 1 and 2, respectively while the green component that has the best contrast and less noise was retained using Eq. 3:

$$\text{inp\_img}\,(:,:,1) = 0 \qquad (1)$$

$$\text{inp\_img}\,(:,:,3) = 0 \qquad (2)$$

$$G\,(:,:,2) = \text{inp\_img}\,(:,:,2) \qquad (3)$$

Furthermore, every coloured image is made up of intensity, hue and saturation information and the most important of these for medical analysis is the intensity (since it shows the effect of varying degrees of light on the acquired retinal images). Hence, the hue and saturation information in the extracted green component were removed using Eq. 4, this is called gray scale conversion.

$$I = \text{rgb2gray}\,(\text{RGB}) \qquad (4)$$

where the extracted image intensity is denoted by I.

Furthermore, to enhance the intensity of the extracted green component, mahalanobis distance and CLAHE as proposed by Rahim *et al.*[23] were employed to identify and eliminate the background pixel while enhancing the foreground pixels only. In order to achieve this, the mean $\mu_N$ and standard deviation $\sigma_N$ of the statistical distribution of the intensities in input retinal image N were calculated. Thereafter, a sample mean $\widehat{\mu_N}$ and a sample standard deviation $\widehat{\sigma_N}$ were chosen as the estimators for $\mu_N$ and $\sigma_N$, respectively. The intensities of the image pixel (x, y) tagged I(x, y) were then compared with the mean intensity using Eq. 5. If I(x, y) is close to $\mu_N$ or if $d_M$ is lower than a specified threshold t then the pixel belongs to the background image β, then the foreground image was enhanced:

$$F_{enc} = \left| \frac{I(x,y) - \widehat{\mu_N}}{\widehat{\sigma_N}} \right| < t \qquad (5)$$

where, $F_{enc}$ is the enhanced foreground image. Prior to the blood vessels segmentation, the coloured fundus images were preprocessed in MATLAB programming environment. The preprocessing task entails extracting green component from the coloured fundus images as it is believed to have the best contrast and less noise[24]. Afterwards, the remaining colour information was removed from the green component by converting it to grayscale. Subsequently, median filtering, mahalanobis distance and contrast limited adaptive histogram equalization were all used to further enhance the intensity of the retinal images.

**Segmentation:** Segmenting blood vessels entails detecting them prior to the identification of their paths. To achieve this, preliminary vessel edge information and vessel map for the input retinal image was obtained using Dempster-Shafer (D-S) edge based detector proposed by Li and Wee[25]. D-S uses a probability-based fusion to merge the outputs of Laplacian of Gaussian (LoG) and canny edge detection filters in determining the continuous paths of a vessel after the starting point has been determined. The LoG filter was used to determine which pixels of the input retinal image is an edge pixel using Eq. 6-8:

$$h(x, y) = \exp\left(-\frac{x^2 + y^2}{2\sigma_N{}^2}\right) \tag{6}$$

$$\Delta^2 h\ (x, y) = \left(\frac{x^2 + y^2 - \sigma^2}{\sigma_N{}^4}\right)\exp\left(-\frac{x^2 + y^2}{2\sigma_N{}^2}\right) \tag{7}$$

$$g(x, y) = \Delta^2 h\ (x, y) \times F_{enc} \tag{8}$$

where, $F_{enc}$ remains the input enhanced foreground image of the input retina , g (x, y) is the output image, $\sigma_N$ remains the standard deviation, h (x, y) is the 2D Gaussian function and $\Delta^2 h$ (x, y) is the LoG filter.

Furthermore, in the edge detection task, after determining the edge pixels in the input image, canny filter was used to determine the horizontal, vertical and diagonal edges. The resulting edge gradient and direction was determined using Eq. 9:

$$G = \sqrt{(\delta_x I(x.y))^2 + (\delta_y I(x.y))^2} \tag{9}$$

Subsequently, the horizontal direction $G_y$ and the vertical direction $G_x$ were computed from gradient G using Eq. 10 and 11, respectively:

$$G_x = \delta_x F_{enc}(x, y) \tag{10}$$

$$G_y = \delta_y F_{enc}(x, y) \tag{11}$$

To achieve a more accurate and stable vessel edge detection, D-S based edge detector fuses the outputs g (x,y) of the LoG filter and the output of the canny edge. This is referred to as a joint $m_1 \oplus m_{2,}$ where, $m_1$ and $m_2$ are the outputs of LoG and Canny edge filter, respectively. The joint was obtained using Eq. 12 while the conflicting events caused by LoG and canny filter were removed using Eq. 13. Finally, the basic probability mass 'K' associated with the conflicts was calculated using Eq. 14:

$$m_1 \oplus m_2(A) = \frac{\sum_{B \cap C} = A^{m_1}(B) m_2(C)}{1 - K} \tag{12}$$

$$(m_1 \oplus m_2)(\ell) = 0 \tag{13}$$

$$K = \Sigma_{B \cap C = \ell}\ m_1(B)\ m_2\ (C) \tag{14}$$

Any edge detection algorithm could detect an edge or a non-edge vessel pixel, therefore, attempts must be made to distinguish the edge from the non-edge vessel pixel. To achieve this, the confidence level of an edge vessel pixel needs to be computed, this was represented by E while that of the non-edge vessel pixel was represented by subsequently, the edge confidence levels of the LoG filter $m_1$ was represented by $Em_1$, while that of canny filter and D-S was represented by $Em_2$ and $E_{DS}$, respectively.

These confidence levels were computed using Eq. 15, 16 and 17, respectively:

$$Em_1 = \frac{g(x, y)}{g_{max}} \tag{15}$$

$$Em_2 = \frac{g(x, y)}{\text{threshold}} \tag{16}$$

$$E_{DS} = \frac{Em_1 Em_2}{1\text{-}\ Em_1 Nm_2 - Nm_1 Em_2} \tag{17}$$

where, $Nm_1$ is the non-edge confidence level for the LoG filter is $Nm_2$ is the non-edge confidence level for canny edge filter, threshold is the max intensity gradient value. The non-edge confidence level for the D-S filter $NE_{DS}$ was calculated using Eq. 18:

$$NE_{DS} = 1\text{-}E_{DS} \tag{18}$$

A, B and C are event set produced by the D-S fusion, LoG filter and canny edge filter, respectively. The implementation was carried out in MATLAB R2015a programming environment.

**Performance evaluation:** The performance evaluation of the segmentation technique was carried out using sensitivity, specificity and Area Under Receiver Operating Characteristics Curve (AUC). These are metrics that have become a standard for evaluating segmentation techniques among others[26]. They are a function of the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values. Sensitivity of the technique can be calculated using Eq. 19 while specificity can be determined using Eq. 20:

$$\text{Sensitivity (Sn)} = \frac{TP}{TP + FN} \tag{19}$$

$$\text{Specificity (Sp)} = \frac{TN}{TN + FP} \quad (20)$$

The AUC of the segmentation technique was computed using Eq. 21 such that:

$$\text{AUC} = \frac{Sn + Sp}{2} \quad (21)$$

An AUC value that is less or equal to 0.50 signifies a fair segmentation result while a value equal to 1 denotes a perfect segmentation technique[12,16]. So the closer the ROC value is to 1, the more accurate is the segmentation result.

## RESULTS AND DISCUSSION

Figure 1 provides samples of pre-processed retinal images using median filter, CLAHE and mahalanobis distance. Samples of blood vessels extracted and the respective retinal images are provided in Fig. 2.

A sensitivity of 0.9885 and specificity of 0.9785 were achieved after the technique was evaluated with retinal images obtained from DRIVE. An AUC value of 0.9835 was also recorded. These values were compared with results obtained from similar segmentation techniques reported in the literature in Table 1.

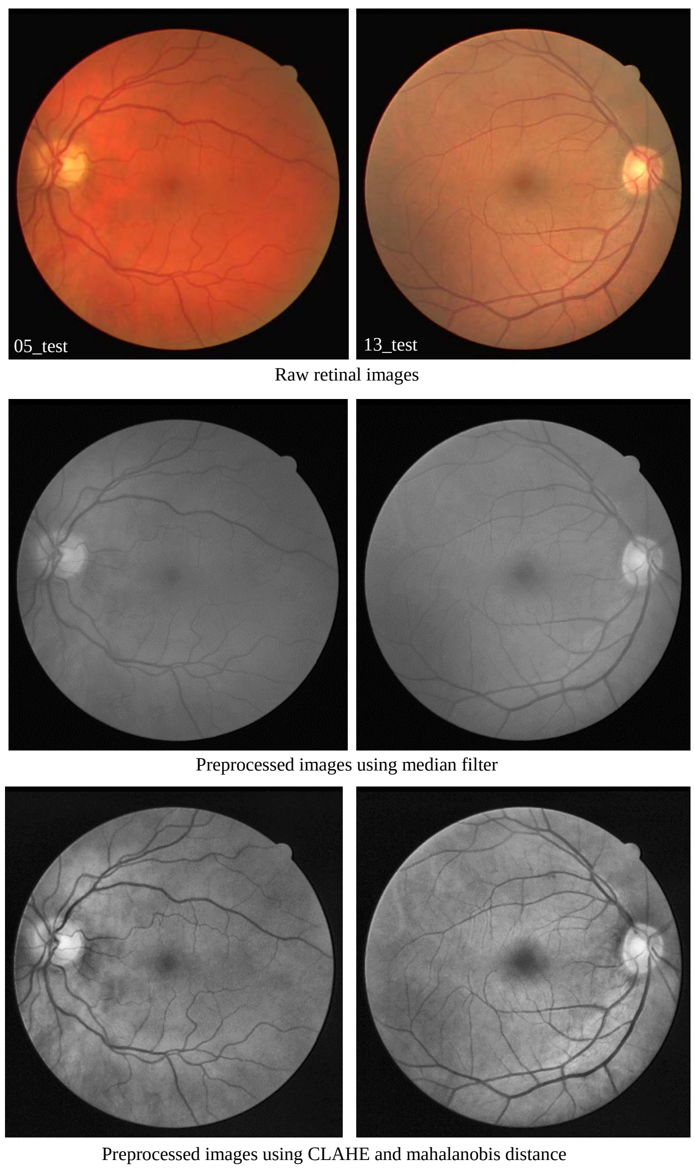


Fig. 1: Pre-processed retinal images using median filter, CLAHE and mahalanobis distance

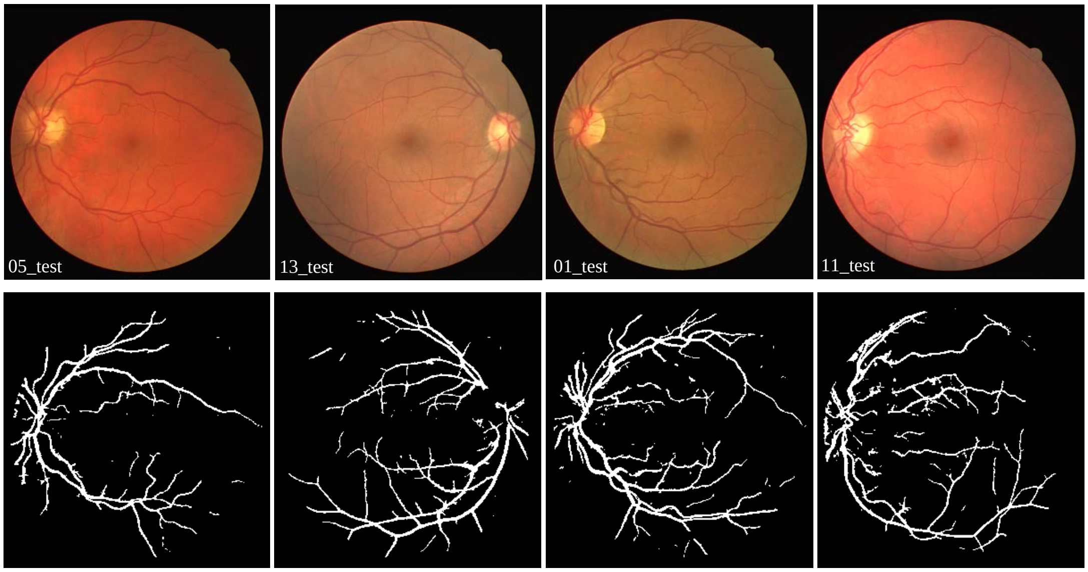


Fig. 2: Samples of raw images available in DRIVE and their respective segmented blood vessels

Table 1: Performance evaluation results of segmentation techniques

| Authors | Segmentation technique/validation dataset | Performance evaluation metrics | | |
|---|---|---|---|---|
| | | Sn | Sp | AUC value |
| Zhao *et al.*[10] | U-Net (DRIVE) | 0.7440 | 0.9780 | 0.9530 |
| Lazar and Hajdu[11] | Directional response vector similarity and region growing (DRIVE) | - | - | <0.8000 |
| Khan *et al.*[12] | Region based Otsu thresholding (DRIVE) | 0.746 | 0.9800 | 0.8820 |
| Vengalil *et al.*[13] | Deep convolutional neural network (DRIVE) | - | - | 0.8940 |
| Memari *et al.*[14] | Matched filtering and AdaBoost Classifier (DRIVE) | 0.8390 | 0.9915 | 0.9795 |
| Fan *et al.*[15] | Hierarchical image matting mode (DRIVE) | 0.7360 | 0.9810 | 0.8810 |
| Hassan *et al.*[16] | Hidden Markov model (DRIVE) | 0.8100 | 0.9700 | 0.9000 |
| Guleryuz and Ulusoy[17] | Convolutional neural network (DRIVE) | 0.9566 | 0.9802 | 0.9802 |
| Luo *et al.*[18] | Condition random field (DRIVE) | - | - | 0.9748 |
| Peng *et al.*[19] | CDNet (DRIVE) | 0.8112 | 0.9843 | 0.9841 |
| Proposed technique | Dempster-shafer edge based detector (DRIVE) | 0.9885 | 0.9785 | 0.9835 |

## DISCUSSION

The results of the preprocessing techniques adopted revealed that median filter does not enhance the contrast of the retinal images, it rather smoothens and removes noise from the input images as well as preserving the edges in the image. However, the application of mahalanobis distance and CLAHE made the blood vessels in the retinal images to be more visible for segmentation as shown in Fig. 2. Furthermore, the sensitivity value of 0.9885 achieved is the highest so far when compared to other segmentation techniques. Also, a specificity of 0.9785 achieved is good. An AUC value of 0.9835 recorded is also high when compared to other segmentation techniques as it is only surpassed by Peng *et al.*[19]. However, a comparison of the extracted blood vessels with the ground truth showed that, there are some thin blood vessels that D-S edge based detector could not capture. Therefore, future works can be tailored at enhancing D-S edge based detector so as to accommodate these thin blood vessels.

## CONCLUSION

Blood vessels detection and extraction from retinal images remains a vital research area that have witnessed new techniques being introduced day by day. Literature has revealed that the detection and analysis of structural changes in blood vessels could greatly help in determining several biological diseases traceable to the retina. Future research can be directed at exploring other diseases whose symptoms are traceable to retinal blood vessels. Such diseases include hypertensive retinopathy, Glaucoma, arteriolar narrowing, mosaic synthesis, retinopathy of prematurity etc.

## SIGNIFICANCE STATEMENT

This study has explored D-S edge based detector as an effective technique for retinal blood vessel segmentation. It has also established the effect of median filter and CLAHE preprocessing techniques on enhancing retinal images before segmentation. Therefore, prospective researchers can adopt the technique for other segmentation task especially towards discovering the symptoms of other diseases.


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## REFERENCES


1. Fasanmade, O.A. and S. Dagogo-Jack, 2015. Diabetes care in Nigeria. Ann. Global Health, 81: 821-829.
2. Akande, N.O., O.C. Abikoye, P. Ayegba, B. Gbadamosi and A.A. Adegun, 2018. Segmented retinal blood vessels of healthy and diabetic retinopathy individual. J. Eng. Applied Sci., Vol. 22.
3. Mahendran, G. and R. Dhanasekaran, 2015. Investigation of the severity level of diabetic retinopathy using supervised classifier algorithms. Comput. Electr. Eng., 45: 312-323.
4. Gupta, A. and R. Chhikara, 2018. Diabetic retinopathy: Present and past. Procedia Comput. Sci., 132: 1432-1440.
5. Imani, E., H.R. Pourreza and T. Banaee, 2015. Fully automated diabetic retinopathy screening using morphological component analysis. Comput. Med. Imag. Graphics, 43: 78-88.
6. Akande, N.O., O.C. Abikoye, B. Gbadamosi, J. Ayoola and P. Ayegba *et al*., 2018. Vascular networks segmented from retinal images of hypertensive retinopathy and glaucoma patients. J. Eng. Applied Sci., (In Press).
7. Patil, S.R. and N.M. Gawade, 2015. Implementation of segmentation of blood vessels in retinal images on FPGA. Proceedings of the International Conference on Information Processing, Pune, India, December 16-19, 2015, Vishwakarma Institute of Technology, pp: 516-519.
8. Ramani, R.G. and L. Balasubramanian, 2016. Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis. Biocybernet. Biomed. Eng., 36: 102-118.
9. Wang, L., G. Liu, S. Fu, L. Xu, K. Zhao and C. Zhang, 2016. Retinal image enhancement using robust inverse diffusion equation and self-similarity filtering. PloS One, Vol. 11, No. 7. 10.1371/journal.pone.0158480.
10. Zhao, Y., Y. Liu, X. Wu, S.P. Harding and Y. Zheng, 2015. Retinal vessel segmentation: An efficient graph cut approach with retinex and local phase. PloS One, Vo. 10, No. 4. 10.1371/journal.pone.0122332 .
11. Lazar, I. and A. Hajdu, 2015. Segmentation of retinal vessels by means of directional response vector similarity and region growing. Comput. Biol. Med., 66: 209-221.
12. Khan, K.B., A.A. Khaliq and M. Shahid, 2016. A morphological hessian based approach for retinal blood vessels segmentation and denoising using region based otsu thresholding. PloS One, Vol. 11, No. 7. 10.1371/journal. pone. 0158996.
13. Vengalil, S.K., N. Sinha, S.S.S. Kruthiventi and R.V. Babu, 2016. Customizing CNNs for blood vessel segmentation from fundus images. Proceedings of the International Conference on Signal Processing and Communications, June 12-15, 2016, Bangalore, India, pp: 1-4.
14. Memari, N., A.R. Ramli, M.I.B. Saripan, S. Mashohor and M. Moghbel, 2017. Supervised retinal vessel segmentation from color fundus images based on matched filtering and AdaBoost classifier. PloS One, Vol. 12, No. 12. 10.1371/journal. pone.0188939.
15. Fan, Z., J. Lu, W. Li, C. Wei, H. Huang, X. Cai and X. Chen, 2017. A hierarchical image matting model for blood vessel segmentation in fundus images. Computer Vision and Pattern Recognition, pp: 1-10. http://arxiv.org/abs/1701.00892.
16. Hassan, M., M. Amin, I. Murtza, A. Khan and A. Chaudhry, 2017. Robust hidden markov model based intelligent blood vessel detection of fundus images. Comput. Methods Programs Biomed., 151: 193-201.
17. Guleryuz, M.S. and I. Ulusoy, 2018. Retinal vessel segmentation using convolutional neural networks. Proceedings of the IEEE 26th Signal Processing and Communication Applications Conference, May 2-5, 2018, Izmir, Turkey, pp: 1-4.
18. Luo, L., D. Chen and D. Xue, 2018. Retinal blood vessels semantic segmentation method based on modified U-net. Proceedings of the Chinese Control and Decision Conference (CCDC), June 9-11, 2018, Shenyang, China, pp: 1892-1895.
19. Peng, S., C. Zheng, F. Xu, H. Xiao, H.D. Nam and Y. Wu, 2018. Blood vessels segmentation by using CDNet. Proceedings of the IEEE 3rd International Conference on Image, Vision and Computing, June 27-29, 2018, Chongqing, China, pp: 305-310.
20. Anonymous, 2004. DRIVE: Digital retinal images for vessel extraction. Database, Utrecht, The Netherlands, University Medical Center Utrecht, Image Sciences Institute. http://www.isi.uu.nl/Research/Databases/DRIVE/
21. Tan, T.S., N.E. Ameen, W.H.W. Hitam, Y.C. Hum and C.K. Teoh, 2017. Preprocessing digital retinal images for vessel segmentation. Res. J. Applied Sci. Eng. Technol., 14: 1-6.

22. Zhu, C., B. Zou, R. Zhao, J.Cui, X. Duan, Z. Chen and Y. Liang, 2017. Retinal vessel segmentation in colour fundus images using extreme learning machine. Comput. Med. Imag. Graphics, 55: 68-77.
23. Rahim, H.A., A.S. Ibrahim, W.M.D.W. Zaki and A. Hussain, 2014. Methods to enhance digital fundus image for diabetic retinopathy detection. Proceedings of the IEEE 10th International Colloquium on Signal Processing and Its Applications, March 7-9, 2014, Kuala Lumpur, Malaysia, pp: 221-224.
24. Li, M., Z. Ma, C. Liu, G. Zhang and Z. Han, 2017. Robust retinal blood vessel segmentation based on reinforcement local descriptions. BioMed Res. Int., Vol. 2017. 10.1155/2017/2028946.
25. Li, X. and W.G. Wee, 2014. Retinal vessel detection and measurement for computer-aided medical diagnosis. J. Digital Imag., 27: 120-132.
26. Hajian-Tilaki, K., 2013. Receiver Operating Characteristic (ROC) curve analysis for medical diagnostic test evaluation. Caspian J. Intern. Med., 4: 627-635.