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DIGITAL IMAGE EDGE DETECTION USING DIRECTIONAL ANT COLONY OPTIMIZATION BASED ON GRADIENT MAGNITUDE AND DIRECTION

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Abstract- ***Ant Colony Optimization (ACO) is a method that imitates the foraging behavior of ants that can be applied to improve the edge detection. Generally, pheromone of ants is guided by local variation in image intensity which is less sensitive for detect edge, thus we need addition of edge information. In this study we propose Directional ACO (DACO) which uses the addition of edge information based on gradient magnitude and direction. In the proposed method, the weight of gradient magnitude and directional initialized firstly, and then ant construct edge using probabilistic which is not only considered by pheromone and local variation of intensity, but also gradient magnitude and direction. in the each iteration, the edge is constructed by applying a threshold using Otsu. Final edge is determined if the difference of edge number has reach a threshold. Experiments were conducted using images from private synthetic dataset and CID's natural image dataset*. Figure of merit was used to evaluate quantitatively performance of the proposed method. The experiment showed that DACO reached 0.812 (81.2%), whereas standard ACO reached 0.494 (49.4%). Experiment results showed that DACO outperforms standard ACO.***

Keywords - Ant Colony Optimization, Gradient Direction, Gradient Magnitude, Ant Movement Rule

I. INTRODUCTION

Edge detection plays a critical role in some applications. Edge localizes boundaries of objects in an image which was used as features in image recognition, segmentation, enhancement, and compression [1]. Moreover, the edges can be segmented if the edges connect fully. However, traditional edge detection approaches usually extract edges by adopting a convolution mask which often leads broken edge [1] [2]. These approaches make edge segmentation more difficult. Therefore, many methods have been proposed to reduce the broken edge and link them.

One of improved edge detection algorithms is Ant Colony Optimization (ACO). ACO is a heuristic method that imitates the foraging behavior of ants to solve optimization problems [3]. The improved results of ACO for edge detection were indicated by reduction of broken edge [2] [4]. This reduction is caused by flexibility of searching which is not fixated by a convolution mask.

ACO construct solution using artificial ants which move from one state to destination using local communication which is performed by movement to neighbor pixel. However, the transition of ants is guided by pheromone. In edge detection, pheromone is influenced by information heuristic. Generally, information heuristic is determined using local variation in the image intensity values which is less sensitive to detect the edge, even in presence of noise or in smooth edge. That increases the chances of ants to trap in a local optima was indicated by some lost edges [5].

To avoid local optima, Baskan et al (2009) and Rahebi et al (2010) proposed combining ACO and genetic algorithm [5] [6]. The ants of ACO were distributed to better pixels that were recommended by genetic algorithm. Their proposed method showed the better result than gradient edge detection qualitatively. However, they did not evaluate performance of their proposed algorithm quantitatively.

Liantonie (2014) proposed another improved distribution of ants that were regulated by gradient ratio [7]. This study assumed an edge has a higher gradient magnitude. Therefore, the number of edges can be estimated using gradient ratio on each region. The results showed that the precision and recall of their proposed method more efficient than the traditional ACO. However, the ants cannot detect edges accurately because the variation of grey level that can't guide the ant on the low intensity variations correctly, event in the presence of noise. Thus, there are non-edge is detected as edge.

However, the distribution of ant cannot classify each pixel either as an edge or a non-edge successfully, even in presence of noise or in smooth edge. Thus, Zhang (2010) optimize edge detection algorithm using addition of direction on probability

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transition rules which was proposed using statistical theory [8]. However, the method results in drawback, such as the higher computational costs that caused by the wider neighbor pixel calculation. In addition, the direction weight of this method did not follow edge shape adaptively.

Aforementioned research improved local ant communication for avoid local optima. However, a more the communication of ant is increased, a more the computing cost is increased. Another way to avoid local optima is addition of local edge information using characteristic of edge.

In this study, we propose Directional Ant Colony Optimization (DACO) which uses the addition of edge information based on gradient magnitude and direction. Edge has the bigger gradient magnitude [7]. The edge also has direction as well [8]. We can explore edge using gradient direction which it commonly perpendicular to edge direction. This method adjusts the edge shape without bigger computation cost.

The rest of this paper is organized as follows. In section 2, we give the literature of standard ACO edge detection. In section 3, we explain our research methodology about DACO (data, proposed method, experiment and evaluation). We also give our result and discussion in Section 4. The section 5 concludes the result.

II. LITERATURE REVIEW

2.1 Ant Colony Optimization

Ant Colony Optimization (ACO) is a probabilistic technique that's used to solve optimization problems of computing. This algorithm was proposed by Marco Dorigo in 1992 [3]. The first algorithm aims to find the optimal path in the graph. The path searching imitates the behavior of ant in the finding of food source.

Development of ACO algorithm was derived from the ACO meta-heuristic. The pseudo code of ACO meta-heuristic is showed in Figure 1. There are the fourth steps on ACO was included by *Parameter Initialization*, *Ant Solutions Construct*, *Update Pheromones*, and *Daemon Actions*.

Parameter Initialization is performed at the beginning. Initial value of the parameter is set by the fix value. The parameters initialization was included by sum of ant (K), first pheromone (τ_0), pheromone decay (φ), pheromone evaporation rate (ρ), weight of pheromone (α), and weight of heuristic information (β).

In *Ant Solutions Construct*, a set of artificial ants construct solutions based on movement of ants from source to destination. The ants estimated transition probability to move the best node. The formulation of probability (p) is according to Equation 1.

```
ACO
PARAMETER INITIALIZATION
WHILE terminator conditions no met do
    ANT SOLUTIONS CONSTRUCT ( )
    UPDATE PHEROMONES ( )
    DAEMON ACTIONS ( ) optional
END WHILE
```

Fig. 1 Meta Heuristic of ACO

$$p = \frac{(\tau_J)^{\alpha}(\eta_J)^{\beta}}{\Sigma(\tau_J)^{\alpha}(\eta_J)^{\beta}}, \tag{1}$$

where ant transition probability (p) was influenced by heuristic information (η_j) and pheromone (τ_J). is a normalization factor which limits the value of p within [0,1].

Information heuristic is the measurement of the heuristic preference for moving from one state to another state, whereas the pheromone is measurement of the previous transitions deposition of ant pheromone from one state to another state [9]. Then, the ant move to neighbor pixel which has maximum probability. Information heuristic is given by:

$$\eta_J = \begin{matrix} |I(x-1,y) - I(x,y-1)| + \\ |I(x-1,y-1) - I(x-1,y+1)| + \\ |I(x-1,y) - I(x,y+1)| + \\ |I(x+1,y-1) - I(x-1,y-1)| + \\ |I(x-1,y+1) - I(x+1,y-1)| + \\ |I(x,y-1) - I(x+1,y)| + \\ |I(x+1,y-1) - I(x+1,y+1)| + \\ |I(x+1,y) - I(x,y+1)| \end{matrix}, \tag{2}$$

where heuristic information of edge (η_j) is present by variation of grey level on local group *(I)*

In *Update Pheromones*, pheromone is changed. We usually call this step with local pheromone update. That was done at the each of ant movement where the pheromone value was decay. The equation of local pheromone updates is showed as followed:

$$\tau_J = (1 - \varphi)\tau_J + \varphi\, \tau_{0.} \tag{3}$$

where the pheromone at pixel J (τ_J) is modif using pheromone decay (φ) and first pheromone ($\boldsymbol{\tau_0}$).

Daemon Actions is an optional stage where is converted based on global standpoint. At this steps, strengthening of pheromone on path which is considered as best solution was done[10]. After each ant construction, pheromone was increase the by evaporating all the pheromone values and increasing the pheromone values associated with the good solutions. Global pheromone update is given by:

$$\tau_j = (1-\rho)\tau_j + \rho\,\Delta\tau_j \ \textit{where}\ \Delta\tau_j = \begin{cases} \frac{1}{L}, & \textit{if the ant move to } J \\ 0, & \textit{otherwise.} \end{cases} \tag{4}$$

At each iteration, the pheromone at store pixel J (τ_J) is a modified using pheromone evaporate rate (ρ) and total pheromone ($\Delta\tau$) which was set by fix number. Quantity of pheromone ($\Delta\tau$) was determined based on sum of reward on the pixel J from all of reward on ant's path. We calculate the moving pixel reward with one per path length (L).

2.2 Gradient

Gradient is one of the operators in vector calculus useful to seek a change in direction and speed in the scalar field. On the image, gradient represent the transitions or changes color gradually [11]. For a two-dimensional image, the application is done using derived spatial gradient. Gradient has a direction and a magnitude [12]. Gradient magnitude is given by Equation 5. In addition, Gradient direction is calculated by Equation 6.

$$\nabla F = \sqrt{F_x^{\,2} + F_y^{\,2}} = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} . \tag{5}$$

$$\theta = tan^{-1}\left(\frac{f_y}{f_x}\right) = tan^{-1}\left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}}\right). \tag{6}$$

where the gradient magnitude (F) is degradation value of image intensity which was interpreted by vertical derivative (F_x) and horizontal derivative (F_y). Gradient direction (θ) also estimated horizontal and vertical derivative.

III.METHODOLOGY

3.1 Data

There are two dataset which is included by CID's natural image and private synthetic image. CID image dataset is a dataset that consist of various free images, such as Matlab's images and USP-SIPI images. The synthetic image created manually using image painting software. Seven images are used for synthetic image, whereas 26 images are used for natural image. Ground truth is composed by expert.

3.2 Directional Ant Colony Optimazation

The preprocessing of edge detection is to convert the input into gray scale image. Main process is to detect the gray scale image into edge image using DACO. The main steps of DACO consist of parameter initialization, edge construction, local pheromones update, global pheromones update, and decision process. The main step of DACO is depicted by Figure 2. The detail step of DACO is depicted by Figure 3.

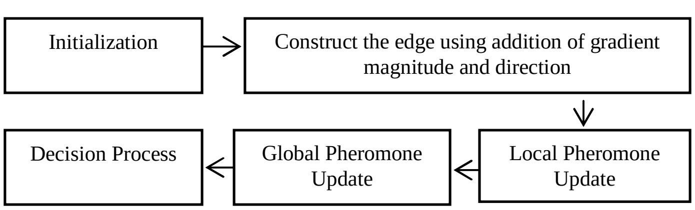


Fig. 2 Design of DACO

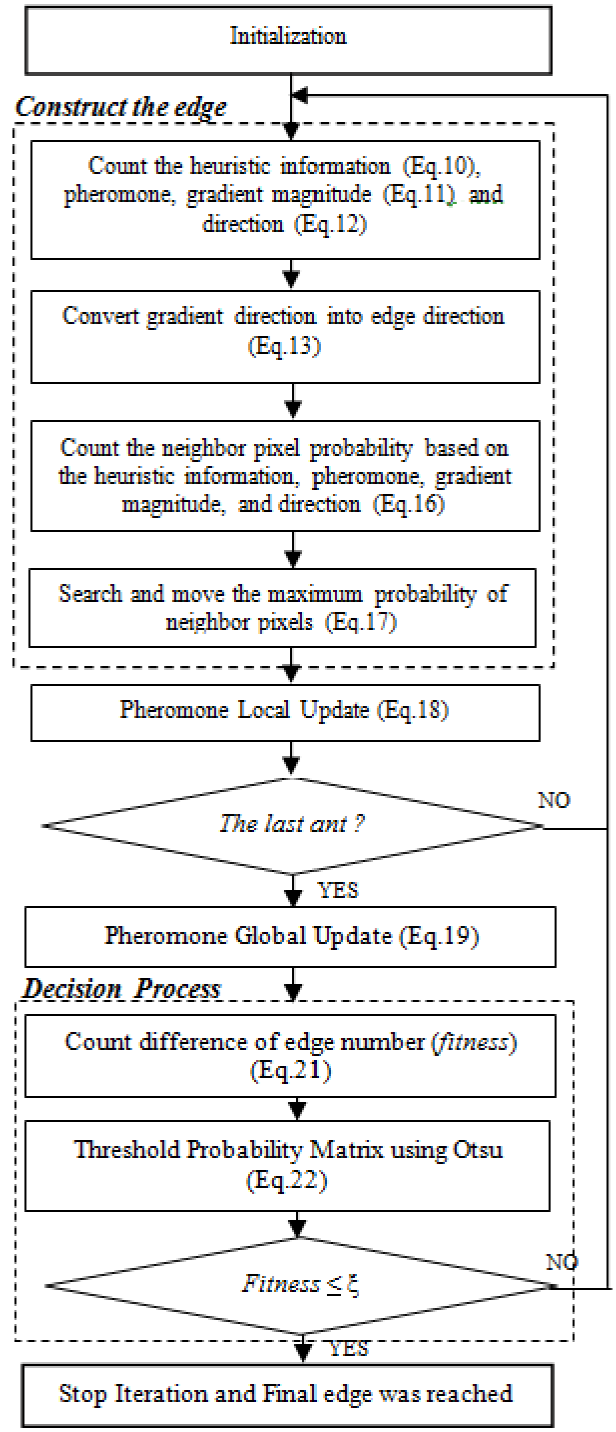


Fig. 3 Detail Design of DACO

3.2.1 Parameter Initialization

The first step of this proposed method is the parameter initialization. The number of ant (K) was initialized based on the square root of image width (N) and image height (M) that was given by:

$$K = \sqrt{N * M} , \tag{7}$$

where K ant was placed on nest (*nest*). The placement of nest was influenced by maximum probability and was determined by:

$$nest\,(k) \;= nest\big(Pmax\,(k)\big), \tag{8}$$

where nest will build on K pixels that have maximum probability from another where ant-k stays on nest-k. The maximum probability is calculate according to:

$$pmax\,(k) \;= max_k \frac{(\tau_J)^{\alpha}(\eta_J)^{\beta}(\Delta\vec{F}_j)^{\gamma}}{\Sigma(\tau_J)^{\alpha}(\eta_J)^{\beta}(\Delta\vec{F}_j)^{\gamma}}, \tag{9}$$

where the maximum probability (*pmax*) of ant-k was founded when pheromone (τ_J), heuristic information (ηj), and gradient magnitude (ΔFj) at pixel-J was highest. Influence of those parameters was controlled by weight. τ_J was controlled by the weight of pheromone (α). η_j was controlled by the weight of information heuristic (β). ΔF_j controlled by the weight of gradient magnitude (γ).

3.2.2 Construct the Edge

Based on Figure 3, the edge construction is included by: (1) calculated the information heuristic, pheromone, gradient direction, and gradient magnitude, (2) converted the gradient direction into the edge direction, (3) calculated the probability rule based on the heuristic information, the pheromone, the direction, and the gradient magnitude, (4) moved to the next pixel based on the maximum probability.

First pheromone, image heuristic information, gradient direction, and gradient magnitude was defined firstly. The first pheromone (τ_0) was initialized by fix number. The heuristic information (η_j) is the variation of gray level on local group which was computed based on local variation of image intensity value (I) at center pixel position (x, y), where x is horizontal position and y is vertical position in the image. The heuristic information as follows.

$$\eta_J = \begin{cases} |I(i-1,j) - I(i,j-1)| + \\ |I(i-1,j-1) - I(i-1,j+1)| + \\ |I(i-1,j) - I(i,j+1)| + \\ |I(i+1,j-1) - I(i-1,j-1)| + \\ |I(i-1,j+1) - I(i+1,j-1)| + \\ |I(i,j-1) - I(i+1,j)| + \\ |I(i+1,j-1) - I(i+1,j+1)| + \\ |I(i+1,j) - I(i,j+1)| \end{cases} \tag{10}$$

Gradient magnitude was the degradation of image intensity which was taken by:

$$\nabla F = \sqrt{{F_x}^2 + {F_y}^2} \tag{11}$$

where gradient magnitude (F) was calculated using vertical derivative (F_x) and horizontal derivative (F_y).

Gradient direction (θ) is arch tan between horizontal derivative (F_y) and vertical derivative (F_x). The gradient direction (θ) was developed as follows:

$$\theta = \begin{cases} \arctan\left(\frac{F_y}{F_x}\right) & , \; if\; F_x \geq 0 \\ \arctan\left(\frac{F_y}{F_x}\right) + \pi & , \; if\; F_x < 0 \end{cases}, \tag{12}$$

where $\theta \in [0,2\pi]$.

The gradient direction (θ) and edge direction (θ_e) are perpendicular. Therefore, gradient direction was converted into the edge direction (θ_e) that was given by:

$$\theta_e = \theta - 90°. \tag{13}$$

Then, the edge direction was collected into eight orientations. Figure 4 depicts eight orientations. The eight orientations were chosen based on neighbor pixel connectivity's that were shown at Figure 5. These eight orientations can be represented by Equation 14.

$$\text{orientation}_{(x,y)} = \begin{cases} 1, & -22.5 \leq \theta_e < 22.5 \\ 2, & 22.5 \leq \theta_e < 67.5 \\ 3, & 67.5 \leq \theta_e < 112.5 \\ 4, & 122.5 \leq \theta_e < 157.5 \\ 5, & 157.5 \leq \theta_e < 202.5 \\ 6, & 202.5 \leq \theta_e < 247.5 \\ 7, & 247.5 \leq \theta_e < 292.5 \\ 8, & 292.5 \leq \theta_e < 337.5 \end{cases}. \tag{14}$$

The orientation of neighbor pixel position on Figure 5(b) and orientation of direction center pixel was used for compute the weight of edge direction which was taken by:

$$\Delta w = \begin{cases} 1, & \text{if neighbor position = direction center pixel} \\ n, & \text{otherwise}, \end{cases} \tag{15}$$

where weight of edge direction $(\Delta\, w)$ was set by 1 if the position of neighbor pixel and the edge direction in the same direction. Another pixel that hasn't the same direction was set by n where n is initiated $0 \leq n < 1$.

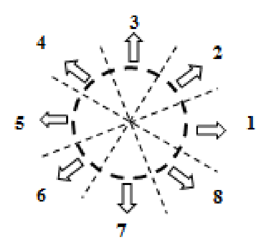


Fig. 4 Orientation of Edge

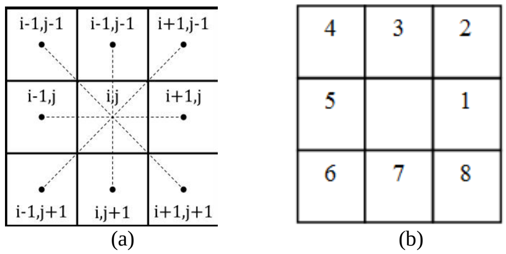


Fig. 5 Neighbor Pixel Connectivity
(a) Position of Neighbor Pixels [9] (b) Orientation of Neighbor Position

In this study, the ants moved to the next pixel using a new improved probabilistic rule which was given by:

$$p_J^k = \frac{(\tau_J)^{\alpha}(\eta_J)^{\beta}(\nabla\vec{F}_J)^{\gamma}\Delta w_{IJ}}{\sum(\tau_J)^{\alpha}(\eta_J)^{\beta}(\nabla\vec{F}_J)^{\gamma}\Delta w_{IJ}},\ \ \textbf{\textit{if } } \boldsymbol{j \in NE_I}. \tag{16}$$

Transition probability *(p)* of ant-*k* at pixel-*J* not only was influenced by pheromone (τ_J) and heuristic information (η_j), but also addition of gradient magnitude (ΔF_j) and the weight of direction (Δw) at pixel-*J*. However, Influence of those parameters was controlled by weight factor. τ_j was controlled by the weight of pheromone (α). η_j was controlled by the weight of information heuristic (β). ΔF_j controlled by the weight of gradient magnitude (γ).

Then the movement of ant was calculate according to:

$$p_{J^*}^k = pmax\,(j) = \ max\left(P_J^k\right), \tag{17}$$

where ant-*k* choose and move to the next pixel *(J*)* that has the maximum probability of neighbor pixel (*pmax*).

3.2.3 Local Pheromone Update

Local pheromone update (τ_J) is done after the ant leave pixel-*J*. The pheromone update is showed at Equation 18.

$$\tau_J = (1-\ \varphi)\tau_J +\ \varphi\ \tau_0, \tag{18}$$

where τ_0 is first pheromone and φ is the pheromone decay. The pheromone decay is a useful processes to exploration other pixel.

3.2.4 Global Pheromone Update

After all of ants finish the construction process, global pheromone update was done. The global pheromone update is performed by:

$$\tau_J = (1-\ \rho)\tau_J +\ \rho\,\Delta\tau_J\ . \tag{19}$$

Based on the Equation 19, pheromone at pixel J (τ_j) was increase the pheromone values associated with good solutions and decrease those associated with bad ones. That was commonly done by pheromone evaporation rate (ρ). Pheromone updating was also associated with quantity of pheromone which was shown as follows.

$$\Delta\tau_J = \begin{cases} \frac{1}{K},\ \textit{if the ant move to the pixel} - J \\ 0, \qquad\qquad\qquad\qquad \textit{otherwise}, \end{cases} \tag{20}$$

where quantity of pheromone $(\Delta\tau)$ was set by 1/K if the ants have been moved to the pixel-*J*, and $\Delta\tau$ *is* zero if the ants never visited to the pixel-*J*.

3.2.5 Decision Process

Edge was calculated after binary decision process. The binary decision process is made at each pixel location to determine whether it is on the edge or non-edge, by applying a threshold (*t**) on the final probabilistic matrix using Otsu. *Otsu* thresholding was computed by:

$$\sigma_\beta^2\ (t^*) = max_{1\le i\le L}\left(\frac{\left[\sum_{i=1}^t i\ p_i \sum_{i=1}^t p_i - \sum_{i=1}^t i\ p_i\right]^2}{\sum_{i=1}^t p_i[1-\sum_{i=1}^t p_i]}\right) \tag{21}$$

where selected edge threshold (*t**) was calculated using between class variance (σ_β^2) that considered probability to be edge (p_i) and value on probability matrix (*i*). The probability to be edge (p_i) was computed using Equation 22. *L* presents the maximum value on matrix probability. The Otsu thresholding calculate the threshold using probability theory. The probability of edge was calculated by:

$$p_i = \frac{n_i}{N} \tag{22}$$

where n_i is sum of pixel that has value-*i* on probability matrix, whereas *N* is the total pixel on the image.

The criterion for stopping the algorithm is solely based on the objective function. The ant will stop and get global solution for edge detection if the objective function has been reached as count according to:

$$\frac{\sum edge_L - \sum edge_{L-1}}{\max(\sum edge_L, \sum edge_{L-1})} \le \xi. \tag{23}$$

The objective function of this study used number of edge (*Σedge*) in iteration-*L* and the before iteration (*L-1*). If difference of edge number has been reached the threshold *(ξ)*, the global solution of edge was founded. In this paper, we set ξ with 0.001.

3.3 Evaluation

The proposed method was conducted using 26 CID's natural image and 7 synthetic images. *Figure of merit* are used to evaluate performance of the proposed algorithm quantitatively as given by:

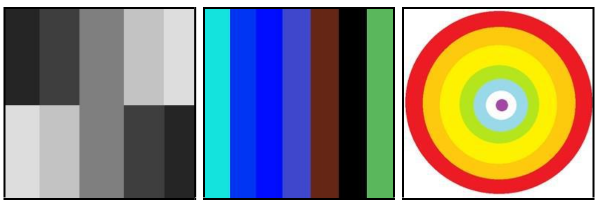
$$F = \frac{1}{\max(N_i, N_d)} \sum_{i=1}^{N_d} \frac{1}{1+\xi d_i^2}. \tag{24}$$

Figure of Merit (*F*) will have the higher result if the number of real edge (N_i) and the number of detected edge (N_d) has a value that is almost the same. If the edges detect accurately, the distance (*d*) between the real edge and the detected edge is set by 0. ξ is limit. Furthermore, [13] set value of ξ *with 0.004*.

We evaluate the best parameter value for optimize the proposed method result firstly, and then the proposed method also was compared with standard ACO and Prewitt edge detection. We analyzed using quantitative analysis and qualitative analysis.

IV. RESULT AND DISCUSSION

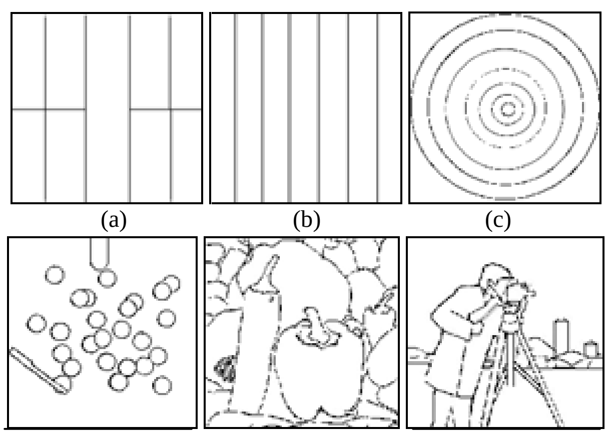
Series of experiments are conducted to find best parameter of proposed method. At this paper, *SYN* is the initial of synthetic image and *CID* is the initial of CID's natural image. The image and ground truth is present at Figure 6 and Figure 7.We evaluated the best initialization parameter value at beginning, such as: weight of pheromone, local variation, gradient magnitude, and edge direction. Evaluation of those parameters is showed at Figure 8. Based on Figure 8, the best weight of gradient magnitude, local variation intensity and pheromone is 1. When one of them is higher, the probability would increase, so that caused non-edge pixels were classified as edges. However, one of them is smaller, the probability is smaller too. Thus, some edge was detected incompletely.



(a) (b) (c)

(d) (e) (f)

Fig. 6 Image (a-c) Synthetic Image (d-f) Natural Image



(a) (b) (c)

(d) (e) (f)

Fig.7 Ground Truth (a-c) Synthetic Image (d-f) Natural Image

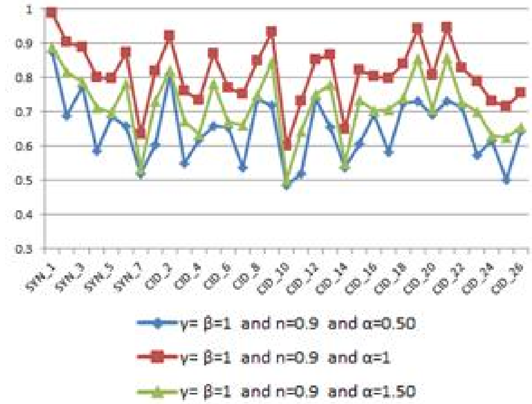


Fig. 8 Evaluation of Pheromone Weight

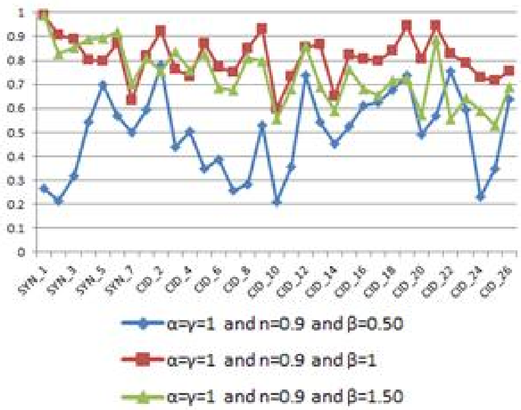


Fig. 9 Evaluations of Local Intensity Weight

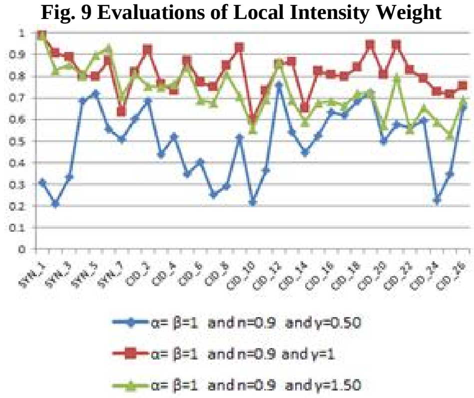


Fig. 10 Evaluations of Gradient Magnitude Weight

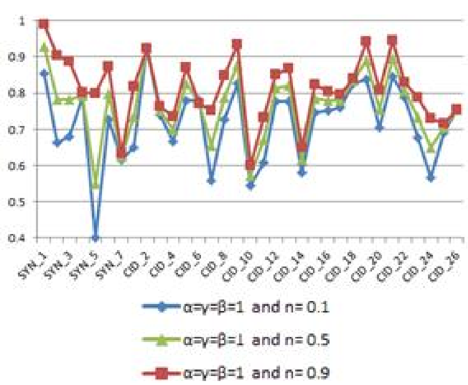


Fig. 11 Evaluations of Gradient Direction Weight

Based on Figure 8, 9, and 10, the best weight of gradient magnitude, local variation intensity and pheromone is 1. When one of them is higher, the probability would increase, so that caused non-edge pixels were classified as edges. However, one of them is smaller, the probability is smaller too. Thus, some edge was detected incompletely. Based on Figure 11, the best weight of direction for unselected pixel (n) is initialized 0.9. The smaller direction caused probability of unselected pixel smaller. However, there are some edge pixels on unselected pixels that reduce performance of edge detection. Based on our various experiments, we initialized the best parameter according to Table 1.

Table 1. Figure of Merit Result

Parameter	Parameter Value
K	256
τ_0	0.005*
φ	0.0001*
p	0.0001*
α	1
β	1
γ	1
n	0.9

* Our experiment showed that the value on Zhang research was the best result on our experiment (without explain in this paper)

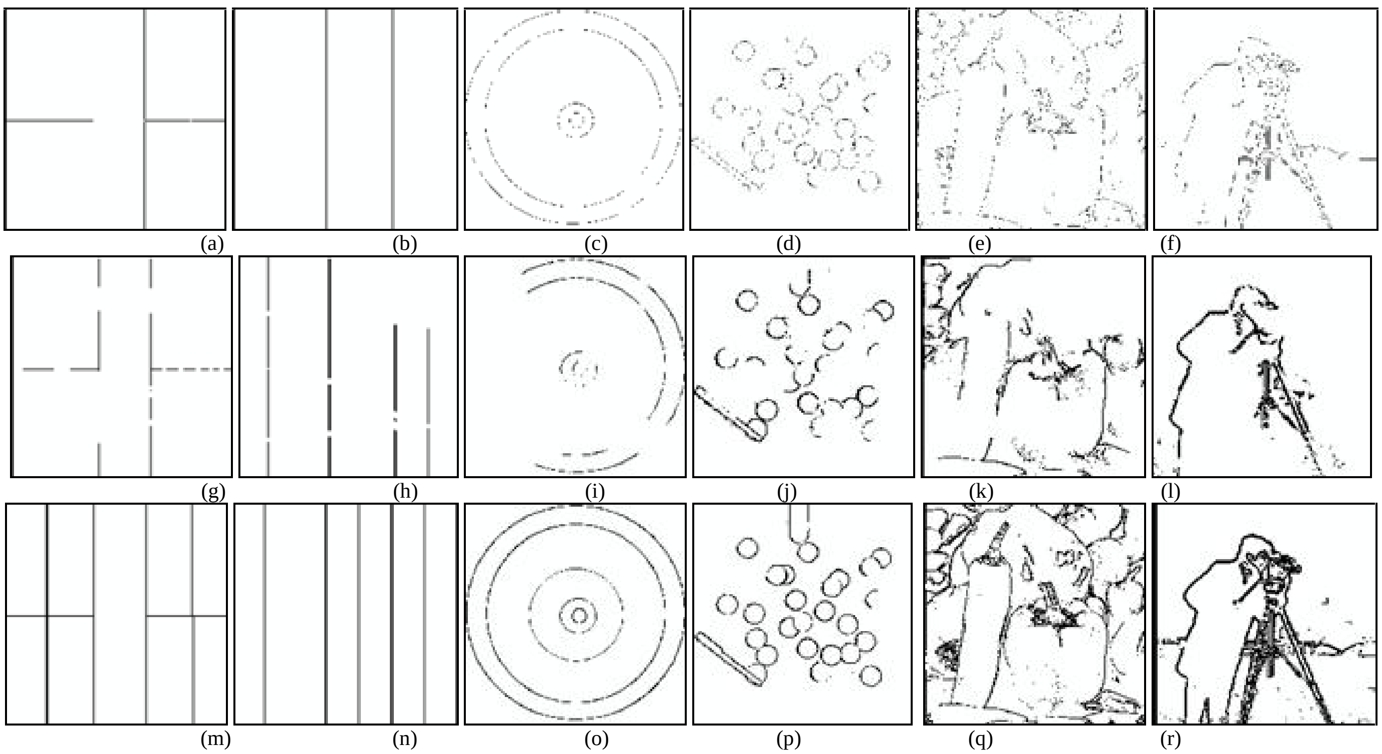


Fig. 12 Comparison of Edge Detection Result (a-f) Prewitt Edge Detection (g-l) Standard ACO Edge Detection (m-r) DACO Edge Detection

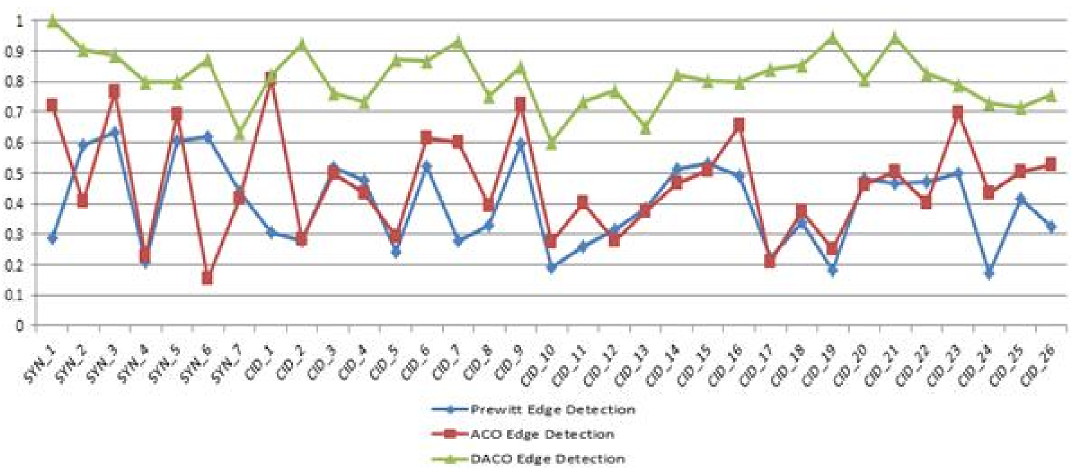


Fig.13 The Graphics of Compared Methods

The comparisons of edge detection result are presented at Figure 12. The Graphics of edge detection result is showed at Figure 13. The results for *figure of merit* are showed at Table 2.Based on the Figure 12, Figure 13, and Table 2, DACO showed the better results than standard ACO and Prewitt. The addition of gradient direction and direction on DACO outperforms than ACO GM.

The direction recommended ants explored the edge accurately. Gradient direction and edge directions commonly are perpendicular, thus the ants easily searched and detected the edges using the direction. The addition of gradient magnitude increased the probability of edge, so it could reinforce the edge information Therefore, the combination of gradient magnitude and direction reduced the broken edge.

Table 2. Figure of Merit Result

Images	Edge Detection Algorithm		
	Prewitt	**Standard ACO**	**ACO GMD**
SYN_1	0.28854	0.71987	0.99000
SYN_2	0.59031	0.40530	0.90438
SYN_3	0.63520	0.76792	0.88776
SYN_4	0.20853	0.22793	0.80089
SYN_5	0.60352	0.69484	0.79808
SYN_6	0.6196	0.15227	0.87243
SYN_7	0.44066	0.41650	0.63426
CID_1	0.30455	0.80688	0.81963
CID_2	0.27778	0.28321	0.92278
CID_3	0.51985	0.49871	0.76265
CID_4	0.47510	0.43459	0.73433
CID_5	0.24365	0.29049	0.87185
CID_6	0.52421	0.61318	0.86886
CID_7	0.27742	0.60235	0.93408
CID_8	0.32942	0.39265	0.75188
CID_9	0.59693	0.72510	0.84953
CID_10	0.19197	0.27565	0.60096
CID_11	0.26106	0.40160	0.73259
CID_12	0.31715	0.27621	0.77043
CID_13	0.38536	0.37419	0.65088
CID_14	0.51346	0.46833	0.82272
CID_15	0.53297	0.50961	0.80551
CID_16	0.49058	0.65508	0.79663
CID_17	0.22167	0.20812	0.84005
CID_18	0.33890	0.37708	0.85207
CID_19	0.17985	0.25208	0.94400
CID_20	0.48180	0.46103	0.80602
CID_21	0.46544	0.50513	0.94638
CID_22	0.47027	0.40171	0.82856
CID_23	0.50073	0.69601	0.78878
CID_24	0.17346	0.43693	0.72999
CID_25	0.41709	0.50342	0.71557
CID_26	0.32215	0.52558	0.75572
Average	**0.412017**	**0.494618**	**0.812129**

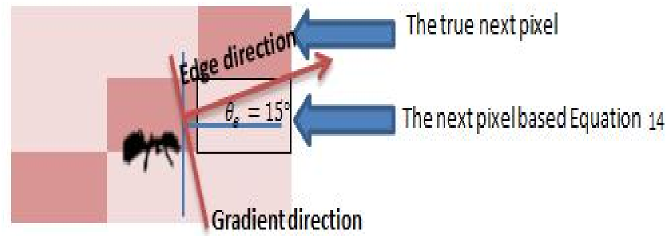


Fig. 11 Weakness of ACO GMD

However, fixed orientation of edge caused movement of ant incorrectly, thus some edges was undetected, such as Figure 12(O). The shape of edge in Figure (O) is circle. The movements of direction are smooth, thus ants false detects the collecting of direction. For example, if the edge direction is 15°. Based on Equation 14, the collecting of direction is 1, so the ant will move to the direction 1. However, the ant should move to the direction 2. The weakness of our proposed method is showed at Figure 11.

Although DACO has the weakness, the proposed method can reduce the fracture edge because ant can follows the edge direction to gets better edge. Besides that, the gradient magnitude can to reinforcement the information of edge, so the combining of the ACO, gradient direction, and gradient magnitude can improve the result of edge detection.

V. CONCLUSION

Based on the result, the gradient magnitude and direction can help the ants detect the edges accurately. The gradient magnitude reinforces the information of edge. Another way, ant can follows the edge direction for link the edge. However, sometimes the fix collecting of edge direction recommended the false pixel. However, the combining of gradient magnitude and gradient direction on DACO reach the figure of merit value higher than standard ACO and Prewitt edge detection, thus we can claim the proposed method can enhance the result of edge detection.

For next research, we can improve the orientation of edge direction more adaptive. We can improve ACO GMD for multi-level edge detection to classify the necessary edge and unnecessary edge too, such as classifying the shape of leaves and bone of leaves.

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