Gradient based ant spread modification on ant colony optimization method for retinal blood vessel edge detection

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Abstract. Retinal blood vessels are a very important object to diagnosing illness. Fast, automatic, adaptive, and accurate systems to segment the retinal vessels are particularly useful. The retinal blood vessels can be detected by edge detection. This research will compare the edge detection techniques with adaptive ant colony optimization (Adaptive ACO). Generally, the early ants on the conventional ant colony optimization (ACO) are randomly distributed. This condition can cause the ant distribution imbalances. Based on this problem, the ant distribution modification on ACO is proposed to optimize the ant placement based on the gradient. The gradient values are used to determine the ants’ placement. The ants are not randomly distributed but placed in the highest gradient. The so-called Adaptive ACO is expected to be used for better and faster path discovery optimization. The average PSNR of Prewitt edges, Sobel edges, conventional ACO, and the proposed method are 11.605, 11.913, 9.783, and 15.874 respectively. The PSNR of the proposed method has the greatest value than others. It shows that the placement of ants based on gradient can improve edge detection accuracy. The application of the Adaptive ACO method has successfully optimized the result of retinal vessel edge detection.

1. Introduction

Eyes are an important organ for humans that acts as a very sensitive vision. The occurrence of abnormalities in the eyes will be very disturbing. Almost all eye diseases can still be prevented. Eyes disease with a precise initial diagnosis will ease the healing process. The identification of some parts of retinal anatomy is a prerequisite diagnosis of some diseases [1]. Some eye fundus images are used to detect some retinal diseases such as retinal nerve tissue, optical disc, and fovea early. One cause of eye disorders is the abnormal growth of blood vessels in the eyes called neovascularization. This abnormal growth causes the retina to move backward from its original position. If not treated promptly, it will lead to vision loss, a kind of blindness. Neovascularization in the retinal fundus image is associated with changes in bifurcation point (BP), which is the branched point in the blood vessels and crossovers point (CP) from the cross point in the blood vessels [2], [3]. The changes that occur in the retinal blood vessels can be a signal of abnormalities in the eyes. Some abnormalities are characterized by blood vessel disorders in the eyes caused by certain diseases, such as diabetic retinopathy. Abnormalities in the vessels of the eyes can be known quickly and accurately through early detection. Preliminary detection can be done by looking at the abnormal branching of blood vessels, the changing number of retinal blood vessel cut points, etc. Periodic cut point detection that
consists of a branch point and cross point of a retinal vessel can be used to detect retinal blood vessel anomalies.

Research that aims to develop and test the early detection system of diabetic retinopathy has been done by researchers with different media and methods. An algorithm with math morphology to detect microaneurysm is proposed in research [4]. Mathematical morphology is chosen because microaneurysm has a distinctive shape. The proposed algorithm consists of 3 parts: preprocessing, detects, and post-processing microaneurysm candidates.

Retinopathic detection using image processing is performed in [5]. This paper shows an audit of the most recent work on the utilization of digital image processing techniques for DR highlight identification. In [6], the detection of retinal vessels using structural predictors of bright lesions is performed. In the study, Gabor filters are applied to the grayscale image to lesion enhancement.

Usually, the image used in detection is not in ideal condition. This condition is a shadow disturbance, photos including blurred images [7]. Various problems with analysis and planning can affect the results of interpellation. Therefore, image processing techniques are required to obtain the ideal image. Many approaches have been used to perform edge detection on an image. Some commonly used methods are Sobel, Prewitt, and Canny [8], [9]. Research using ant colony optimization (ACO) to perform edge detection in the image has been done in [10], [11]. Singh et al [12] approaching Fuzzy-ACO. The number of ants is calculated and placed at the endpoint of the image using a double detector. The Fuzzy derivative technique implements a fuzzy probability factor to determine which next pixel is most likely to be the edge. Wong et al [13] performed improvements to edge detection by combining the Canny method with ACO.

Previous research about ACO by dividing of picture and count the number of ants based on gradient each division area is done [14]. However, the initial ant spreading process is still done randomly as the traditional ACO, thus allowing ants to be trapped under optimal local conditions. In this study, gradient values are used to determine the initial ant placements. Ants are not randomly distributed but placed in a high gradient. At the highest gradient, the ants travel to determine the path first. This method is expected to be used for pathfinding optimization.

2. Methods
This research is done by several steps include the selection of image data, preprocessing, and edge detection. Figure 1 below describes the steps to be performed.

2.1. Preprocessing
The used data input in the system is the RGB image. From the RGB image then converted into a gray image [15], [16]. The process of changing the color image into a gray image using lightness and average counting method. In addition to that method, there is also a luminosity method which is the

![Figure 1. Research model.](image-url)
development of the lightness and average method. The luminosity method calculates the value of each color element of the image, red, green, and blue and adding the weight according to the perception of human vision. The calculation is shown in Equation 1.

\[
Luminosity = \frac{R \times 299 + G \times 587 + B \times 114}{1000}
\]  

(1)

Where R represents the red, G represents the green, and B represents the blue channel. The luminosity method is chosen because of the nature of the luminosity method. It is closer to the perception of human vision. After the grayscale image is obtained, the next process is edge detection using the Adaptive ACO method.

2.2. Gradient

The initial step of digital image processing for edge detection is a gradient [8]. The gradient values of the area are indicated by the presence of edges in the area. Gradients are made from transitions or color changes.

\[
\nabla f = \begin{bmatrix}
G_x \\
G_y
\end{bmatrix} = \begin{bmatrix}
\frac{\partial f}{\partial x} \\
\frac{\partial f}{\partial y}
\end{bmatrix}
\]  

(2)

For the magnitude of the vector shown by Equation 3.

\[
|\nabla f| = \left( \left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2 \right)^{\frac{1}{2}}
\]  

(3)

The component of the vector gradient itself is a linear operator, but the magnitude of the vector is not a linear operator because it is quadratic and square root operations. In image processing, the derived based operator becomes the basis of calculation. Some examples are using the operator Sobel, Prewitt, Robert [8]. Figure 2 shows a pseudo-convolution kernel that is used to calculate the gradient magnitude (G) quickly.

|   |   |   |
|---|---|---|
| a1 | a2 | a3 |
| a4 | a5 | a6 |
| a7 | a8 | a9 |

Figure 2. Pseudo-convolution kernels with the size of 3 x 3

To calculate the kernel on the summing process of the magnitude shown in Equation 4.

\[
|G| = |(a_1 + 2 \times a_2 + a_3) - (a_7 + 2 \times a_8 + a_9)| + |(a_3 + 2 \times a_6 + a_9) - (a_1 + 2 \times a_4 + a_7)|
\]  

(4)

One method to determine image gradient is the Sobel operator. The first step of a Sobel operator is to estimate the value of horizontal gradient (Gx) and vertical gradient (Gy). This is done by kernel operation of the image matrix as shown in Figure 2. The kernel matrix for Gx is defined as the Kx operator, while the kernel matrix for Gy is defined as Ky, as in Equation 5.

\[
Kx = \begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix}, \quad 
Ky = \begin{bmatrix}
-1 & -2 & -1 \\
0 & 0 & 0 \\
1 & 2 & 1
\end{bmatrix}
\]  

(5)

After obtaining the gradient values in the vertical and horizontal direction, then search matrix calculation values that produce image gradient values. The gradient values are also used to determine the angular direction of the edge (θ). The value of θ will affect the treatment of a pixel against its neighboring pixels. The counting edge value is calculated by Equation 6.

\[
\theta = \tan^{-1} \left( \frac{Gy}{Gx} \right)
\]  

(6)
After calculating pixel’s gradient value, choose gradients that have values equal or more than the threshold. The number of adequate gradients then become the number of ants \(K\).

### 2.3. Adaptive Ant Colony Optimization (Adaptive ACO)

Ant Colony Optimization (ACO) is a heuristic method to imitate the behavior of ants to solve discrete optimization problems [17]. In general, pseudocode is shown in Figure 3.

\[
K = \text{Number of gradients} >= \text{threshold} \quad (7)
\]

The number of ants obtained on the gradient will be the input parameter. Ants are not randomly distributed but are placed on pixels that have a high gradient in the image. Ants on the gradient based pixel position will move to the neighbor pixel to determine the edge. ConstructAntSolutions is an ant trip activity. The construction process contains a number of construction steps. Ants will move in an image until the target number of construction steps are formed. In the construction process to \((n^{th})\) the number of ants \((k^{th})\) will move from node \(i\) to a node \(j\) following the probability displacement \(p_{i,j}^{(n)}\). This pseudorandom proportional rule is shown in Equation 8.

\[
p_{i,j}^{(n)} = \frac{(\tau_{i,j}^{(n-1)})^\alpha (\eta_{i,j})^\beta}{\sum_{j \in \Omega_i} (\tau_{i,j}^{(n-1)})^\alpha (\eta_{i,j})^\beta} \text{ if } j \in \Omega_i
\]

where \(\Omega_i\) is the neighboring node of the ant given to node \(i\), pheromone update is denoted by \(\tau\), and \(\eta\) is the heuristic information.

DoDaemonActions is a construction solution for additional steps before pheromone value updates. This activity is an additional measure of updating pheromone values. This process can not be done by only single ant. UpdatePheromones is a pheromone update activity after the construction and daemon actions are performed. Counting local pheromone updates are shown in Equation 9.

\[
\tau_{i,j} = (1 - \phi)\tau_{i,j} + \phi\tau_0 
\]

Where \(\phi\) is a pheromone damage and \(\tau\) is a pheromone update. The global update of pheromones is shown in Equation 10.

\[
\tau_{i,j} = (1 - \rho)\tau_{i,j} + \rho\Delta\tau_{i,j} 
\]

In ACO there is a displacement rule with a probability factor at eight neighboring pixels. The pixels with the maximum probability factor in detecting neighbors have edge pixels. To reduce the repetitive repetition of ants the stopping criteria are made, ie the displacement of the ant will stop if it passes through the path that the other an ant has passed and when all pixels of neighbor (8 pixels) have been passed by all the ants then the displacement will stop [12].

In the next step, a decision is taken on each pixel to determine the edge or not. This is done by implementing a threshold \((T)\) on the final pheromone matrix \((\tau^{(N)})\) [11]. In this proposed study, the threshold value \((T)\) was adapted based on the Otsu method [18]. Otsu thresholding is implemented to
determine the best solution based on the number of pheromones stored in each pixel. The Otsu approach can define a useful variable that distinguishes two or more naturally occurring groups. Edge determination is based on the final pheromone matrix value. The Otsu threshold technique will reduce the gray image results to binary images with two possible values for each pixel. From the final pheromone matrix value, a pixel will show if it is an edge or not.

The initialization threshold \( T^{(0)} \) is chosen based on the mean pheromone value matrix. Furthermore, the pheromone matrix is classified into two categories with a value criterion less than \( T^{(0)} \) or more than \( T^{(0)} \). The initialization value of \( T^{(0)} \) is calculated based on Equation 11.

\[
T^{(0)} = \frac{\sum_{i=1}^{M_1} \sum_{j=1}^{M_2} \tau^{(N)}_{i,j}}{M_1 M_2}
\]  

(11)

Where \( M_1 \) vaporizes the width of the image, while \( M_2 \) is the height of the image. The threshold value \( T \) will be compared with the final pheromone results used as the fitness value in determining the edge or not. The edge determination with a fitness value that determines a pixel as an edge \( (E_{ij} = 1) \) or not \( (E_{ij} = 1) \) is based on the criteria as shown in Equation 12.

\[
E_{ij} = \begin{cases} 
1 & \text{if } \tau^{(N)}_{i,j} \geq T^{(1)} \\
0 & \text{other }
\end{cases}
\]  

(12)

In this research, the number of small construction and iteration parameters aim to speed up the edge detection process. The used values are shown in Table 1.

| Parameter              | ACO | Adaptive ACO |
|------------------------|-----|--------------|
| \( K \) - Total number of ants | \( \sqrt{\text{width} \times \text{height}} \) | Number of gradients \( \geq \) threshold |
| \( L \) - An ant movement steps within each construction step | 10 | 10 |
| \( N \) - Total number of construction steps | 4 | 4 |
| \( \alpha \) - Weighting factor of pheromone information | 0.5 | 0.5 |
| \( \beta \) - Weighting factor of heuristic information | 0.1 | 0.1 |
| \( \rho \) - Evaporation rate | 0.1 | 0.1 |
| \( \phi \) - Pheromone decay coefficient | 0.05 | 0.05 |
| \( \tau_{init} \) - Initial value of each element of pheromone matrix | 0.0001 | 0.0001 |
| \( \Omega \) - The tolerable ant’s movement range | 8 | 8 |

There are several steps performed on adaptive ACO edge detection. In this research, adaptive ACO is proposed in the process of initial ants placement based on gradient values. The edge detection process that will be performed on adaptive ACO can be seen in Figure 4.

**Figure 4.** The proposed method.

A numerical assessment can be used to determine the accuracy of the edge detection test results. The testing of image edge detection result is based on Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE) method. PSNR is a relationship between the ratio of the maximum value and the value of damage (noise) that shows the accuracy of the process. Its value will be high on the good quality image. The calculation of MSE and PSNR values is shown in Equation 13 and 14.
\[ MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2 \] (13)

\[ PSNR = 10 \log_{10} \left( \frac{MAX^2}{MSE} \right) \] (14)

3. Results and Discussion

The tests are conducted to determine the success level of the system in producing image edge detection. The pre-processing stage will get the gray image. The results of the pre-processing images are used as input at the image edge detection stage. Testing is done by comparing the image edge detection results between ant algorithm optimization with the conventional edge detection algorithm. An example of image capture is shown in Figure 5.

![Figure 5. A retinal image in RGB.](image1)

Figure 5 will be used as an input image on the pre-processing phase. The input image in the form of an RGB image is converted to a gray image. The gray image conversion results are shown in Figure 6. After the gray image data obtained then the edge detection performed. The result of the edge detection image will be compared to other selected edge detection method result. The edge detection results sample are shown in Figures 7, and 8.

![Figure 6. A retinal image in grayscale.](image2)

![Figure 7. Image 1: (a) Prewitt edges, (b) Sobel edges, (c) ACO, and (d) proposed method.](image3)
Figure 8. Image 2: (a) Prewitt edges, (b) Sobel edges, (c) ACO, and (d) proposed method.

Based on the testing of the retinal blood vessels, the proposed Adaptive ACO edge detection results provide a more detailed outline than the other edge detection techniques. It proves that the process of placement of ants based on the value of gradient is influential in determining the edge of an image with the Adaptive ACO method. Table 2 and 3 is the value of the test results.

| Table 2. MSE Values |
|---------------------|
| Result | MSE          |
|        | Prewitt | Sobel | ACO   | Proposed Method |
| Mean   | 0.090   | 0.087 | 0.103 | 0.072           |
| Stdev  | 0.062   | 0.060 | 0.081 | 0.051           |
| Min    | 0.019   | 0.018 | 0.057 | 0.009           |
| Max    | 0.217   | 0.212 | 0.327 | 0.167           |

| Table 3. PSNR Values |
|---------------------|
| Result | PSNR          |
|        | Prewitt | Sobel | ACO   | Proposed Method |
| Mean   | 11.605  | 11.913 | 9.783 | 15.874          |
| Stdev  | 3.497   | 3.617  | 2.638 | 5.992           |
| Min    | 6.625   | 6.994  | 5.071 | 9.761           |
| Max    | 19.111  | 19.712 | 16.512| 27.322          |

Tables 2 and 3 show the average MSE and PSNR. The proposed method has the smallest average MSE value compared to conventional edge detection techniques and ACO methods. The average PSNR of the proposed method also has the greatest value compared to conventional edge detection techniques and ACO methods. Conventional PSNR ACO values are smaller than the edge detection techniques (Prewitt and Sobel) method because the used parameter values are minimal.

4. Conclusions

Based on the research, it can be concluded that the optimization of Adaptive ACO algorithm performance for the retinal blood vessel detection process could produce a good feature compared to other edge detection methods. This condition is shown from the results which produce an image with a more detailed edge (has a thicker border). The greatest value of PSNR and the smallest value of MSE of the proposed method compared to the other shows that the process of ants placement by gradient could improve the accuracy of image edge detection results.
5. References

[1] M. Badar, M. Haris, and A. Fatima, “Application of deep learning for retinal image analysis: A review,” Comput. Sci. Rev., vol. 35, p. 100203, Feb. 2020.

[2] J. Malek, A. T. Azar, B. Nasralli, M. Tekari, H. Kamoun, and R. Tourki, “Computational analysis of blood flow in the retinal arteries and veins using fundus image,” Comput. Math. with Appl., vol. 69, no. 2, pp. 101–116, Jan. 2015.

[3] R. Geetharamani and L. Balasubramanian, “Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis,” Biocybern. Biomed. Eng., vol. 36, no. 1, pp. 102–118, 2016.

[4] A. Purwita and K. Adityowibowo, “Automated Microaneurysm Detection using Mathematical Morphology,” Int. Conf. Instrumentation, Commun. Inf. Technol. Biomed. Eng., pp. 1–4, 2011.

[5] A. Pattanashetty and S. Nandyal, “Diabetic Retinopathy Detection using Image Processing: A Survey,” Int. J. Comput. Sci. Netw., vol. 5, no. 4, 2016.

[6] J. Amin, M. Sharif, M. Yasmin, H. Ali, and S. L. Fernandes, “A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions,” J. Comput. Sci., pp. 153–164, 2017.

[7] M. Foracchia, E. Grisan, and A. Ruggeri, “Luminosity and contrast normalization in retinal images,” Med. Image Anal., vol. 9, no. 3, pp. 179–190, 2005.

[8] R. Gonzales and R. Wood, Digital Image Processing. Prentice-Hall, Inc., United State, America, 2007.

[9] F. Al-Hafiz, S. Al-Megren, and H. Kurdi, “Red blood cell segmentation by thresholding and Canny detector,” Procedia Comput. Sci., vol. 141, pp. 327–334, 2018.

[10] B. Anna and C. Oppus, “Image Edge Detection Using Ant Colony Optimization,” Int. J. Circuits, Syst. Signal Process., vol. 4, no. 2, pp. 24–33, 2010.

[11] J. Tian, Y. Wei, and X. Shengli, “An Ant Colony Optimization Algorithm For Image Edge Detection,” IEEE Congr. Evol. Comput., pp. 751–756, 2008.

[12] G. Singh, N. Kumar, and A. Kumar Verma, “Ant colony algorithms in MANETs: A review,” J. Netw. Comput. Appl., vol. 35, no. 6, pp. 1964–1972, Nov. 2012.

[13] Y.-P. Wong, V. Soh, K.-W. Ban, and Y.-T. Bau, “Improved Canny Edges Using Ant Colony Optimization,” IEEE Comput. Graph. Imaging Vis., pp. 197–202, 2008.

[14] F. Liantoni, C. K. Kartika, H. M. Tri, K. C. Kirana, and T. H. Muliaawati, “Adaptive Ant Colony Optimization based Gradient for Edge Detection,” J. Ilmu Komput. dan Inf., vol. 7, no. 2, pp. 76–82, Aug. 2014.

[15] M. Foracchia, E. Grisan, and A. Ruggeri, “Luminosity and contrast normalization in retinal images,” Med. Image Anal., vol. 9, no. 3, pp. 179–190, Jun. 2005.

[16] F. Liantoni, R. Indra Perwira, S. Muharom, R. Agung Firmansyah, and A. Fahruzi, “Leaf classification with improved image feature based on the seven moment invariant,” J. Phys. Conf. Ser., vol. 1175, p. 012034, Mar. 2019.

[17] M. Dorigo, M. Birattari, and T. Stutzle, “Ant Colony Optimization: Artificial Ants as a Computational Intelligence Technique,” IEEE Computational Intelligence Magazine, 2006.

[18] N. Otsu, “A threshold selection method from gray level histograms,” IEEE Trans. Syst. Man. Cybern., vol. 9, no. 1, pp. 62–66, 1979.