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Image Edge Detection Using Ant Colony Optimization with Genetic Algorithm

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***Abstract*— This paper presents Ant Colony Optimization (ACO) along with genetic algorithm-based optimization technique for edge detection. The problem of edge detection is formulated as one of choosing a minimum cost edge configuration. ACO can be used to find good solutions to combinatorial optimization problems that can be transformed into the problem of finding good paths through a weighted construction graph. Similarly, the genetic algorithm views edge configurations as two-dimensional chromosomes with fitness values inversely proportional to their costs. The design of the crossover and the mutation operators in the context of the two-dimensional chromosomal representation is described. In this paper, an edge detection technique that is based on ACO and genetic algorithm is presented. The proposed method establishes a pheromone matrix that represents the edge information at each pixel based on the routes formed by the ants dispatched on the image. The movement of the ants is guided by the local variation in the image's intensity values. The proposed ACO-based edge detection method takes advantage of the improvements introduced in ant colony system, one of the main extensions to the original ant system. In genetic algorithm, the design of the crossover and the mutation operators in the context of the two-dimensional chromosomal representation is described. The knowledge-augmented mutation operator which exploits knowledge of the local edge structure is shown to result in rapid convergence. The incorporation of meta-level operators and strategies such as the elitism strategy and various combinations of meta-level operators can be tested on synthetic and natural images.**

Keywords: Image edge detection, ant colony optimization, genetic algorithm.

I. INTRODUCTION

Edge is the most basic feature of images, which includes the most part information of images [1]. Edge detection is widely used in image analysis and processing such as feature description, image segmentation, image enhancement and pattern recognition etc., and has turned into a hot spot in research on image processing and analysis technology [2]. Finding the actual borderline of the target image corresponding to the true edge has been a hot topic in the field of image processing [3]. So far, many algorithms have been presented in edge detection field [4]. Despite all this, the edge detection of digital image has not been fully solved. But still it is the major challenge in image processing to improve the accuracy and the signal-to-noise ratio of edge detection algorithm [5]. This is because the traditional edge detection algorithm is based on gradient differential; there are different degrees of limitations of these algorithms [6].

In this paper, ACO is combined with GA to tackle the image edge detection problem, where the aim is to extract the edge information presented in the image, since it is crucial to understand the image's content. The proposed approach exploits a number of ants, which move on the image driven by the local variation of the image's intensity values, to establish a pheromone matrix, which represents the edge information at each pixel location of the image. The partial solution given by ACO acts as initial population of GA on which GA operators: *selection, crossover* and *mutation* are applied.

The paper is organized as follows. In Section II, a brief introduction is provided to present the fundamental concepts of ACO based edge detection technique proposed by Jing Tian *et al* [12] and basic framework of GA. Then, an ACO-GA based image edge detection approach is proposed in Section III. Experimental results are presented in Section IV. Finally, Section V concludes this paper.

II. ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) is a recently proposed metaheuristic approach for solving hard combinatorial optimization problems [19], [20]. Its central component is the pheromone model, which is used to probabilistically sample the search space. In Jing Tian's method, ACO aims to iteratively find the optimal solution of the target problem through a guided search (i.e., the movements of a number of ants) over the solution space, by constructing the pheromone information. To be more specific, suppose totally K ants are applied to find the optimal solution in a space χ that consists of M1×M2 nodes, the procedure of ACO can be summarized as follows.

- Initialize the positions of total K ants, as well as the pheromone matrix $\tau(0)$.
- For the construction-step index n=1: N
  - For the ant index k=1: K,
    - consecutively move the k-th ant for L steps, according to a probabilistic transition matrix $p(n)$.
  - Update the pheromone matrix $\tau(n)$.
- Make the solution decision according to the final pheromone matrix $\tau(N)$.

III. BASIC FRAMEWORK OF GA

Genetic Algorithms are heuristic search approaches that are applicable to a wide range of optimization problems. This

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flexibility makes them attractive for many optimization problems in practice. Evolution is the basis of Genetic Algorithms. The classic Genetic Algorithm is based on a set of candidate solutions that represent a solution to the optimization problem we want to solve. A solution is a potential candidate for an optimum of the optimization problem. Algorithm below shows the pseudo code of the basic Genetic Algorithm. At the beginning, a set of solutions, which is denoted as population, is initialized. This initialization is recommended to randomly cover the whole solution space or to model and incorporate expert knowledge. The representation determines the initialization process. For bit string representations a random combination of zeros and ones is reasonable, for example the initial random chromosome 1001001001 as a typical bit string of length 10. The main generational loop of the Genetic Algorithm generates new offspring candidate solutions with crossover and mutation until the population is complete.

Basic Genetic Algorithm

```
initialize population
Repeat
    Repeat
        Crossover
        Mutation
        phenotype matching
        fitness computation
    until population complete
    selection of parental population
until termination condition
```

IV. PROPOSED ACO-GA BASED EDGE DETECTION

The proposed approach starts from the initialization process, and then runs for N iterations to construct the pheromone matrix by iteratively performing both the construction process and the update process. Before the final update process, the result from the construction process of ACO is passed through GA, where most fit individuals are selected, cross-overed and then mutated. Finally, the decision process is performed to determine the edge. Each of this process is presented in detail.

A. *Initialization Process*

Total K ants are randomly assigned on an image I with a size of M1×M2, each pixel of which can be viewed as a node. The initial value of each component of the pheromone matrix $\tau^{(0)}$ is set to be a constant τ_{init}.

B. *Construction Process*

At the n-th construction-step, one ant is randomly selected from the above-mentioned total K ants, and this ant will consecutively move on the image for L movement-steps. This ant moves from the node (l, m) to its neighboring node (i, j) according to a transition probability that is defined as

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

where $\tau_{i,j}^{(n-1)}$ is the pheromone value of the node (i, j), $\Omega_{(l,m)}$ is the neighborhood nodes of the node (l, m), $\eta_{i,j}$ represents the heuristic information at the node (i, j).The constants α and β represent the influence of the pheromone matrix and the heuristic matrix, respectively.

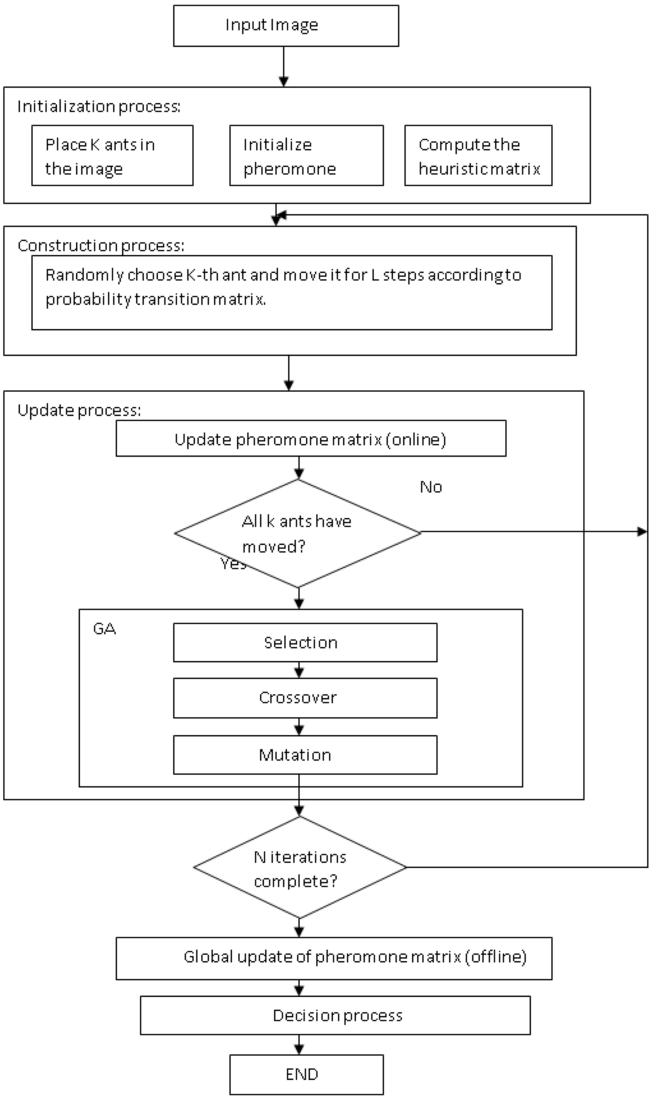


Fig. 1. The proposed method

. There are two crucial issues in the construction process. The first issue is the determination of the heuristic information $\eta_{i,j}$ in (1).

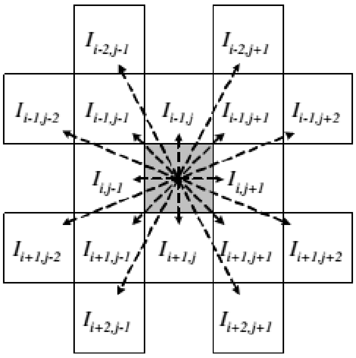


Fig. 2. A local configuration at the pixel position $I_{i,j}$ for computing the Variation $Vc(I_{i,j})$ defined in (3). The pixel $I_{i,j}$ is marked as gray square.

In this paper, it is proposed to be determined by the local statistics at the pixel position (i, j) as:

$$\eta_{i,j} = \frac{1}{Z} V_c(I_{i,j}) \qquad (2)$$

where $Z = \sum_{i=1:M_1} \sum_{j=1:M_2} V_c(I_{i,j})$, which is a normalization factor, $I_{i,j}$ is the intensity value of the pixel at the position (i, j) of the image I, the function $V_c(I_{i,j})$ is a function of a local group of pixels c (called the **clique**), and its value depends on the variation of image's intensity values on the clique c (as shown in Figure 1). More specifically, for the pixel $I_{i,j}$ under consideration, the function $V_c(I_{i,j})$ is

$$\begin{aligned} V_c(I_{i,j}) = f\big(&|I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}| \\ &+ |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j-1} - I_{i+1,j+1}| \\ &+ |I_{i-1,j} - Ii+1,j| + |I_{i-1,j+1} - I_{i-1,j-1}| \\ &+ |I_{i-1,j+2} - I_{i-1,j-2}| + |I_{i,j-1} - I_{i,j+1}|\big) \end{aligned} \qquad (3)$$

To determine the function f (·) in (3), the four functions ((4) to (7)) are considered in Tian's method; they are mathematically expressed as follows

$$f(x) = \lambda x, \quad for\ x \geq 0, \qquad (4)$$

$$f(x) = \lambda x^2, \quad for\ x \geq 0, \qquad (5)$$

$$f(x) = \begin{cases} Sin\left(\frac{\pi\lambda}{2\lambda}\right) & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \qquad (6)$$

$$f(x) = \begin{cases} \frac{\pi x Sin(\frac{\pi x}{\lambda})}{\lambda} & 0 \leq x \leq \lambda \\ 0 & else \end{cases} \qquad (7)$$

C. Update Process

The proposed approach performs two updates operations for updating the pheromone matrix.

1) The first update is performed after the movement of each ant within each construction-step. Each component of the pheromone matrix is updated according to:

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho).\tau_{i,j}^{(n-1)} + \rho.\Delta_{i,j}^{(k)}, if\ (i,j) is\ visited\ by\ the\ current\ k-th\ ant \\ \tau_{i,j}^{(n-1)} \qquad otherwise, \end{cases} \qquad (8)$$

where ρ is defined in (2), $\Delta_{i,j}^{(k)}$ is determined by the heuristic matrix; that is , $\Delta_{i,j}^{(k)} = \eta_{i,j}$.

2) The second update, i.e. the global update, is carried out after the movement of all ants within each construction-step according to

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

This update is done only after the process of selection, crossover and mutation of GA takes place.

D. Decision Process

In this step, a binary decision is made at each pixel location to determine whether it is edge or not, by applying a threshold T on the final pheromone matrix $\tau^{(N)}$. In this paper, the above-mentioned T is proposed to be adaptively computed based on the method developed in [13].

The initial threshold $T^{(0)}$ is selected as the mean value of the pheromone matrix. Next, the entries of the pheromone matrix is classified into two categories according to the criterion that its value is lower than $T^{(0)}$ or larger than $T^{(0)}$. Then, the new threshold is computed as the average of two mean values of each of above two categories. The above process is repeated until the threshold value does not change any more (in terms of a user-defined tolerance **ε**). The above iterative procedure can be summarized as follows.

Step 1: Initialize $T^{(0)}$ as

$$T^{(0)} = \frac{\sum_{i=1:M_1} \sum_{j=1:M_2} \tau_{i,j}^{(N)}}{M_1\ M_2} \qquad (10)$$

and set the iteration index as l=0.

Step 2: Separate the pheromone matrix $\tau^{(N)}$ into two class using $T^{(l)}$, where the fist class consists entries of τ that have smaller values than $T^{(l)}$, while the second class consists the rest entries of τ.

Next, calculate the mean of each of the above two categories via

$$m_L^{(l)} = \frac{\sum_{i=1:M_1} \sum_{j=1:M_2} g_{T^{(l)}}^L(\tau_{i,j}^{(N)})}{\sum_{i=1:M_1} \sum_{j=1:M_2} h_{T^{(l)}}^L(\tau_{i,j}^{(N)})} \qquad (11)$$

$$m_U^{(l)} = \frac{\sum_{i=1:M_1} \sum_{j=1:M_2} g_{T^{(l)}}^U(\tau_{i,j}^{(N)})}{\sum_{i-1:M_1} \sum_{j=1:M_2} h_{T^{(l)}}^U(\tau_{i,j}^{(N)})} \qquad (12)$$

where

$$g_{T^{(l)}}^L(x) = \begin{cases} x, & if\ x \leq T^{(l)}; \\ 0 & otherwise. \end{cases} \qquad (13)$$

$$h_{T^{(l)}}^L(x) = \begin{cases} 1, & if\ x \leq T^{(l)}; \\ 0 & otherwise. \end{cases} \qquad (14)$$

$$g_{T^{(l)}}^U(x) = \begin{cases} x, & if\ x \geq T^{(l)}; \\ 0, & otherwise. \end{cases} \qquad (15)$$

$$h_{T^{(l)}}^U(x) = \begin{cases} 1, & if\ x \geq T^{(l)}; \\ 0, & otherwise. \end{cases} \qquad (16)$$

Step 3: Set the iteration index l =l+1, and update the threshold as:

$$T^{(l)} = \frac{m_L^{(l)} + m_U^{(l)}}{2} \qquad (17)$$

Step 4: If $|T^{(l)} - T^{(n-1)}| > \boldsymbol{\varepsilon}$, then go to Step 2; otherwise, the iteration process is terminated and a binary decision is made on each pixel position(i, j) to determine whether it is edge (i.e., $E_{i,j} = 1$) or not (i.e., $E_{i,j} = 0$), based on the criterion

$$E_{i,j} = \begin{cases} 1, & if\ \tau_{i,j}^{(N)} \geq T^{(l)}; \\ 0, & otherwise. \end{cases} \qquad (18)$$

E. Genetic Algorithm Approach:

The GA is applied after the local update of pheromone at each construction step and before global update when all the construction steps are over.

1) Initialization

Initially many individual solutions are randomly generated to form an initial population. The population contains several hundreds or thousands of possible solutions [27]. The partial solutions obtained from the local pheromone update acts as the initial population for GA.

2) Selection

During each successive generation, a proportion of existing population is selected according to the Rastrigin function. The Rastrigin function is given by:

$$f(x) = An + \sum_{i=1}^{n} [x_i^2 - ACos(2\pi x_i)] \tag{19}$$

Where A=10 and x_i € [-5.12, 5.12]. It has the global maximum at x=0, where f(x)=0 and n=2.

The selected population is conserved for the new generation [28]. The selection step chooses parents for the next generation based on their scaled values from the fitness scaling function. The algorithm applied Roulette Wheel selection moves along the line in steps of equal size, one step for each parent. Fitness proportionate selection, also known as roulette wheel selection, is a genetic operator used in genetic algorithms for selecting potentially useful solutions for recombination. In fitness proportionate selection, as in all selection methods, the fitness function assigns a fitness to possible solutions or chromosomes. This fitness level is used to associate a probability of selection with each individual chromosome. If f_i is the fitness of individual i in the population, its probability of being selected is

$$p_i = \frac{f_i}{\sum_{j=1}^{n} f_j} \tag{20}$$

where N is the number of individuals in the population.

3) Crossover

A pair of parents is selected for producing a child solution. The new generation shares many of the characteristics of its parents [30]. Crossover operator generates two children from two parents selected by the genetic algorithm solver.

For example, if p1 and p2 are the parents

p1 = [z y x u v w s t]

p2 = [1 2 3 4 5 6 7 8]

and the crossover point is 3, the function returns the following child.

child = [z y x 4 5 6 7 8]

The fraction of the next generation that crossover produces, is set at 0.8. Mutation produces the remaining individuals in the next generation [27].

4) Mutation

A parent solution is selected for producing a child solution. The new generation shares the same information than its parents, with random modifications [28]. Although Crossover and Mutation are the main genetic operators, it is possible to use other operators, such as regrouping, colonization - extinction or migration in genetic algorithm. The mutation function applies the same workflow as the active contour method, but only on the selected parents [30].

V. EXPERIMENTAL RESULTS

To explore the utility and demonstrate the efficiency of the proposed method, experiments were carried out on the image of mushroom, statue, tiger, moon and truck respectively. All the pictures are 8 bits per pixel and size of 128* 128. The methods proposed by [12] will be applied to the image after setting the values of all the required parameters. These results will then be compared with the result of the proposed method.

The constant parameters are given below with their values:

- k = √(M$_1$*M$_2$), total number of ants.
- **τ_{init}** = 0.0001, the initial value set to every element of pheromone matrix.
- **α** =1, the weighing factor of the pheromone value in (1).
- **β** =0.1, the weighing factor of the heuristic information in (1).
- **Ω** :8-connectivity, the permissible range for movement of ant in (1).
- **ρ**= 0.1, the evaporation rate of pheromone in (9).
- Ψ= 0.05, the pheromone decay rate in (10).

The varied parameters are also given below with their values and the experiments are carried out accordingly on the five images.

- λ= 10, the factor used to adjust the shape of functions in Tian's method.
- L= 40, total number of ant's movement steps within each construction steps.
- N, given construction steps.

The test images given in this paper are:

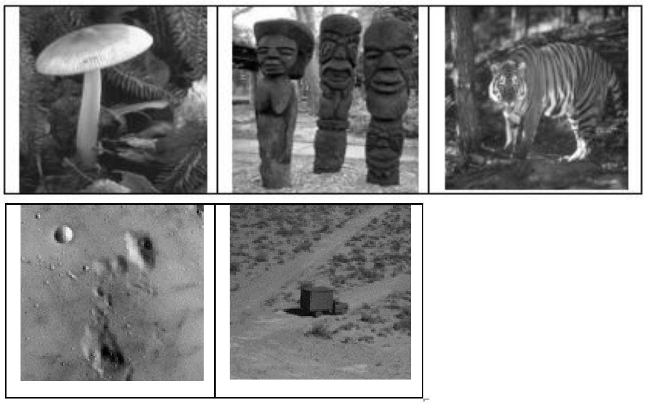


Fig. 3. Test images of mushroom, statue, tiger, moon and truck respectively.

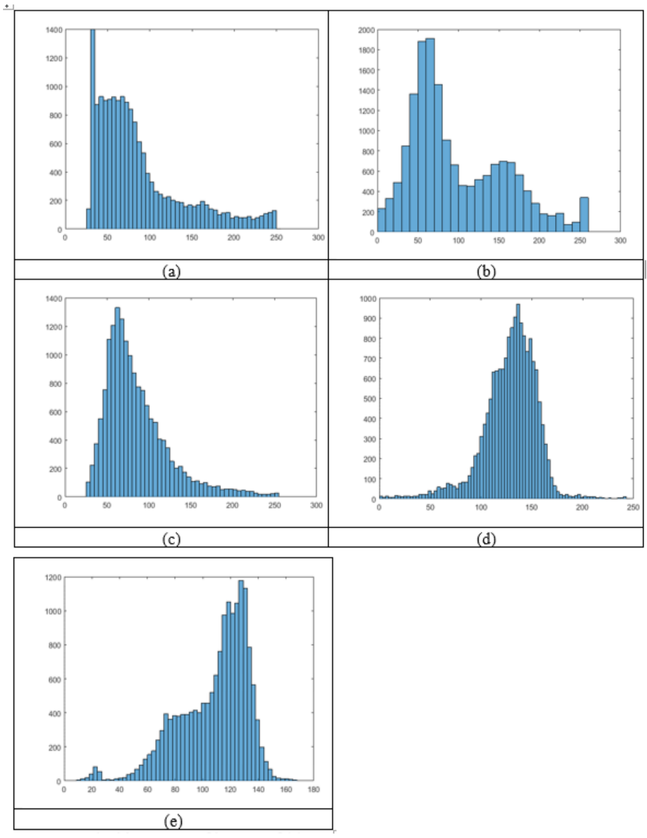
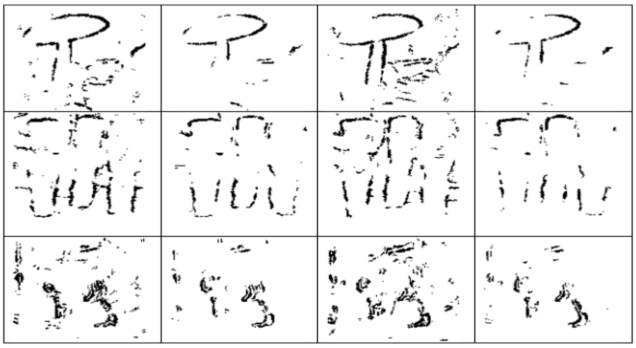


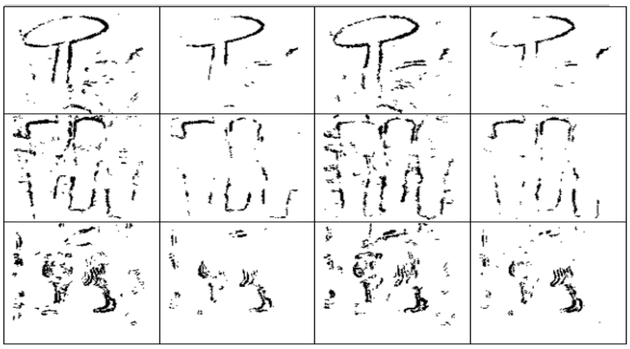
Fig. 4. The histograms of images of (a) mushroom, (b) statue, (c) tiger, (d) moon and (e) truck.

A. *Output images of ACO-GA*

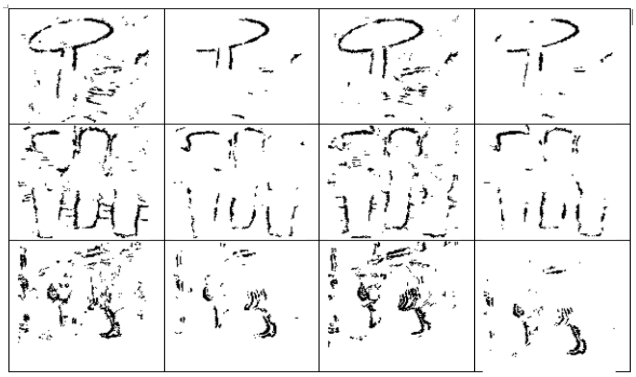
The output with N=1:4, λ=40 and L=400 for mushroom, statue and tiger are:



The output with N=1:4, λ=40 and L=800 for mushroom, statue and tiger are:



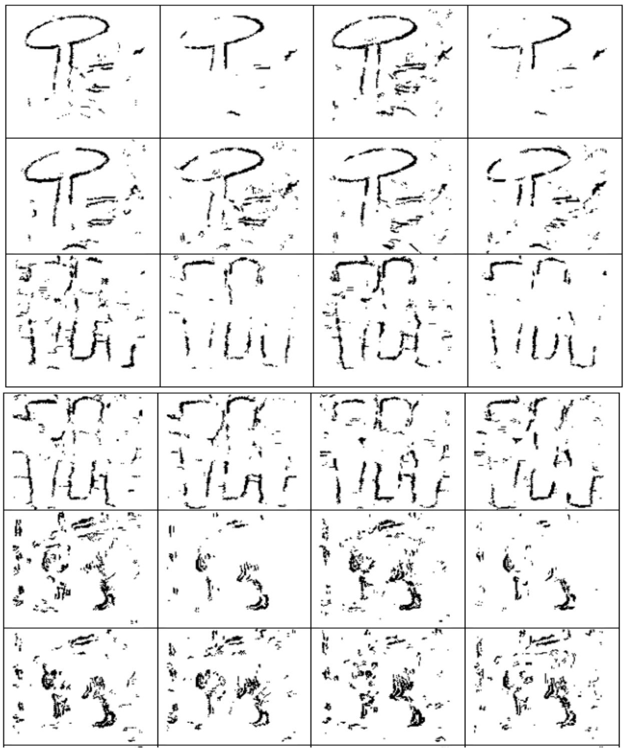
The output with N=1:4, λ=40 and L=1000 for mushroom, statue and tiger are:



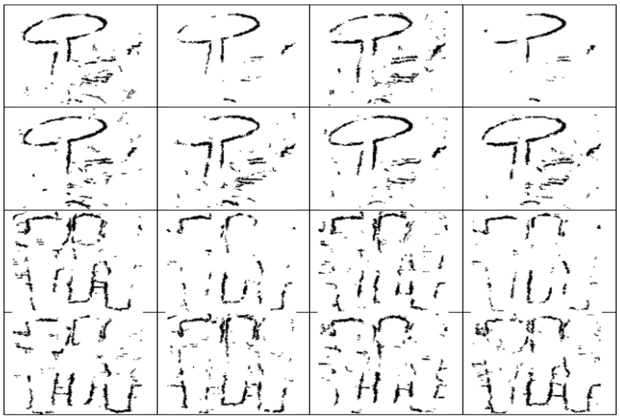
The four output images of the each test image corresponds to the four objective functions used in ACO , given by (4), (5), (6) and (7) respectively.

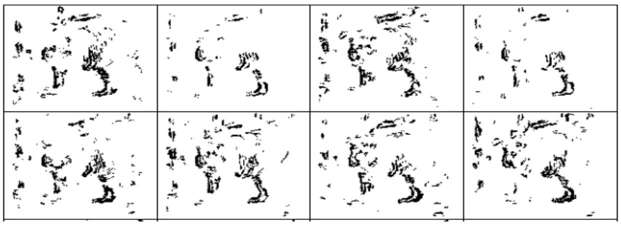
Now increasing the number of construction steps to 1:8 will give two sets of outputs for each test image, which are as follows:

The output with N=1:8, λ=40 and L=400 for mushroom, statue and tiger are:

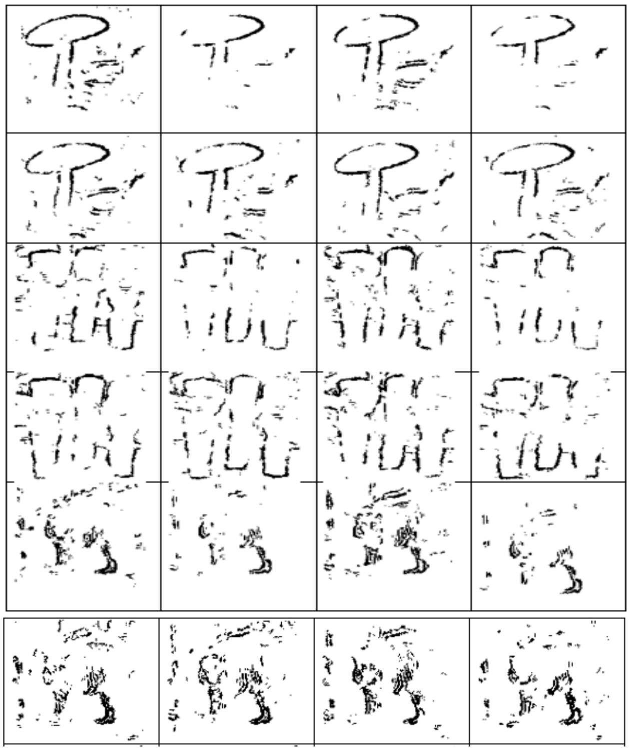


The output with N=1:8, λ=40 and L=800 for mushroom, statue and tiger are:





The output with N=1:8, λ=40 and L=1000 for mushroom, statue and tiger are:



B. Evaluation of the results:

The results of Jing tian's method and the proposed method are compared with respect to the ground truth images of each test images, which are as follows:

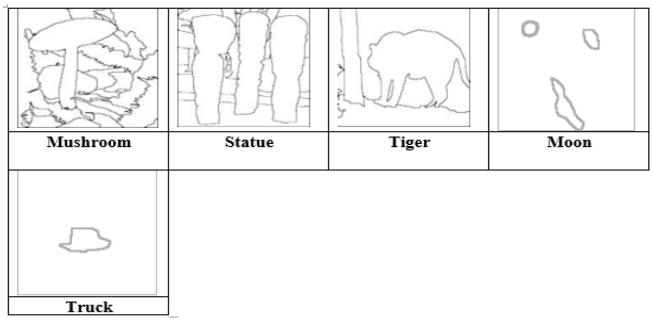


Fig. 5. Ground truth images of the corresponding test images.

1) Mean Square Error

An estimator to quantify the difference between an estimator and the true value of the quantity being estimated is called Mean square error. The mean square error is the squared error averaged over the M × N array.

$$MSE = \frac{1}{MN}\sum_{n=1}^{M}\sum_{m=1}^{N}[g'(n,m) - g(n,m)]^2 \tag{21}$$

TABLE I. MEAN SQUARE ERROR OF TEST IMAGES COMPARED WITH PROPOSED SOLUTION.

Image Name	Mean Square Error (Jing Tian)	Mean Square Error (Proposed Solution)
mushroom.bmp	4.5303e+03	4.4432e+03
statue.bmp	4.9710e+03	4.8375e+03
tiger.bmp	5.4097e+03	5.1306e+03
moon.bmp	3.1157e+03	2.7775e+03
truck.bmp	1.6165e+03	1.3253e+03

2) Root Mean Square Error

It is very common and excellent general purpose error metric for numerical predictions. Compared to the similar Mean Squared Error, RMSE amplifies and severely punishes large errors.

TABLE II. ROOT MEAN SQUARE ERROR OF TEST IMAGES COMPARED WITH PROPOSED SOLUTION.

Image Name	Root Mean Square Error (Jing Tian)	Root Mean Square Error (Proposed Solution)
mushroom.bmp	67.3075	62.6573
statue.bmp	70.5053	63.5521
tiger.bmp	73.5507	68.6282
moon.bmp	55.8185	52.7020
truck.bmp	40.2057	32.4047

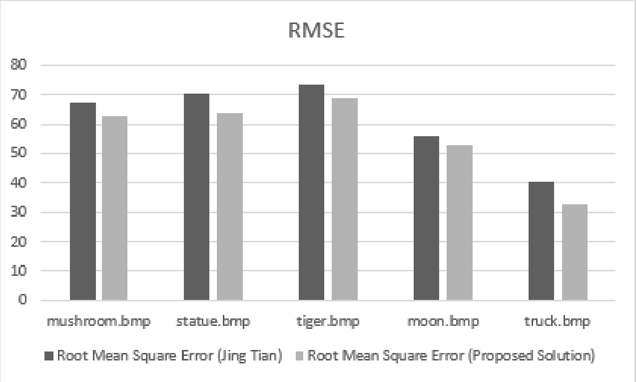


Fig. 6. Graph comparing the RMSE between Jing Tian and proposed solution.

3) Peak Signal to Noise Ratio

The ratio between the maximum possible powers to the power of corrupting noise is known as Peak Signal to Noise Ratio. It affects the fidelity of its representation. It can be also said that it is the logarithmic function of peak value of image and mean square error.

$$PSNR = 20\log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \tag{22}$$

TABLE III. PEAK SIGNAL TO NOISE RATIO.

Image Name	Peak Signal to Noise Ratio (Jing Tian)	Peak Signal to Noise Ratio (Proposed Solution)
mushroom.bmp	174.4707	186.1725
statue.bmp	166.5575	178.8401
tiger.bmp	159.6611	173.9464
moon.bmp	226.6215	239.8224
truck.bmp	292.0776	332.5733

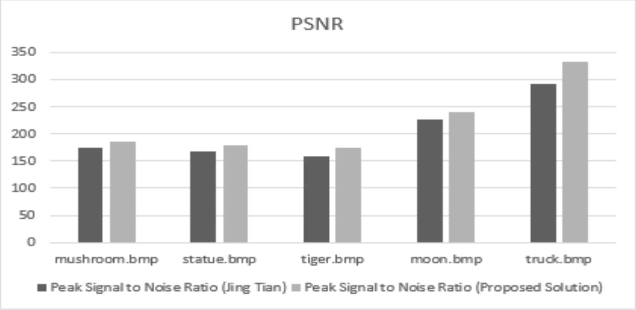


Fig. 7. Graph comparing the PSNR between Jing Tian and proposed solution.

The subjective analysis of the outputs shows that all the objective functions work better for image of mushroom and tiger. It is seen that out of four objective functions, (4) and (6) outperforms other objective functions. It is also evident from the output images that as the number of construction steps and number of steps of the ants were increased, the results improved. The subjective analysis correlates with the values obtained from objective analysis as shown in Table.2 and 3.

VI. CONCLUSION

In this paper, a novel ACO-GA algorithm was introduced for edge-detection. Proposed algorithm has a strong search capability in the graph space and can effectively find optimal solutions. Experimental results show that this approach considers both running time and solution quality as well.

Several areas where information is lacking were highlighted in the literature review. Whilst some of these were addressed by the research in this thesis, others remain. In particular, there is a lack of observational studies of any changes in the explanation of three control parameters in the basic ACO; the number of food sources which is equal to the number of ants, the value of limit and the maximum cycle number (MCN). Future studies might, for example, look for trends in the parameter tuning of Ant Colony Algorithm separately or with tuning parameters in the Genetic Algorithm. The global thresholding used in the proposed technique works very well for bimodal histogram and may not work equally well for other type of thresholding. With some post-processing work on the results obtained, proposed technique can prove to be worthy for edge detection.

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