Automated Approach for Extraction of Retinal Blood Vessels

Dheyaa M. Abdulsahib¹,* and Hussain F. Jaafar²

¹College of Engineering, university of Babylon, Iraq - E-mail: diyaaalkaby@gmail.com
²College of Engineering, university of Babylon, Iraq E-mail: hussain_enga@yahoo.com
* Corresponding author: College of Engineering, university of Babylon, Iraq. Tel: +9647706050150.

Abstract. In the field of ophthalmology, retinal image analysis is crucial to extract many details that help doctors identifying retinal diseases at early stages, such details are the blood vessels, optic disk, and fovea. The exponential increase in number of diabetic retinopathy patients necessitates the use of computers to help doctors to diagnose and treat retinal diseases of the human eyes. Computer vision effectively helps doctors by analyzing and treating human retinas. In the field of ophthalmology, a color image (RGB image) of the eye fundus is captured by ophthalmoscopy. In this work, an automatic technique for extraction of human retinal blood vessels is proposed. The proposed method is based on three main stages, namely image pre-processing, initial segmentation of blood vessels and image post-processing. In the first stage, the contrast-limited adaptive histogram equalization is applied to the green component image to improve its contrast, and then it is remerged again with the red and blue components. In the second stage, the blood vessels are extracted using mean-C thresholding. Finally, in the third stage, many morphological operations are used to refine the segmented blood vessels image. The proposed method is validated using the expert ground truths with the DRIVE dataset in terms of pixels, and experimental results show sensitivity, specificity, accuracy and positive predictive value of 0.770816, 0.977575, 0.959993 and 0.7611835, respectively. The performance measures are compared with many recent related works and found to outperform most of them. The superior performance of this method proves that it is promising for mass screening of human fundus images.

Keywords: Biomedical imaging; Human retinal blood Vessels; Image Enhancement; Mean-C thresholding; Mathematical morphology.
1. Introduction

The exponential growth in the medical field necessitates the use of computers to help doctors diagnose and treat retinal diseases. Computer vision effectively helps doctors by analyzing and treating human retinas. In the field of ophthalmology, a color image (RGB image) of the eye fundus is captured by ophthalmoscopy. This method is called fundus imaging, and it shows all the details of the retina including the blood vessels (BVs), the fovea and the optic disk. Fundus imaging is used to diagnose numerous eye diseases, like hypertension, cardiovascular, diabetic retinopathy (DR), and glaucoma. This method uses a specialized camera which works with low-power microscope Saine and Tyler (2002). Figure 1 shows the main structures of a retinal fundus image.

![Fundus image with the main structures](image)

Retinal BVs are spread throughout the whole retina, and their details can provide significant information for the detection of many eye diseases including DR, hypertension, glaucoma, and arteriosclerosis. Moreover, extraction of the BVs can help locate other major retinal structures, namely the fovea and also help the doctors diagnose many measurable features of different eye diseases.

Many BVs segmentation methods are proposed in the literature. An automatic approach for extraction of BVs was proposed by Fraz et al. (2011) using combination of morphological operations and differential filtering. To extract the centerlines, the Gaussian first-order derivative is applied in four orientations. BVs shapes and orientations map are obtained by applying a multidirectional morphological operator, and a bit plane slicing of a grayscale image with enhanced BVs. The Gaussian first-order derivative is a very efficient tool in segmentation of BVs. This tool can detect BVs perfectly by Gaussian-shaped profile, but it is not suitable when the arterioles of the retinal image show prominent light reflexes, such as those of younger patients.

Fraz et al. (2013) proposed a new method using combination of retinal BVs skeleton extraction and multidirectional morphological operations. Directional differential operators are used to detect the skeleton of the main vessels, and mathematical morphology is used to obtain the retinal vasculature in RGB fundus image. Zhao et al. (2014) used contrast-limited adaptive histogram equalization (CLAHE) and 2D Gabor wavelet to improve image quality as pre-processing stage, and the image is then filtered by an anisotropic filter. The technique of region growing and models of region-based active contour are used to detect the BVs. This method could extract all wide and thin vessels precisely and because it is unsupervised method, it does not require manual segmentation in the training stage. The performance of this approach can be further improved by removing the active contour which moves to the pathological region in several abnormal retinal images.
Sreejini and Govindan (2004) used particle optimization to find the suitable filter among the Gaussian-matched filters and then to improve the accuracy of the retinal BVs detection. The green component image is filtered using median filter followed by applying optimized matched filter, and then the filtered image is thresholded using global thresholding. The experimental results showed that the multi-scale matched filter can achieve better performance than the single-scale matched filter in the BVs extraction.

Dash and Bhoi (2017) proposed a method which works on the basis of local adaptive thresholding by mean-C thresholding using three stages. Firstly, the image was enhanced by the CLAHE and median filter. Secondly, the mean-C thresholding was used to detect initial BVs, and in third stage, morphological operations were used to refine the initial results from the artifacts. Dash and Bhoi (2019) proposed morphological approach to extract the BVs by enhancing and smoothing the image using CLAHE. Kirsch’s method was used to extract the BVs, and morphological operations were used to refine the results. The main advantage of this approach is in its ability to identify the BVs without small artifacts.

Although the presented related methods could extract BVs with good performance measures but there are noticeable limitations and drawbacks to be overcome. These limitations are in the presence of high undesired false positives (FPs) in the BVs results, which affect the positive predictive value (PPV) dramatically. In this work, a novel method to extract retinal BVs in efficient and fast approach is proposed. This method is based on three stages: image pre-processing to enhance image quality, extraction of course BVs as preliminary BVs image and then refining the BVs image by filtering and morphological operations. In the image pre-processing, the green component image is used because it has better contrast than those in the other components, so it is pre-processed to improve its contrast and then the pre-processed image is merged again with the red and blue channels to achieve additional details that are helpful in the segmentation stage. In the second stage, mean-C thresholding is used to detect the BVs, and the C value is set by many experimental processes to achieve optimal outcomes. In the third stage, the segmented BVs image is refined to obtain the final result with superior performance measures.

The organization of this paper is as follows: section 2 includes pre-processing operations, segmentation of initial BVs, and refining of the segmented image. Section 3 presents the databases, used in this work, experimental results and discussions. Sec. 4 presents the conclusions and future works.

2. Methodology

The proposed method consists of three stages: the first stage is the image preprocessing to achieve image with better quality, the second stage is the segmentation stage to extract BV candidates, and the final stage is the post-processing stage to refine the image from non-BVs. In the Figure 2 a block diagram for the stages of the proposed method is presented.
Figure 2. A block diagram indicating the proposed method steps for detection of BVs.

2.1 Image pre-processing
Because of variability in the acquisition of fundus images and physical features of patient retinas, like iris, skin and color, most of retinal images are different in the illumination, and they are sometimes poorly contrasted. The BVs are not easily extracted from the background when the retinal image is uneven illuminated and/or poorly contrasted. Then, contrast enhancement is essential to improve the contrast of the image and to facilitate the extraction of the BVs accurately. In this work, image pre-processing for image improvement is proposed, where the green component image is obtained from the RGB color image and it is used for extraction of the BVs because it appears more contrasted against the background than the other components. The features of the green component are clearly obvious by its histogram as shown in Figure 3.
In this stage, the green image is enhanced using the CLAHE. The CLAHE is designed to operate on small tiles in the image, and not on the whole image. For each particular tile, the contrast transform function is calculated with adaptive histogram equalization. The contrast of each tile is improved in such a way that the histogram of the output region will match that specified region by the distribution value. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that may be presented in the image. Thus, the contrast of the image can be increased, and the BVs appear more contrasted. The last pre-processing image is achieved by merging and concatenating the pre-processed green component with the original red and blue components. Figure 4 illustrates visual comparison between original image and the result of pre-processing image for both color image and green component image.
Figure 4. Visual comparison for the pre-processing results (a) Original color image. (b) Color image after the pre-processing (c) Green component image (d) Pre-processed green component image. (e) Histogram of the green component image. (f) Histogram of the pre-processed green component image.
2.2 Segmentation of blood vessels

Image segmentation is a process of subdividing an image into multiple objects, it is also known as image objects (the objects represent a set of pixels with particular features). The purpose of image segmentation is to make it increasingly meaningful and easy to analyze. The greyscale image (known as black-and-white image) could be generated by setting image pixels to black for the values which are beyond a certain threshold, while the other pixels to white. In this work the mean-C thresholding has been used to extract the BVs from the pre-processed image. The advantage of using this method is that it can be used even for bad quality and uneven illuminated images. The mean-C thresholding (where C is a threshold value) is used to extract the BVs. The mean-C segmentation could be used by applying the following steps:

1. Select N as window of the mean filter.
2. Select value of C threshold.
3. Convolve the pre-processed image with the mean filter corresponding to the window size.
4. Subtract the convolved image from the pre-processed image.
5. The subtracted image is segmented with the threshold C.
6. Obtain the complement of the segmented image.

For selecting optimal value of the threshold C, a number of values between 0.02 and 0.06, with a step of 0.002 were examined. As shown in Figure 5, the PPV and sensitivity (SE) values are inversely correlated. When the value of C is increased, the PPV is increased, but the SE value will be decreased. Dash and Bhoi (2017) proposed that the optimal value of C is 0.042 to achieve reasonable balance between SE and PPV. This value is similar to the results that we obtained to achieve the best compromise between the PPV and SE. Dash and Bhoi proposed that the optimal value of window size is 13 × 13 which is the same we found as the optimal window size.

![Figure 5. The response of performance measures due to variation in the C.](image-url)
The two-dimensional convolution is used to convolve the pre-processed image with the mean filter. In spatial form, implementation of the two-dimensional convolution could be mathematically expressed as follows:

\[
c(n_1, n_2) = \sum_{k_1=-\infty}^{\infty} \sum_{k_2=-\infty}^{\infty} a(k_1, k_2) b(n_1 - k_1, n_2 - k_2)
\]

where \(c\) refers to the convolution operation, \(a\) and \(b\) represent the functions of the discrete variables \(n_1\) and \(n_2\).

The resulting image from the segmentation phase contains a lot of noises as shown in Figure 6. Thus, post-processing is crucial to remove the noises and then to achieve better results.

![Figure 6. Segmentation result. (a) Original green component image. (b) Blood vessels image using the mean-C thresholding.](image)

2.3 Post-processing

In the segmentation stage we have achieved a coarser BVs image with some artifacts (non-BVS). In this stage we try to refine the coarser BVs image to increase the accuracy of the results. As shown in Figure 6, a circle structure around the segmented vessels which is not BV can be observed. This circle structure should be removed to enhance the BVs image. Mask of fundus image refers to the parts of the fundus image which contain the eye details and area out of the mask is the background. Therefore, it is essential to generate the mask and then to be used in removing the circle structure around the detected BVs.

The retinal image consists of two main regions, region of interest (ROI) and dark surround region (DSR). The main ocular details of the retina are concentrated in the ROI, which is circular or semicircular-shaped and it occupies about 75% of the retinal fundus image, while the DSR is just a dark background region that surround the ROI and occupies about 25% of the fundus image Jaafar (2012). To detect the FROI of the image, the red channel of the main RGB image has been used because it is the highest brightness compared to the green and blue channels. To obtain the mask of the fundus retinal image (as a binary image) Otsu's method is used with red component image. The Otsu's method is based on choosing the global threshold value to minimize the interclass variance of the thresholded black and white pixels (see Figure 7a). To remove the circle structure, the mask image is subtracted from the coarser BVs as illustrated in Figure 7b. The final step in the refining phase is
based on using some filters and morphological operations, such as closing, dilatation and filling operations. The aim of filtering and morphological operations is to join the gaps in the image together by filling between them and by smoothing their outer edges to remove noises and non-BVs.

The morphological closing is based on dilation followed by erosion; hence it is effective to be used for smoothing the edges of detected vessels. To compensate the reduction in the detected vessels, due to smoothing operation, a morphological dilation is used to retrieve the original size of the BVs, and the suitable structuring element is found to be disk-shaped of radius 3 for both closing and dilation operations. The morphological filling is used to fill some holes in the thick vessels, created during the course BV segmentation. Figure 8 illustrates the final BVs image and the ground truth image (hand labeled by experts).

![Figure 8](image.png)

**Figure 7.** Circle removal. (a) The mask of the image. (b) Result of the blood vessels image after removing the circle.

![Figure 8](image.png)

**Figure 8.** (a) The blood vessels image produced by the proposed method, (b) The blood vessel image annotated by experts.
3. Results and Discussions
In this work, the proposed method was trained using 20 images from the DRIVE database and then tested using other 20 images provided with their ground truth images from the DRIVE database as well. Performance measures of the proposed method are calculated using the Equations (2-5) in terms of pixels. In these equations, the following four pixel types are used:

a. True positives (TPs): number of vessels pixels that are correctly detected as vessels.
b. True negatives (TNs): number of background pixels that are identified correctly as background.
c. False positives (FPs): number of background pixels that are wrongly detected as vessels.
d. False negatives (FNs): number of vessel pixels that are wrongly identified as background.

For each retinal image, the preceding pixel types are determined to calculate the performance measures individually. Then the average of each performance measure is calculated, from the whole image measures, to get the proposed method performance in terms of pixels.

\[
Sensitivity = \frac{TP_s}{TP_s + FN_s} \quad (2)
\]

\[
Specificity = \frac{TN_s}{TN_s + FP_s} \quad (3)
\]

\[
Accuracy = \frac{TP_s + TN_s}{TP_s + FP_s + TN_s + FN_s} \quad (4)
\]

\[
Positive\ predictive\ value = \frac{TP_s}{TP_s + FP_s} \quad (5)
\]

To evaluate the proposed method robustness, a comparison of the proposed method against the other previous related works, in terms of performance measures, are presented in Table 1. In the proposed method it appears that the average values of SE, specificity (SP), accuracy (ACC) and PPV are; 0.771, 0.978, 0.960 and 0.761 respectively. The superiority of SE and PPV indicates that the BVs are marked with more exactness. Although the approach proposed by Dash and Bhoi is similar to our proposed method in some parts, the SE and ACC of the proposed method outperform those in Dash and Bhoi. The reason behind that improvement in the performance is the efficient pre-processing step and the morphological operations which have very effective role in achieving the superior performance. The proposed method is also compared against other related works, which used different approaches, and showed superior performance as illustrated in Table 1.

In this work, the big challenge for obtaining competitive performance is in selecting the main factors, i.e. the C in the mean-C thresholding and the window size of the mean filter. Based on many experiments, it appears that the window of 13 × 13 can ensure optimal influence on the results in terms of average of the performance measures. The manipulation in the C of the mean-C threshold has a noticeable effect on the compromise between the TPs and the FPs and as a result on the compromise between the most informative measures, i.e. the SE and PPV. Experiments on the influence of the threshold C showed that an increase in the C will cause decrease in the SE and increase in the PPV and vice versa. Experimental tests have showed that the best value of the C for reasonable balance between SE and PPV is 0.042. Influence of the proposed method parameters on the rates of the performance measure demonstrates that it is robust and reliable, and the intervention on these parameters values is based on diagnostic requirements which are taken by the doctor. Figure 9 shows three color images, their binary BVs images by the proposed method, and their binary BVs images, annotated by experts.
Table 1. Comparison between the proposed method and other related works using DRIVE database.

| Author                  | SE   | SP   | ACC  | PPV  |
|-------------------------|------|------|------|------|
| Fraz et. al. (2011)     | 0.715| 0.977| 0.943| 0.821|
| Fraz et. al. (2013)     | 0.730| 0.974| 0.942| 0.811|
| Zhao et. al. (2014)     | 0.735| 0.979| 0.948| 0.836|
| Sreejini & Govindan (2015) | 0.713| 0.987| 0.963| Not reported |
| Dash & Bhoi (2017)      | 0.719| 0.976| 0.955| 0.746|
| Dash & Bhoi (2019)      | 0.703| 0.985| 0.951| 0.810|
| **Proposed method**     | **0.771** | **0.978** | **0.960** | **0.761** |

Figure 9. Inputs and results of blood vessels extraction for three images (a) Original color retinal images (b) Binary blood vessels images by the proposed method. (c) Binary blood vessels images, annotated by experts.
4. Conclusions

In this work, a novel approach for extraction of retinal BVs is proposed. The contribution of the proposed approach is in using the technique of remerging the pre-processed green component image with the other raw components, i.e. the red and blue components. The new color image after remerging operation will have additional details compared to the raw color image. Hence, it will be more informative to extract retinal information. In the green image enhancement, the CLAHE is used to increase image contrast. In the extraction of BVs, the mean-C thresholding is used to separate BVs structures from the background. The BVs image may contain some non-BVs due to existence of artifacts which may have similar features of true BVs. To remove detected artifacts and noises, morphological operations are used to refine the BVs image and hence the performance measure will be improved. The DRIVE dataset was used to test the proposed method and it is found to achieve superior performance compared to the state of the art methods. From many experimental results, we can conclude that the behavior of the proposed method with intervention to parameter values is robust. Intervention on the parameters is based on the diagnostic requirements and may be taken by the clinician to manipulate between the performance measure rates. The proposed approach has obtained SE, SP, ACC, and PPV of 0.771, 0.978, 0.960 and 0.761, respectively. In future, we will try to develop the current algorithm to detect the other retinal structures i.e. the fovea and the optic disk with competitive performance to recent related works.

Acknowledgements

The authors would like to thank the DRIVE Database Centre, (Staal et al.) for the cooperation in providing retinal images.

References

[1] Dash, J., & Bhoi, N. (2017). A thresholding based technique to extract retinal blood vessels from fundus images. Future Computing and Informatics Journal, 2(2), 103-109.

[2] Dash, J., & Bhoi, N. (2019). Retinal Blood Vessel Extraction Using Morphological Operators and Kirsch’s Template. In: Soft Computing and Signal Processing, Springer, Singapore, 603-611.

[3] Fraz, M. M., Remagnino, P., Hoppe, A., Uyyanonvara, B., Owen, C. G., Rudnicka, A. R., & Barman, S. A. (2011). Retinal vessel extraction using first-order derivative of Gaussian and morphological processing. In: International Symposium on Visual Computing, Springer, Berlin, Heidelberg, 410-420.

[4] 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), 274-286.

[5] Hasby, M., & Khodra, M. L. (2013). Optimal path finding based on traffic information extraction from Twitter. In: International Conference on ICT for Smart Society, IEEE, 1-5.

[6] Jaafar, H. F., Nandi, A. K. and Al-Nuaimy, W. (2011). Decision support system for the detection and grading of hard exudates from color fundus photographs. Journal of biomedical optics, 16(11), p.116001.

[7] Niemeijer, M., Staal, J. J., Ginneken, B. V., Loog, M., & Abramoff, M. D. (2017). DRIVE: digital retinal images for vessel extraction; 2004. WebLink: http://www.isi.uu.nl/Research/Databases/DRIVE

[8] Saine, P. J., & Tyler, M. E. (2002). Ophthalmic photography: retinal photography, angiography, and electronic imaging, Boston: Butterworth-Heinemann., 132.

[9] Sreejini, K., & Govindan, V. (2015). Improved multiscale matched filter for retina vessel segmentation using PSO algorithm. Egypt. Inform. J., 16 (3), 253–260.

[10] Staal, J. J., Abramoff, M. D., Niemeijer, M., Viergever, M. A., van Ginneken, B. (2004). Ridge based vessel segmentation in color images of the retina, IEEE Transactions on Medical Imaging, 23, 501-509.

[11] Zhao, Y. Q., Wang, X. H., Wang, X. F., & Shih, F. Y. (2014). Retinal vessels segmentation based on level set and region growing. Pattern Recognition, 47(7), 2437-2446.