Detection of Blood Vessels in Optic Disc with Maximum Principal Curvature and Wolf Thresholding Algorithms for Vessel Segmentation and Prewitt Edge Detection and Circular Hough Transform for Optic Dis

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RESEARCH PAPER

Detection of Blood Vessels in Optic Disc with Maximum Principal Curvature and Wolf Thresholding Algorithms for Vessel Segmentation and Prewitt Edge Detection and Circular Hough Transform for Optic Disc Detection

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Abstract

The retina is the part of the eye that protects parts of light-sensitive cells. The retina consists of four main parts, namely the blood vessel system, fovea, macula and optic discs. Blood vessels are one of the characteristics that can help in the diagnosis of various retinal diseases. This research discusses the application of algorithms for detection of blood vessels in optic discs. The blood vessels are segmented using the Maximum Principal Curvature algorithm. Before the segmentation process, images are filtered using a Gaussian filters and the optic disc removal is performed. After that the segmentation of vessels uses Wolf thresholding to convert images into binary images. The final step in blood vessels segmentation is removing fine lines that are not vessels using morphological operations. Optic disc detection is done using Prewitt edge detection and circular Hough transform. In optic disc detection, the input image is converted to grayscale and then complemented and improved contrast using contrast-limited adaptive histogram equalization. Then, the opening morphology and median filter were performed. After that, the Prewitt edge and circular Hough transform methods are applied to detect the location of the optic disc. After getting the blood vessel segmentation and knowing the location of optic disc, the last stage is combining the results of blood vessel segmentation with the location of the optic disc. The methods applied are quite efficient in detecting blood vessels at the optic location of the disc.

Keywords Maximum principal curvature · Wolf thresholding · Blood vessel · Prewitt edge detection · Circular Hough transform

1 Introduction

The eye is one of the most important senses for humans, whose function is to see. Various diseases can affect vision such as diabetic retinopathy (DR). The World Health Organization reports that the number of diabetics increased from 108 million in 1980 to 422 million in 2014 (Islam et al. 2017). Diabetic retinopathy causes complications such as heart disease, kidney failure, and diabetic retinopathy. Diabetic retinopathy (DR) is a condition that occurs due to damage to the retinal blood vessels. Patients with diabetic retinopathy must undergo regular eye checkups to detect vision problems early. Symptoms caused by diabetic retinopathy include hard exudate, soft exudate, bleeding, and micro aneurism (Fiandono and Firdausy 2018).

The retina is the part of the eye that protects parts of light-sensitive cells. The retina consists of four main parts, namely the blood vessel system, fovea, macula and optic discs. There are many types of diseases of the retina such as glaucoma, diabetic retinopathy, and maculopathy. Blood vessels are important features in the diagnosis and detection of retinal diseases so that the analysis of blood vessels becomes important in various clinical fields such as

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laryngology, oncology, ophthalmologists, and neurosurgery (Moccia et al. 2018).

Various methods have been widely applied to segment blood vessels. The thresholding method is a parametric and nonparametric approach. In the parametric approach modeling, every class is very exclusive, whereas the nonparametric method employs different criteria such as class variants (Dash 2018).

Likewise, optic discs can help detect various retinal diseases such as diabetic retinopathy in terms of shape, depth of optic disc or color of optic disc. Optic disc is divided into two regions, namely neuroretinal rim and optic cup (OC). The optic disc also helps to diagnose glaucoma which can cause blindness. This optic disc detection can help in diagnosing various diseases quickly so that it can help prevent and provide timely treatment of various diseases that cause blindness (Hamednejad 2016).

The results of blood vessel segmentation and optic disc location detection can be combined to detect blood vessels in the optic disc and help doctors to see the condition of them on the optic disc. This is done because the area is where the blood vessels come in and out, and it can also be seen how many blood vessels enter the retina. These conditions can help in detecting eye disease.

Bahadarkhan et al. (2016) conducted research on blood vessel segmentation using the Hessian morphological-based approach and Otsu thresholding in that framework, proposing CLAHE and morphological filters to eliminate noise. The Hessian matrix and eigenvalues are used to convert the retinal image to be larger and thinner. Otsu thresholding is used for blood vessel extraction. The method works efficiently (Bahadarkhan et al. 2016). Palgunadi (2019) conducted research on retinal fundus blood vessel segmentation using the hybrid method of Frangi filter and Otsu thresholding and morphology produces 86,896% specificity and AUC 89,041%, so that this method can be used as an alternative in blood vessel segmentation, but still produces little accuracy (Palgunadi 2019). Dash (2018) conducted research on retinal fundus blood vessel segmentation using Otsu thresholding with principal component analysis; it is found that the combination of principal component analysis and CLAHE methods provides a better image to be input during blood vessel segmentation. The entire process of the proposed method is simple but still requires a very long time. Thanh et al. (2019) conducted research on retinal fundus blood vessel segmentation using adaptive principal curvature and image derivative operators produce suitable segmentation, but there is still an optic disc in the final segmentation results. Blood vessel segmentation research was also carried out by Nagendra Pratap Singh and Rajeev Srivastava using SDOG matched filters; this study still yields an accuracy of 93% in the DRIVE dataset (Pratap and Rajeev 2018). Research on optic disc detection uses the Haralick correlation texture feature for optic disc segmentation. This research uses grayscale which produces pretty good accuracy, but the segmentation is still not perfect because there are still missing optic disc parts (Fatoki and Ojo 2018). Subsequent research on optic discs carried out by Porwal et al. (2018) using the IDRiD dataset and MESSIDOR resulted in quite good optic disc segmentation, but the resulting performance was still small at around 80.23%. Similar research conducted by Elbalaoui et al. (2018) still yields 84% performance in the DRIVE dataset.

2 Method

The methodology used in this study is the maximum principal curvature algorithm with Gaussian filter and Wolf thresholding for blood vessel segmentation using image input from the DRIVE dataset. Software design is done using MATLAB by converting images to green channels; after that, it is filtered using a Gaussian filter. Then, the maximum principal curvature algorithm is used to detect lines in blood vessels, and CLAHE is used to further clarify blood vessels. The optic disc is eliminated by removing the Gaussian filter with the results of the maximum principal curvature that has been given CLAHE. The results from CLAHE cause a little noise because a median filter is added to eliminate noise. The blood vessel segmentation stage uses Wolf thresholding to convert images into binary images. The last step is cleaning the image segmentation results of objects that are not included in blood vessels such as fine lines using the opening morphology, erosion morphology and the region of interest selection. The framework can be seen in Fig. 1.

In Fig. 1 after the blood vessel segmentation stage uses the maximum principal curvature, the next stage detects the optic location of the disc using Prewitt edge detection and circular Hough transform. In optic detection, the input disc

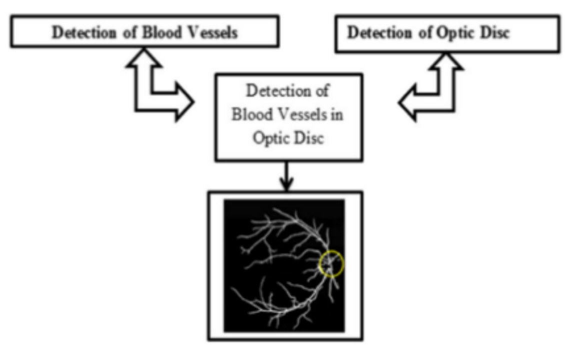


Fig. 1 Block diagram of the proposed method for detecting blood vessels and optic discs

image is converted to grayscale, and then complement and contrast are enhanced using CLAHE. The opening morphology and median filter were performed. After that, the Prewitt edge and circular Hough transform methods are applied to detect the location of the optic disc. After getting the blood vessel segmentation and knowing the optic location, the results of blood vessel segmentation are combined with the optic location of the disc.

2.1 Blood Vessel Segmentation

Figure 2 shows a process of blood vessel segmentation using maximum principal curvature and Wolf threshold.

2.1.1 Preprocessing

2.1.1.1 Green Channel The green channel component was chosen because blood vessels are more clearly seen than blue and red channels. Green channel is used in the preprocessing stage in the detection of blood vessels because it makes the blood vessel candidates more clearly visible. The green channel has a balanced histogram that is not too bright and dark than the red channel and blue channel, so it is better used in the segmentation process.

The results of the green channel process can be seen in Fig. 3.

2.1.1.2 Gaussian Filter Gaussian filter method is a method used to eliminate noise and blur an image. Gaussian filters are non-uniform low-pass filters. Gaussian filters do not maintain image brightness (Rahman et al. 2018). Gaussian filter uses Eq. (1):

$$G(n,m) = \frac{1}{2\pi\sigma^2} e^{\frac{-(n^2+m^2)}{2\sigma^2}} \tag{1}$$

where σ is the standard deviation that serves as a defense effect on the blur in the image. n, m are the pixel coordinates. G (n, m) is a Gauss matrix element at position [n, m]

If the value deviation is greater, the resulting image is more blurred. In this research, a Gaussian filter is applied at the preprocessing stage at the blood vessel segmentation stage.

Standard deviations are statistical values used to determine how the data are distributed in a sample, and determine the individual data points to the mean—or average—sample value.

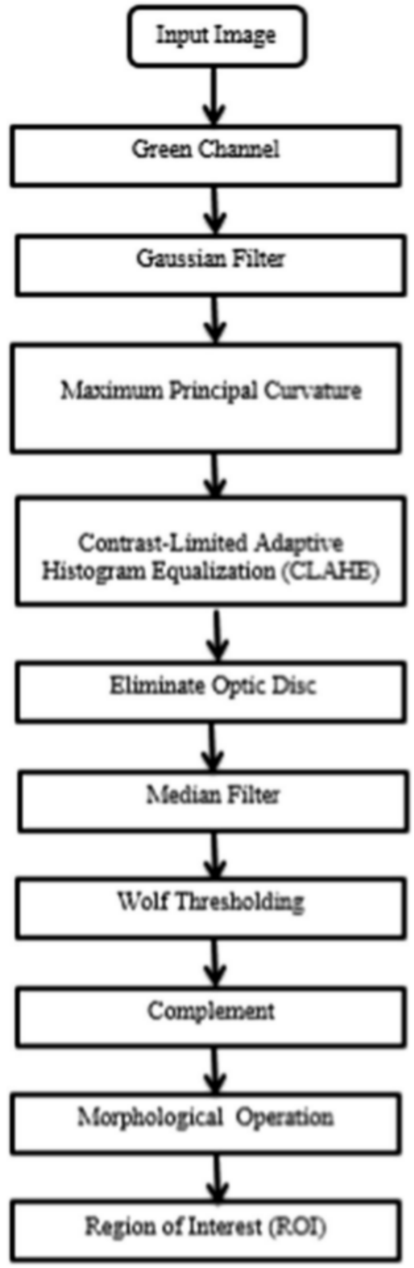


Fig. 2 Block diagram blood vessel segmentation with maximum principal curvature and wolf thresholding

2.1.1.3 Maximum Principal Curvature In the differential geometry, the principal curvature characterizes the level of curvature of the surface that can be calculated with the Hessian matrix. The eigenvalues and Eigen vectors of the Hessian matrix represent the essential features of the image. A large eigenvalue represents a greater Principal Curvature. While the smaller eigenvalues represent smaller Principal Curvatures (Xiao et al. 2019). The maximum and minimum Principal Curvature is defined as Eq. (2):

Fig. 3 Green channel obtained from the RGB channel separation in the DRIVE dataset image (Tuba and Mrkela 2017)

$$\lambda_{ij}^{+} = \max\left\{\lambda_{ij}^{(1)}, \lambda_{ij}^{(2)}\right\},$$
$$\lambda_{ij}^{-} = \min\left\{\lambda_{ij}^{(1)}, \lambda_{ij}^{(2)}\right\} \tag{2}$$

where λ is wavelength.

The Hessian matrix is a square matrix of second-order partial derivatives with scalar-valued functions, or scalar fields.

2.1.1.4 Contrast-Limited Adaptive Histogram Equalization (CLAHE) After getting a blood vessel candidate, the image is given enhancement separately to increase the contrast so that the blood vessels are sharper at this stage. Contrast-limited adaptive histogram equalization (CLAHE) is a method for increasing contrast in images to further sharpen blood vessels in this study. Contrast-limited adaptive histogram equalization divides the image into sections of identical size. At the contrast-limited adaptive histogram equalization stage, it can cause excessive noise (Dash 2018). The results of contrast-limited adaptive histogram equalization of blood vessels are more clearly visible.

2.1.1.5 Eliminating Optic Disc The segmentation results from contrast-limited adaptive histogram equalization (CLAHE) still have optic discs. Therefore, at this stage, the results of the Gaussian filter process are subtracted from the results of the maximum principal curvature process that has been given a CLAHE before.

2.1.1.6 Median Filter Median filter is a method for removing noise in images. The median filter is very effective for removing salt and pepper noise and can protect image edge information. Median filter uses Eq. (3):

$$y[m,n] = \text{median}\{\, x[i,j], (i,j)\,\epsilon\,\omega, \tag{3}$$

where ω user-defined environment, centered around the location $[m, n]$ in the image.

2.1.2 Segmentation

After preprocessing, the next step is segmentation using Wolf thresholding.

2.1.2.1 Wolf Thresholding After the preprocessing stage, the next stage is the vessel segmentation. Thresholding is a method for segmentation in digital image processing. Thresholding is also a process for separating images into two classes depending on the threshold. Thresholding is divided into global thresholding and local thresholding. Global thresholding is a general value that applies to all pixels in an image, whereas the locale calculates a threshold for each pixel. Wolf thresholding used in this study is local thresholding. The thresholding value depends on the standard deviation for each pixel in the image (Zidan et al. 2016). Wolf thresholding uses Eq. (4):

$$T = \sqrt{(1-k) * \text{mean} + \frac{k * \text{dev}}{R * (\text{mean} - M)}} + k * M \tag{4}$$

where T is the thresholding value, k is the initial upper threshold value, the standard deviation is symbolized by dev while R is the maximum deviation and M is the minimum intensity value in the image.

2.1.2.2 Complement This method is an inversion method. In this process, each pixel value is reduced by the maximum pixel value. Complement changes high-intensity images to low and vice versa. The output of this process that is the dark area will turn to light and vice versa. Complement is used to resemble the results of segmentation with ground truth. The complement equation can be given in Eq. (5).

$$xc = 255 - x \tag{5}$$

where xc is the pixel complement image value, x is the previous pixel value.

Suppose an image is symbolized by I, then the complement of that image is I' = 255-1.

2.1.3 Post Processing

2.1.3.1 Morphological Operations Initial morphological operations were dated as the application of lattice theory to spatial structures. Morphology is related to the shape in the image, not from pixel intensity. Morphological operations can be used on binary images, gray and color images. Various types of morphological operations such as erosion, dilation, opening, and closing. Erosion operations are operations to reduce objects that are not needed in an image. Opening operations are operations that are used to remove unwanted structures in an image by applying erosion followed by dilation (Almotiri et al. 2018). At the stage of detection of blood vessels after blood vessel segmentation, there is still a circle that separates the blood vessels and background and there are still fine lines that are not blood vessels. To overcome this problem, in this study erosion and opening operations were used. The equation for erosion operation is shown in Eq. (6), and the opening operation equation is shown in Eq. (7).

$$A \ominus B \tag{6}$$

$$A \circ B = (A \ominus B) \oplus B \tag{7}$$

where A is an image variable and B is a Structuring Element. $\ominus$ is erosion operation. $\circ$ is opening operation.

Equation (6) is the opening operation equation that the erosion process A by B is followed by dilation. The opening operation has a simple geometric interpretation. $A \circ B$ means the opening operation in figure A by arranging element B.

2.1.3.2 Region of Interest Region of interest (ROI) allows coding differently in certain areas of the digital image so that it has better quality than the surrounding area (background). The main principle in coding this ROI is to shift the bitplane from the coefficient chosen as ROI so that it occupies a higher position than the surrounding bitplane (background).

2.2 Detection of Optic Disc

Figure 4 shows a process of detection of optic disc using maximum principal curvature and Wolf threshold.

2.2.1 Grayscale

Conversion to grayscale changes the input image to a black and white image. In the grayscale stage, there is a reduction of three color dimensions to one color dimension (Bouillon et al. 2018). Characteristics of grayscale images are RGB (red, green, and blue) color equivalents. Contrast ranges from black at the lowest light intensity to white at the highest light intensity

The results of the grayscale process can be seen in Fig. 5.

2.2.2 Complement

This method is an inversion method. In this process, each pixel value is reduced by the maximum pixel value.

Fig. 4 Block diagram detection of optic disc with Prewitt edge detection and circular Hough transform

Complement changes high-intensity images to low and vice versa, so that the output of this process that is the dark area will turn to light and vice versa. Suppose an image is symbolized by l, then the complement of the image is

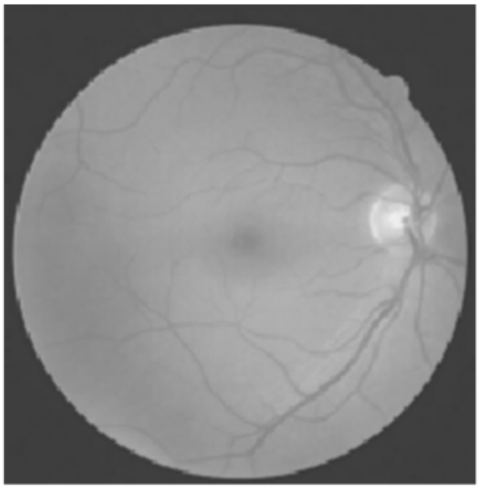


Fig. 5 Grayscale obtained from the RGB channel separation in the DRIVE dataset image (Information et al. 2015)

I′ = 255-1. Complement of grayscale is used to further clarify the optic disc.

2.2.3 Contrast-Limited Adaptive Histogram Equalization (CLAHE)

The contrast in an image is the distribution of light and dark. Contrast can be divided into three types such as low contrast, that is, in an image that looks dark and very low, the histogram is only grouped at a certain value. The image has good contrast if it has a uniform histogram. While high contrast is dominated by dark or light colors, the histogram shows two maximum peaks. CLAHE is used to increase contrast in the optic area of the disc.

Clahe has two parameters to control enhanced image quality. First, CLAHE is given a limit value on the histogram called the clip limit. The clip limit states the maximum height limit on the histogram. The two CLAHE parameters are block size. The more clip limit is increased the brighter the picture. Likewise, with block size, if it is getting bigger, then the dynamic range becomes larger and the image contrast will increase. In CLAHE there is even distribution of histograms (Ma et al. 2017). CLAHE parameters have been proven better than the previous method such as AHE (adaptive histogram equalization). AHE is a method for increasing local contrast of images, where local image contrast is obtained from forming symmetrical grids on an image called region size.

2.2.4 Opening Morphological Operations

The opening operation is used in the process. The opening morphology equation can be seen in Eq. 10, by applying the imopen function to remove pixels that have a distance less than the parameters. After opening morphology, the next process is the median filter. The median filter is used to refine the image. The process of opening morphology and median filter can smooth blood vessels.

2.2.5 Prewitt Edge Detection

Prewitt operator is usually used in image processing for edge detection. Edge detection is a mathematical method that can detect points in an image. Edges represent the boundaries of an object that can be used to identify specific target shapes and areas. Edge detection has various types, namely the Sobel, Robert, Canny, and Prewitt operators. In this study the Prewitt operator was used, because it is a better edge detection (Hoang 2018).

The Prewitt operator looks for differentials in one direction and averages in the other, and the Prewitt operator can also handle gray graded images and images that have noise as well (Fan 2019). The Prewitt operator requires the TP parameter to be used as a threshold value. The structural elements in the Prewitt edge detection are given in Eqs. (8) and (9):

$$P_x = \begin{pmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}$$
$$p_y = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix} \tag{8}$$

where P_x is horizontal Prewitt operator and P_y is vertical Prewitt operator.

Then, the total value of the gradient is calculated as follows:

$$P = \sqrt{(P_x)^2 + (P_y)^2} \tag{9}$$

In optic disc detection after the preprocessing stage, using the opening operation the next step is edge detection to create edge lines on the optic disc area. Large gradients provide information about edge strength. The direction of the gradient is perpendicular to the edge. The Prewitt operator uses two 3 × 3 kernels, namely horizontal and vertical.

2.2.6 Circular Hough Transform

Circular Hough transform is a basic technique in digital image processing that is used to detect circular objects in an image. Candidate circle is selected through the Hough parameter space, where the previous edge detection process is done. The matrix accumulator consists of three dimensions with radius r and a circle centered on [a, b].

After the fingers are determined. The center of the circle is determined by the equation of the circle as Eq. (10):

$$(x-a)^2+(y-b)^2=r^2 \tag{10}$$

where r is the radius. a and b are the center of the circle object.

The parameter space becomes three dimensions (a, b, r). If the radius is fixed, then the parameter space will be reduced to 2D (circle center position).

After getting the results of blood vessel segmentation and optic disc location detection, the next step is to combine the two results so that the blood vessel detection results on the optic disc.

3 Result

The dataset used in this study is used is DRIVE (Digital Retinal Images for Vessel Extraction). The DRIVE database has been created to enable comparative studies on the segmentation of blood vessels in retinal images. Retinal vessel segmentation and depiction of retinal vascular morphological attributes, such as length, width, tortuosity, branching patterns, and angles, are used for diagnosis, screening, treatment, and evaluation of various cardiovascular and ophthalmological diseases such as diabetes, hypertension, coronary arteriosclerosis, and neovascularization. The dataset in DRIVE has 40 images divided into training and test sets, both containing 20 images. This research using 20 images.

The following results of the detection of blood vessels in the optic disc in each image in the dataset can be seen in Fig. 6.

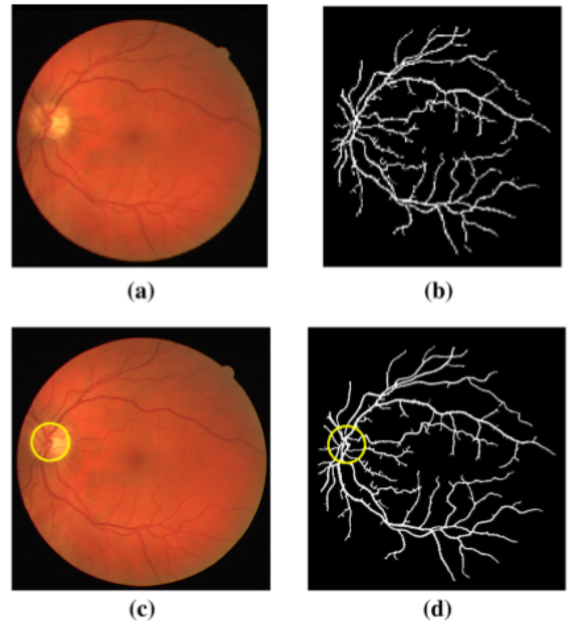


Fig. 6 Detection of blood vessels on optic disc, **a** input image, **b** blood vessel segmentation, **c** detection of optic disc, **d** detection of blood vessels on optic discs

Table 1 shows all the images that have been successfully segmented using proposed methods and compared with ground truth in the segmentation of blood vessels.

General description of the steps of retinal segmentation using the proposed method can be seen in Fig. 7:

Figure 7a shows an input image that has been converted to green channel. Then, in Fig. 7b the green channel image is processed further using a gaussian filter. After filtering, the maximum principal curvature algorithm is applied to detect the blood vessel candidates as shown in Fig. 7c. After that, in Fig. 7d the results of the maximum principal curvature give CLAHE to further enhance contrast and clarify the blood vessel candidates. Next, Fig. 7e shows the process of optic disc elimination by reducing the image of the gaussian filter with CLAHE. After that, a median filter is performed to eliminate noise in the image so that the results of segmentation are better. Finally, Fig. 7f shows segmentation process using Wolf thresholding and post process. First is the segmentation using Wolf thresholding, and then the results of the segmentation are complemented to resemble the ground truth of experts. After that, the process is carried out to improve the results of segmentation such as deleting fine spots that are not blood vessels using opening morphology, separating the results of blood vessel segmentation with the background on the retinal image using the region of interest. The last step is eliminating fine lines after the region of interest uses erosion morphology, so that the final result of segmentation is only segmented blood vessels.

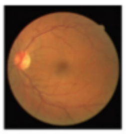
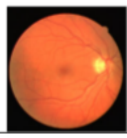
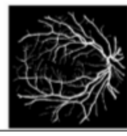
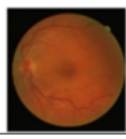
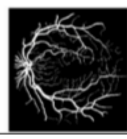
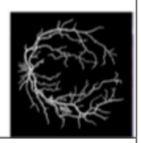
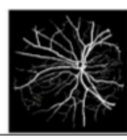
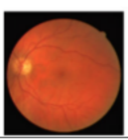
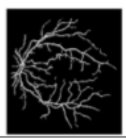
In this research, segmentation of retinal blood vessels is categorized successfully segmented well, if the results of this method match the ground truth by experts. To see the results of the compatibility of this method with ground truth, the confusion matrix calculation is performed. The parameters used are the level of accuracy (Acc) and sensitivity (Sn) using Eqs. (11) and (12):

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FN+FP} \tag{11}$$

$$\text{Sensitivity}=\frac{TP}{TP+FN} \tag{12}$$

where true positive (TP) is the number of pixels that are predicted as blood vessels in the ground truth and segmented as blood vessels in the results of segmentation. False positive (FP) is the number of pixels predicted by the

Table 1 Comparison of DRIVE segmentation results with ground truth

No.	Original image	Segmentation	
		Ground truth	Result
1.			
2.			
3.			
4.			
5.			

background in the ground truth and segmented as a blood vessel in the segmented image. Then, true negative is the number of pixels predicted as background in the ground truth and segmented as background in segmentation results. False negative is the number of pixels that are predicted as blood vessels in the ground truth and segmented as a background in the results of segmentation images.

Table 2 presents the calculation of the accuracy and sensitivity values in the segmentation process of the proposed method using the dataset and ground truth DRIVE. The average accuracy and sensitivity values obtained are 94.74% and 50.09%

The sensitivity value obtained is still low so that it will be corrected in the next step which is optic disc detection.

General description the steps of disc detection using the proposed method can be seen in Fig. 8:

Figure 8a shows an input image that has been converted to grayscale. Then, in Fig. 8b the grayscale image is processed in a complement to further clarify the area on the optic disc. Then, in Fig. 8c the image contrast and contrast are improved using the contrast-limited adaptive histogram equalization to further clarify the optic area of the disc. After that, the opening morphology to smooth and remove blood vessels looks like Fig. 8d. The results of the opening morphology were refined with a median filter so that the blood vessels were smoother and did not look as shown in Fig. 8e. The process in Fig. 8a–e is a preprocessing stage; at this stage it is what influences the next edge detection stage. Finally, the Prewitt edge detection is seen in Fig. 8f. This edge detection stage is also very influential on optic disc detection using circular Hough transform, because this edge detection becomes a parameter in circular Hough transform. Hence, if the edge detection process does not produce good results, the optic disc detection process will cause errors and may even be undetected. In this study using a Prewitt operator can properly check for edge detection so as to produce an effective optic disc detection as shown in Fig. 8g.

To see optic detection performance using the proposed method by calculating the similarity value based on ground truth using the Dice similarity index, if the dice value obtained is more than 0.5 then the method is considered successful in detecting optic discs, whereas if it is below 0.5 the method is deemed unsuccessful in detecting optic discs. The Dice similarity index formula can be seen in Eq. (13).

$$\text{Dice} = \frac{2|A \cap B|}{|B| + |A|} \tag{13}$$

where A is the tested image, B ground truth image.

TP is the optic disc location predicted in ground truth and is successfully detected as an optic disc in the detection results. TN is an optic disc location that is predicted in ground truth and detected as an optic disc in the detection results, but it is a little incorrect, that is only the intersection between the results of processing and ground truth. FP is the optic location of the disc successfully detected, but its location is different from the ground truth. FN is the result of processing that shows that the optic disc is not detected.

The results of the accuracy and comparison of analysts from the proposed method in each dataset can be seen in Table 3.

From Table 3, the accuracy and sensitivity are calculated using Eqs. (11) and (12) and then multiplied by 100% so that 95% accuracy can be produced. A comparison of the results of the proposed method segmentation with previous research is presented in Table 4.

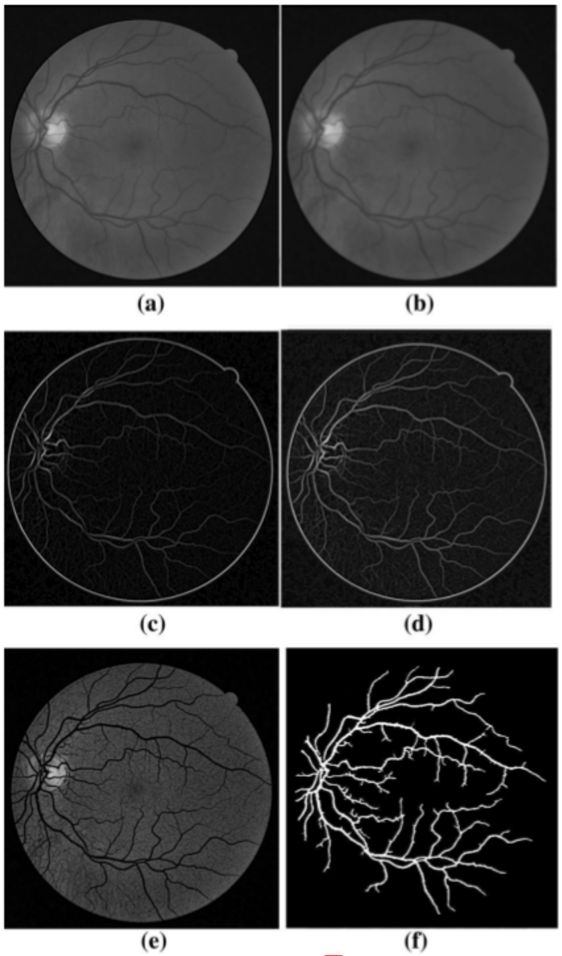


Fig. 7 Vascular segmentation process, **a** green channel, **b** Gaussian filter, **c** maximum principal curvature, **d** maximum principal curvature after CLAHE, **e** optic disc elimination and median filter, **f** Wolf thresholding and post process

Based on the results of these comparisons, the method proposed in this research can match the methods of Pratap and Rajeev (Pratap and Rajeev 2018) and Nergiz and Akin (2017) in experiments using DRIVE datasets with an accuracy of 95% and sensitivity of 94% compared to the other researchers with the results of the accuracy and sensitivity of (Pratap and Rajeev 2018), respectively, 93.74% and 77.38% and (Nergiz and Akin 2017) of 91.83% and 81.23%. Pratap and Rajeev (2018) used an extended matched filter based on second derivative of Gaussian with the process of input image being converted to green channel and then converted to gray scale, after which Clahe is applied, then SDOG matched filter is applied. Nergiz and Akin (2017) used the structure tensor coloring and anisotropy enhancement method with the

Table 2 Accuracy and sensitivity calculation results for segmentation with the DRIVE dataset

No.	Name of image	Acc (%)	Sn (%)
1.	01_test.tif	94.97	60.59
2.	02_test.tif	94.09	60.31
3.	03_test.tif	93.12	56.25
4.	04_test.tif	95.03	54.59
5.	05_test.tif	94.74	58.13
6.	06_test.tif	93.91	42.22
7.	07_test.tif	94.50	54.88
8.	08_test.tif	93.85	43.60
9.	09_test.tif	95.03	43.01
10.	10_test.tif	94.39	56.37
11.	11_test.tif	94.91	51.01
12.	12_test.tif	94.28	53.71
13.	13_test.tif	94.50	47.26
14.	14_test.tif	95.37	46.16
15.	15_test.tif	95.41	58.21
16.	16_test.tif	95.16	52.40
17.	17_test.tif	94.37	35.98
18.	18_test.tif	95.59	54.24
19.	19_test.tif	95.64	67.13
20.	20_test.tif	95.61	57.77
Average		94.74	50.09

steps carried out in the input image which is converted to grayscale and then applied to the Frangi vesselness filter to improve blood vessels. Structure tensor: One of the most important benefits of ST is the concept of coherence which is calculated through its eigenvalue. Then, Clahe is applied to increase contrast, after that tensor coloring is applied. Tensor coloring using ellipsoids is exploited as a segmentation method that has the ability to distinguish vessels from vessels.

Table 5 presents the results of the calculation of accuracy in the optic disc detection process using the proposed method and compared with previous studies.

Based on the expected results, the method proposed in this final study can match the methods of Elbalaoui and Porwal with evaluation results of 84% and 80.23%. Elbalaoui (2018) performed optic disc detection using vesselness filter and active contour with the first process of localization of OD center localization, followed by removal of blood vessel structure using vessel filter. Active contour is applied to OD boundary segmentation. Porwal et al. (2018) used the gradient minimization-based approach method with the steps of analyzing the intensity profile and further segmentation of the selected area using L 0 gradient minimization based on technology. Then, the Otsu thresholding method is used for segmentation.

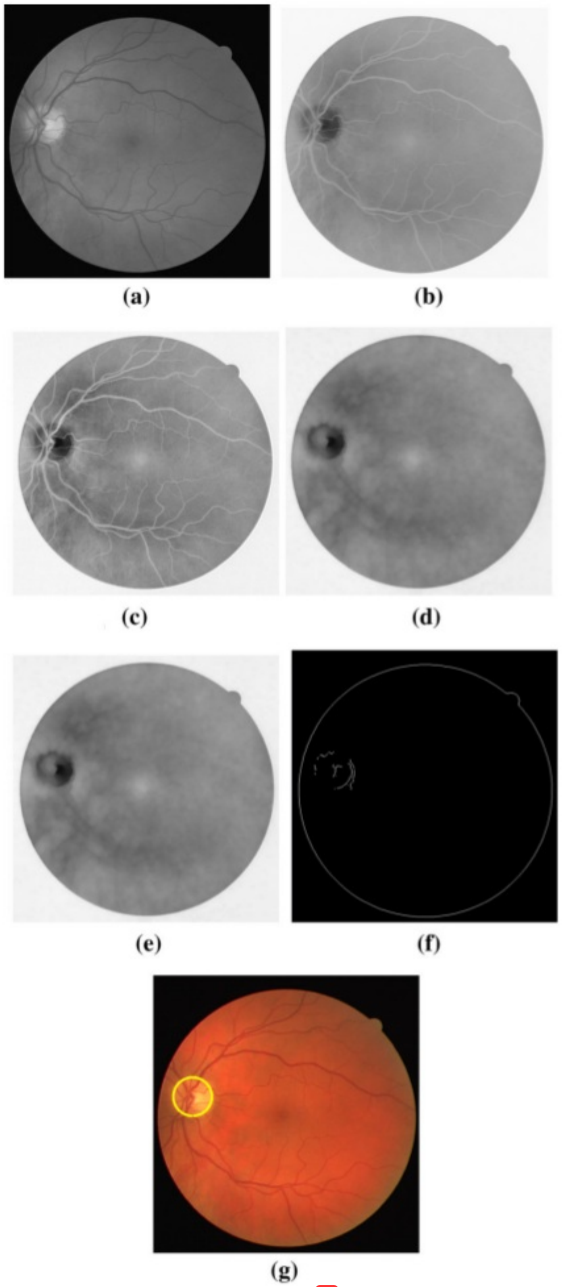


Fig. 8 Optic Disc detection process **a** grayscale, **b** complement, **c** CLAHE, **d** opening morphology, **e** median filter, **f** Prewitt edge detection, **g** optic disc detection

After getting the results of blood vessel segmentation and optic disc location detection which is quite effective using the proposed method, the next step is to combine the two results so that the blood vessel detection results on the optic disc are shown in Table 6.

Table 3 DRIVE dataset results

No.	Name of image	Category overlapping	Value
1.	01_test.tif	0.9012	TP
2.	02_test.tif	0.1731	TN
3.	03_test.tif	0.2548	TN
4.	04_test.tif	0.8845	TP
5.	05_test.tif	0.8729	TP
6.	06_test.tif	0.0935	FN
7.	07_test.tif	0.7576	TP
8.	08_test.tif	0.5470	TP
9.	09_test.tif	0.6089	TP
10.	10_test.tif	0.8974	TP
11.	11_test.tif	0.8227	TP
12.	12_test.tif	0.8027	TP
13.	13_test.tif	0.7623	TP
14.	14_test.tif	0.7340	TP
15.	15_test.tif	0.8473	TP
16.	16_test.tif	0.5939	TP
17.	17_test.tif	0.9294	TP
18.	18_test.tif	0.9275	TP
19.	19_test.tif	0.8729	TP
20.	20_test.tif	0.5802	TP

Table 4 Comparison of results with other researchers' results for blood vessel segmentation

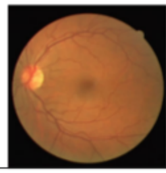
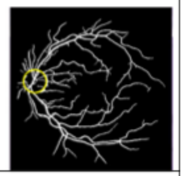
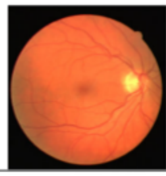
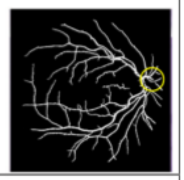
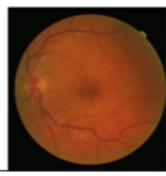
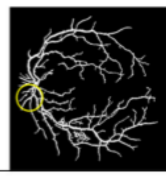
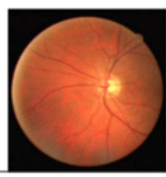
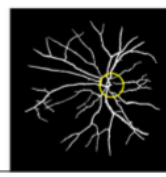
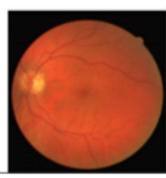
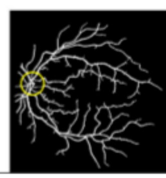
Method	Performance	
	Acc (%)	Sn (%)
Proposed method	95.00	94.00
Pratap and Rajeev (2018)	93.74	77.38
Nergiz and Akin (2017)	91.83	81.23

Table 5 Comparison of results with other researchers' results for detection optic disc

Method	Performance Acc (%)
Proposed method	85
Elbalaoui (2018)	84
Porwal et al. (2018)	80.23

Table 6 shows the image of the retinal input coming from the DRIVE dataset. After processing with the maximum principal curvature algorithm and Wolf thresholding

Table 6 Detection of blood vessels on optic discs

No.	Name of file	Original image	Result detection of blood vessels on optic discs
1.	01_test.tif		
2.	02_test.tif		
3.	03_test.tif		
4.	04_test.tif		
5.	05_test.tif		

to detect blood vessels, and using Prewitt edge detection followed by circular Hough transform to detect the optic location of the disc, the output is the detection of blood vessels on the optic disc.

4 Conclusions

Blood vessel segmentation models using the maximum principal curvature algorithm with Gaussian filter and Wolf thresholding can provide performance with a parameter value of 95% accuracy and sensitivity of 94% in the DRIVE dataset. Likewise in the optic disc detection process, the proposed method can work effectively by producing an accuracy of 85% so that in the process of merging blood vessels and optic location of the disc using the proposed method is very effective in detecting blood vessels in the optic disc.

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Detection of Blood Vessels in Optic Disc with Maximum Principal Curvature and Wolf Thresholding Algorithms for Vessel Segmentation and Prewitt Edge Detection and Circular Hough Transform for Optic Dis

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