Digital image edge detection using an ant colony optimization based on genetic algorithm

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Digital Image Edge Detection Using an Ant Colony Optimization Based on Genetic Algorithm

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***Abstract*— In this paper a new method for enhancement of digital image edge detection using ant colony optimization based on genetic algorithm has been used. In the proposed method first by the series of answers has been formed by artificial ants and then formed in a manner i.e. useful for genetic algorithm, then the answers played the role as initial population for genetic algorithm and the next population is made by genetic algorithm. Our method compared with Jing Tian method enjoys higher speed, less processing time and more answer's optimum. Also the proposed method has a better edge than other classical methods (such as sobel, etc).**

***Keywords*— Edge detection, Ant colony optimization, Genetic Algorithm.**

I. INTRODUCTION

Ant colony optimization algorithm (ACO), are the groups of optimization algorithms i.e. inspired from nature ants exploring for food. In this algorithm, ants search the appropriate way in order to find the solution spaces. The First ACO algorithm, called ant system, was proposed by Dorigo et al. [1]. In this paper, ACO based on genetic algorithm (GA), introduced to solve the edge detection problem that aims to bring out the present edge in the image information. Proposed method uses the number of ants that moves on the local fluctuation of the image intensity values in order to create a pheromone matrix which shows the edge information in each pixel. In the image edge detection problem, investing the population of answers determine the genetic algorithm statistically has more distribution than ants algorithm which is a better way to find the solution. But the average speed of the population answers improvement is low toward the optimum answer and this causes the answer might not converge to the absolute optimum answer. This is the case that ants' algorithm has a low populating dissipation and the answer's formation coverage quickly, but it has a high approaching speed to optimum answer. These are what the exact thing we consider as the correct combination of these two algorithms but this case is not considered in other articles. Therefore, we use this opposite characteristic in these two algorithms by the combination of ants and genetic algorithm. In this paper we study on other algorithms [2] and [3] to show better results. In any case, there are fundamental differences between our proposed method and others. First, our way uses the ant's population combinational algorithm, but Jing Tian and et al way uses the ant's population system [2]. Secondly, we exactly use ACO based on GA to bring out edge information in our proposed method. In the next section, a brief introduction for demonstrating basic concepts of ACO is given. In the third section, conventional method based on ACO is introduced. In the section fourth the proposed method is described and in the fifth, simulation results of this method are given. A conclusion is in the last paper.

II. ANT COLONY PRELIMINARIES [2], [4]

ACO solution aims to find appropriate information pheromone pay through the movement comes in a number of ants.

For better understanding, suppose that K Ant is used to find a suitable solution in the level x including $M_1 \times M_2$ nodules. ACO program can be summarized as follows in:

Position all K ants and the matrix pheromone $\tau^{(0)}$ has been initialized.

- Index for ant $k=1:K$,

- So we transfer k -th possible transition matrix $p^{(n)}$ based on the ant (with a size of $M_1 M_2 \times M_1 M_2$).

- We update the matrix pheromone $\tau^{(0)}$.

According to the final pheromone matrix $\tau^{(N)}$, we find the solution.

There are two basic stages ACO above, it's likely to create a matrix transfer $p^{(n)}$ and incidence matrix by pheromone $\tau^{(n)}$ and each is detailed below.

Initially, k -th ant moves from the likely node i to node j based on the possibility performance that has been cleared by the potential [4].

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$$p_{i,j}^{(n)} = \frac{\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}\left(\eta_{i.j}\right)^{\beta}}{\sum_{j\in\Omega_i}\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}, \quad if\ j \in \Omega_i \qquad (1)$$

So that $\tau_{i,j}^{(n-1)}$ is the amount of information pheromone link node i in the node j. Ω_i is around nodules a_k assumed ant on node i. Fixed values α and β Show the impact of information pheromone and information exploratory respectively. $\eta_{i,j}$ shows the exploratory data from node i to node j i.e. constant for each same projecting. Then, the pheromone matrix requires that the ACO is updated twice. The first stage to update is done after the move of each ant in each stage. To be more dedicated, after moving k -th ant in the stage i, like pheromone matrix [4] is updated like [4].

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho)\cdot\tau_{i,j}^{(n-1)} + \rho\cdot\Delta_{i,j}^{(k)} \\ \tau_{i,j}^{(n-1)} \end{cases} \qquad (2)$$

So that ρ evaporation rate depends on the amount of user choice. The second update is done after all k ants move and according [4] pheromone matrix is updated.

$$\tau^{(n)} = (1-\psi)\cdot\tau^{(n-1)} + \psi\cdot\tau^{(0)} \qquad (3)$$

So that ψ is pheromone failure factor. Note that ant colony system [5] performs by two practice incidence (updating by pheromone (2) and (3)), while the ant colony system [1] only performs an action (i.e. the expression (3)).

III. IMAGE EDGE DETECTION BASED ON ACO [2]

The goals of image edge detection based on ACO are to use the number of ants walking on the image $2-D$ pheromone to build a matrix, each of new information in each pixel shows edge location image. In addition, the movements of ants are directed through the local of fluctuation of image intensity values. Image Edge detection process are given in the following stages.

A. Initialization Process

We dedicated all K ants randomly on the image I by size $M_1 \times M_2$. Each pixel can be considered as a node. The initial value of each component of matrix pheromone $\tau^{(0)}$ is set a fixed amount τ_{init}.

B. Construction Process

In this stage, an ant is chosen randomly from K mentioned ant and this ant for L Stage moving on the image. This ant moves from node (l,m) to neighbouring node (i,j) based on transition probability i.e. defined as following.

$$p_{(l,m),(i,j)}^{(n)} = \frac{\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}}{\sum_{(i,j)\in\Omega_{(l,m)}}\left(\tau_{i,j}^{(n-1)}\right)^{\alpha}\left(\eta_{i,j}\right)^{\beta}} \qquad (4)$$

Where $\tau_{i,j}^{(n-1)}$ is the value of pheromone node $(i.j)$, $\Omega_{(l,m)}$ are nodes the around the node (l,m) and $\eta_{i,j}$ shows heuristic information in node (i,j). Fixed values of α and β Show the influence of matrix pheromone and the exploratory matrix respectively. There are two essential subjects in the planning stage. First is calculating the heuristic information subject $\eta_{i,j}$ in (4). In this paper, we have used statistics, local pixel position (i,j) i.e. expressed by (5) expression.

$$\eta_{i,j} = \frac{1}{Z} V_c(I_{i,j}) \qquad (5)$$

So $Z = \sum_{i=1:M_1}\sum_{j=1:M_2} V_c(I_{i,j})$ is the normalization factor, $I_{i,j}$ is pixel intensity value at position (i,j) in image I, operator $V_c(I_{i,j})$ are the operator of pixels local group c (of categories is called) and its value as shown in Figure (1) depends on the image intensity values fluctuations in c categories.

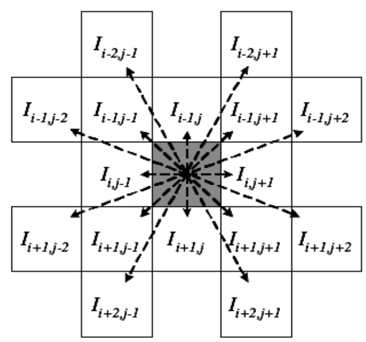


Figure 1. Dead pixels local position $I_{i,j}$ Calculated for changes $V_c(I_{i,j})$ Defined in (6).

For pixels $I_{i,j}$ under study, operator $V_c(I_{i,j})$ is related as (6):

$$\begin{aligned} V_c(I_{i,j}) = f\big(&\left|I_{i-2,j-1} - I_{i+2,j+1}\right| + \left|I_{i-2,j+1} - I_{i+2,j-1}\right| \\ &+ \left|I_{i-1,j-2} - I_{i+1,j+2}\right| + \left|I_{i-1,j-1} - I_{i+1,j+1}\right| \\ &+ \left|I_{i-1,j} - I_{i+1,j}\right| + \left|I_{i-1,j+1} - I_{i-1,j-1}\right| \\ &+ \left|I_{i-1,j+2} - I_{i-1,j-2}\right| + \left|I_{i,j-1} - I_{i,j+1}\right| \end{aligned} \qquad (6)$$

In this paper in order to calculate the function $f(0)$ in related (6) has been used of the function expressed in relation (7); the form (2) is demonstrated.

$$f(x)=\begin{cases}\dfrac{\pi x\sin(\frac{\pi x}{\lambda})}{\lambda} & 0\le x\le\lambda \\ 0 & else\end{cases} \quad (7)$$

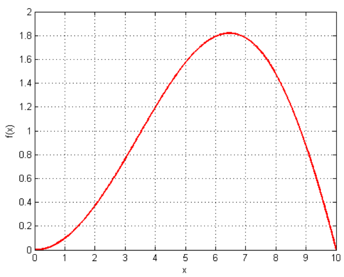
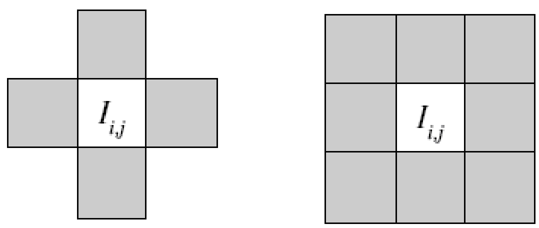


Figure 2. function defined in relation (7) with parameter $\lambda = 10$

Parameter λ In expression (7) will set the shape of relative function. The second topic is calculating the authorized amount of ant movements (i.e. $\Omega_{(l,m)}$ in (4)) is at position (l,m) is. Relationship in this paper around four or eight communication around both the (3) have shown, is introduced.



(a) (b)

Figure 3. neighborhood different pixels: (a) 4 connected neighborhood exposure, (b) 8 connected neighborhood exposure.

C. Update Process

Two operation of updating is used for updating the pheromone matrix. The first incidence is done after the moving of each ant. Each component of Pheromone matrix is updated as following:

$$\tau_{i,j}^{(n-1)}=\begin{cases}(1-\rho)\cdot\tau_{i,j}^{(n-1)}+\rho\cdot\Delta_{i,j}^{(k)} \\ \tau_{i,j}^{(n-1)}\end{cases} \quad (8)$$

where ρ in (2) is defined, $\Delta_{i,j}^{(k)}$ matrix i.e. calculated by the exploratory $\Delta_{i,j}^{(k)}=\eta_{i,j}$. The second incidence is done after moving the entire ant as following:

$$\tau^{(n)}=(1-\psi)\cdot\tau^{(n-1)}+\psi\cdot\tau^{(0)} \quad (9)$$

So that ψ Stage (3) is defined.

D. Summary of Image Edge Detection with ACO Method

Summary of the proposed method in the figure (4) is shown.

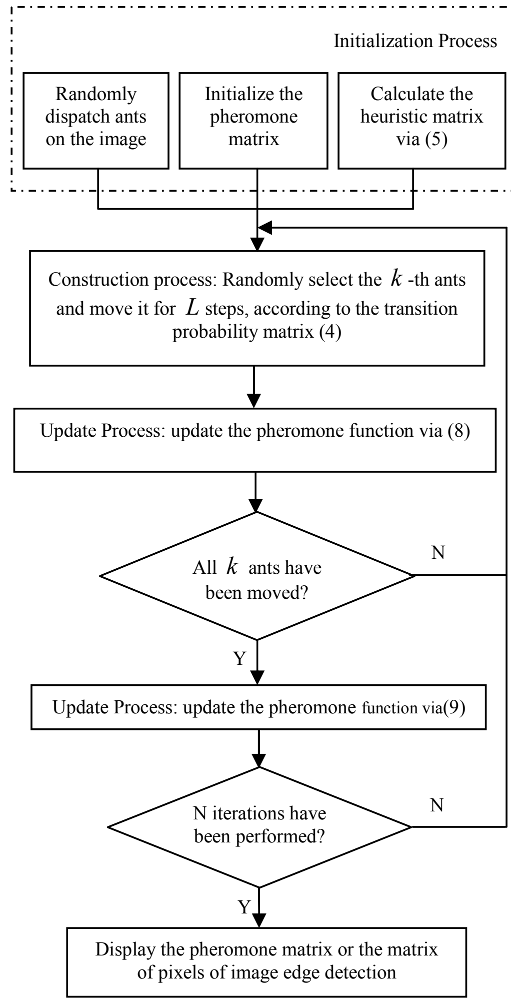


Figure 4. Abstract the performance of ACO for edge detection files

IV. The Combination of ACO and GA

In the proposed method of combined optimization methods, the desirable role in increasing the speed and the answers of optimization problems, we used. The overall trends of solving combined methods are presented. In this method, first a series of answers formed by artificial ants and then the information formed in a manner that it's useful for genetic algorithm, then the answers played a role as initial population as a genetic algorithm and from these answers, the next population is made by GA. At the end of this stage, according to the way that was expressed in ant colony algorithm, updating the pheromone is done based on all taken answers and them the stages will be repeated. As before, we can explain appropriate behavior and genital behavior ants they stated that follows each repetition, ants first will find some answers for problem and based on birth that due to their mating takes place, children ants the first generation to come that there `s dependent on the characteristics of children` s parents are possesses. Implementation of the $L = 40$: total number of ants moving stage planning process. Algorithm shown in the children `s answer is better than the parent's ones. In this algorithm with the mutations and cross over that takes place before the convergence answers has been prevented from the absolute optimum. At the end of each repetition, the caused characteristics and effects generation are transferred bye to the next generations of the answers at the next repeating of algorithm by the pheromone effects.

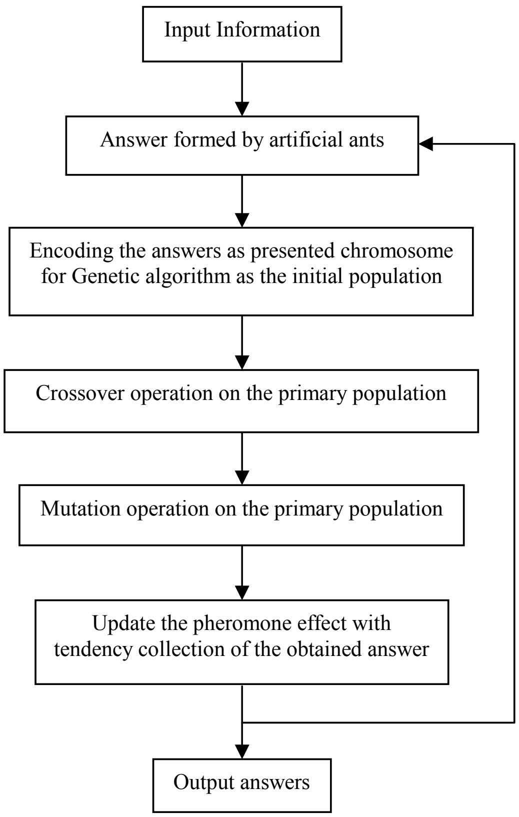


Figure 5. Process of solving the general mixed *GA* and *ACO*

V. EXPERIMENTAL RESULTS

Tests for the assessment of the proposed method using three test image Cameraman, Lena, Pepper the forms (6), (7) and (8) is shown, are performed. Furthermore, the $\psi = 0.05$: Decay factor pheromone expression (9).

Practical method for comparing results of the suggested method to identify Jing Tian [2] has been done. Function defined in relation (7) Attachment is the suggested method and implementation of its result is shown.

Parameters of the suggested method are set as follows.

$K = \lfloor \sqrt{M_1 \times M_2} \rfloor$: Total number of ants, where the function $\lfloor x \rfloor$ shows the highest integer that x is smaller or equal x .

$\tau_{init} = 0.0001$: Initial amount of each component of the matrix pheromone.

$\alpha = 1$: The factors of assessment related to information pheromone in the expression (4).

$\beta = 0.1$: Exploratory information factor assessment related to (4).

$\Omega = 8$: Neighborhood connection, the amount authorized ant movements in relation (4) as the number (3 - b) is shown.

$\lambda = 1$: Regulator operating of the functions related to (7).

$\rho = 0.1$: Evaporation amount of the expression (8).

$L = 40$: Total number of ants moving stage in planning process.

$\psi = 0.05$: Decay factor of the pheromone expression (9).

Practical method for comparing results of the suggested method to identify Jing Tian [2] has been done. Function defined in relation (7) Attachment is the suggested method and implementation of its result is shown.

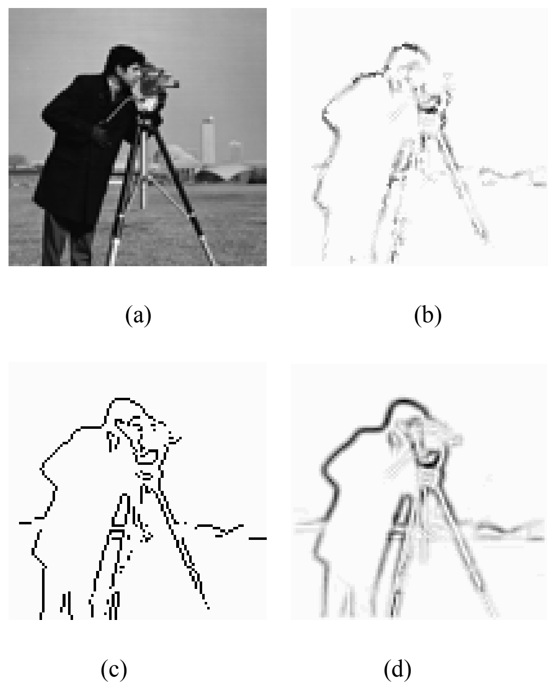
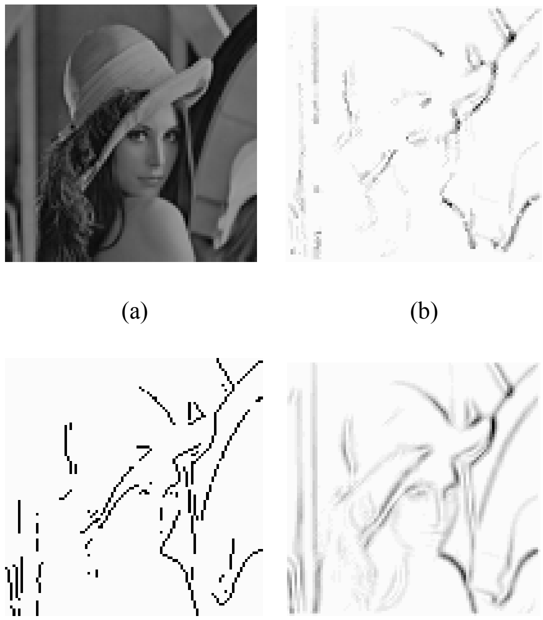
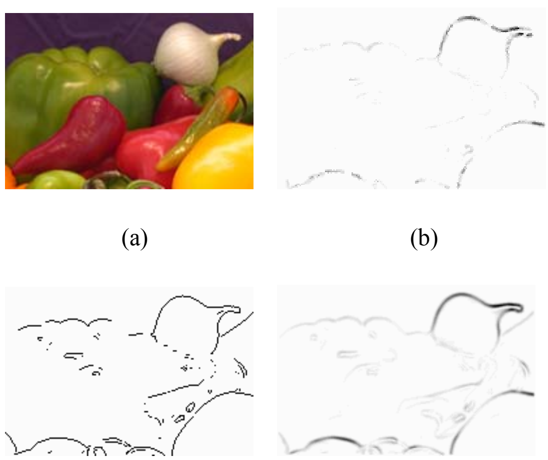


Figure 6. (a) original Cameraman image, (b) edge detection method by ant colony (Jing Tian method), (c) edge detection using Sobel method with desired thresholding and (d) edge detection using proposed method



(a) (b) (c) (d)

Figure 7. (a) original Lenna image, (b) edge detection method by ant colony (Jing Tian method), (c) edge detection using Sobel method with desired thresholding and (d) edge detection using proposed method



(a) (b) (c) (d)

Figure 8. (a) original Pepper image, (b) edge detection method by ant colony (Jing Tian method), (c) edge detection using Sobel method with desired thresholding and (d) edge detection using proposed method

VI. CONCLUSIONS

In this paper a new method for image edge detection using ACO based on GA has been used. That the proposed method is successfully developed, it obtained better implementation of existing algorithms edge detection as has been proven in the simulation results. Our proposed method compared with Jing Tian method enjoys higher speed, less processing time and more answer's optimum. Also the proposed method has a better edge than other classical methods. In addition, our proposed algorithm can be used to reduce the combined capacity of more computational tasks in research.

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