Comparison of A.C.O for Edge Detection Problem using α, β Parameters

[I]Abhishek Sharma, [II]Deepika Chaudhary, [III]Viney Dhawan
[I,II,III]Dept. of ECE, K.I.T.M, Karnal, Haryana, India

Abstract
One of the issues in image processing is Edge detection. A technique ACO has been used to address this problem. The different variants of ACO differ in either the pheromone is updated on the ants or the way in which route is constructed. Researchers have done work with two ACO algorithms: AS(Ant System) & ACS(Ant Colony System).The proposed work is to make a comparison by changing the parameter value of α, β for performance analysis. This proposed work can be considered as an ideal template in the field of image processing to use a typical ACO algorithm out of the different ACO algorithms for this problem.

Keywords
Image processing, Ant colony optimization, Edge detection ,Feature extraction, pheromone matrix

I. Introduction

EDGE
The sudden change of discontinuities in an image are called as edge. Significant transitions in an image are called as edge. Edge is one of the simplest and the most important feature of image particularly in the areas of feature detection and feature extraction ,which aim at identifying points in a digital image. Edges in images are with strong intensity contrasts–a jump in intensity from one pixel to the next. The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world.

A.C.O
Ant colony optimization (ACO) is a nature-inspired optimization algorithm[1] ,motivated by the natural phenomenon that ants deposit pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony.

II. EDGE Detection
Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities. Edges often carry important information about an object when shown as large gradient magnitude. Edge detection strategies seek out obvious edges in an image. Traditional edge filtering methods often result in some drawbacks like broken edges. Therefore ,many methods have been proposed to link these broken edges in order to improve edge detection. An edge can be of almost arbitrary shape and may include junctions. In practice ,edges are usually defined as sets of points in the image which have a strong gradient magnitude. These algorithms (AS, ACS) usually place some constraints on the properties of an edge such as shape, smoothness, and gradient value. Image edge detection refers to the extraction of the edges in a digital image. It is a process whose aim is to identify points in an image where discontinuities or sharp changes in intensity occur.

III. Problem Definition
Edge detection isused to identify the edges in an image ,i.e., a technique formarking sharp intensity changes, and is important in further analyzing image content. An edge detection algorithm to an image may significantly reduce the amount of data to be processed and may filter out information that may be regarded as less relevant, while preserving the important structural properties of an image. If the edge detection step is successful, the subsequent task of interpreting the information contents in the original image may be substantially simplified. In the proposed work, aim is to find out the edges of the images by using the ant colony optimization algorithm. The proposed work aimed at drawing a comparison by changing the parameter value of α for performance analysis.

IV. Ant Colony Optimization
ACO is inspired by food foraging behavior exhibited by ant societies. Ants as individuals are unsophisticated living beings. Thus, in nature, an individual ant is unable to communicate or effectively hunt for food, but as a group, they are intelligent enough to successfully find and collect food for their colony. This collective intelligent behavior is an inspiration for one of the popular evolutionary techniques (ACO algorithms). The adoption of the strategies of ants adds another dimension to the computational domain.The ants communicate using a chemical substance called pheromone. As an ant travels, it deposits a constant amount of pheromone that other ants can follow. When looking for food, ants tend to follow trails of pheromones whose concentration is higher [9].There are two main operators in ACO algorithms. These are:

Route construction: Initially, the moving ants construct a router on their way to food. However, the subsequent ants, follow a probability-based route construction scheme.

Pheromone update: This step involves two important phenomenons. Firstly, a special chemical pheromone □ is deposited on the path traversed by the individual ants. Secondly, this deposited pheromone is subject to evaporation. The quantity of pheromone updated on an individual path is a cumulative effect of these two phenomenons.

V. Proposed ACO Based Approach

A. Initialization Process
Totally 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 t(0) is set to be a constant τ(init.).

ISSN : 2394-2975 (Online)
ISSN : 2394-6814 (Print)

B. Construction Process

At the 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

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

Where $\tau_{i,j}^{(n-1)}$ is the pheromone information value of the arc linking the node i to the node j; Ω_i is the neighborhood nodes for the ant a_k given that it is on the node i; the constants α and β represent the influence of pheromone information and heuristic information, respectively; $\eta_{i,j}$ represents the information for going from node I to node j , which is fixed to be same for each construction-step. There is a crucial issues in the construction process. The first issue is the determination of the heuristic information $_{(i,j)}$in (4) .In this paper, it is proposed to be determined by the local statistics at the pixel position (i,j) as

$H_{i,j=1/Z}$ $(V_c(I_{i,j}))$ ……… (2)

$I_{(i,j)}$ is the intensity value of the pixel at the position (i,j) of the image I, the function $V_c(I_{(Ii,j)})$ is a function of a local group of pixels c (called the *clique*), and its value depends on the variation of image intensity values on the clique c (as shown in Figure 1). More specifically, for the pixel Ii,j under consideration, the function $V_c(I_{i,j})$ is

$$V_c(I_{i,j}) = f(|I_{i-2,j-1}-I_{i+2,j+1}|+|I_{i-2,j+1}-I_{i+2,j-1}|+|I_{i-1,j-2}-I_{i+1,j+2}|+|I_{i-1,j-1}-I_{i+1,j+1}|+|I_{i-1,j}-I_{i+1,j}|+|I_{i-1,j+1}-I_{i-1,j-1}| + |I_{i-1,j+2}- I_{i-1,j-2}| + |I_{i,j-1}- I_{i,j+1}|)$$

…. (3)

To determine the function f(·) in (3), the following four functions are considered in this paper;

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

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

$$f(x)= \begin{cases} \sin(\pi x/2\lambda) & 0\leq x\leq \lambda ; \\ 0 & \text{else.} \end{cases}$$

$$f(x)= \begin{cases} (\pi x\sin((\pi x/\lambda))/\lambda & 0\leq x\leq \lambda ; \\ 0 & \text{else} \end{cases} \qquad (4)$$

The parameter λ in each of above functions adjusts the functions respective shapes.

C. Update Process

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

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

$$T_{i,j}^{(n-1)} = \begin{cases} (1-\rho)\,.\,\tau_{i,j}^{(n-1)} + \rho.\,\Delta_{i,j}^{(k)} & \text{if(i,j) is visited by the current k- than t;} \\ \tau_{i,j}^{(n-1)} & \text{otherwise} \end{cases} \quad ..(5)$$

where ρ is the *evaporation rate.* $\Delta i,j^{(k)}$ is determined by the heuristic matrix; that is, $\Delta i,j^{(k)} = \eta\ i,j$.

These condition update is carried out after the movement of all ants within each construction-step according to

$\tau^{(n)} = (1-\psi).\ \tau^{(n-1)} + \psi.\tau^{(0)}$ ……(6) where ψ is the *pheromone decay coefficient*.

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 computed based on the method developed in [20].

E. Visualize Process

In this step, different values of the α parameter is applied to the above algorithm. Smaller the value of the α parameter more edges the algorithm detects in the image. As we go on decreasing the value of the α parameter, output of the given image becomes more clear.

VI. Experimental Results

Experiments are conducted to evaluate the performance of the proposed approach using different α values (0.01,0.02 0.04,0.06,0.09) and β values (0.1,0.2,0.4,0.6,0.8,0.9) the image which is shown in Figure 1(a). Furthermore, various parameters of the proposed approach are set as follows.

- $K = \sqrt{M1\times M2}$:the total number of ants, where the function [x] represents the highest integer value that is smaller than or equals to x.
- T_{init} =0.0001: the initial value of each component of the pheromone matrix.
- α = 1: the weighting factor of the
- pheromone information in (1) .
- β = 0.1: the weighting factor of the
- heuristic information in (1) .
- Ω= 8-connectivity neighborhood: the permissible ant movement range in (1)
- λ= 1:adjusting factor of the functions
- in (4) .
- ρ= 0.1:the evaporation rate in (5) .

Fig 1 (a) original image

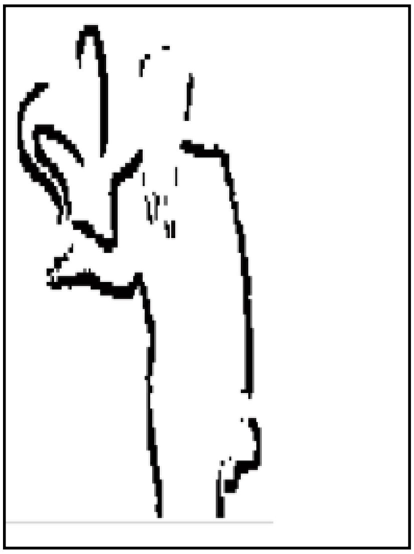

Fig 1 b) β= 0.2, α=0.02

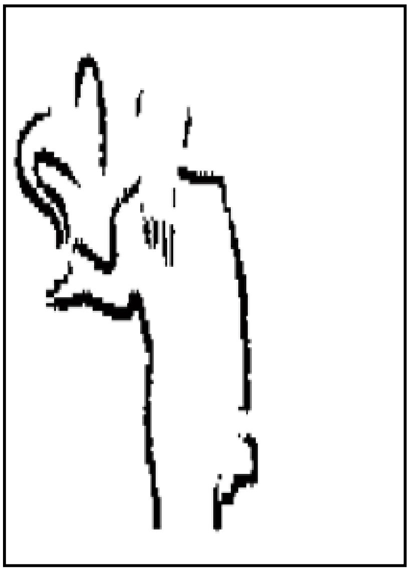

Fig 1 c) β= 0.4, α=0.02

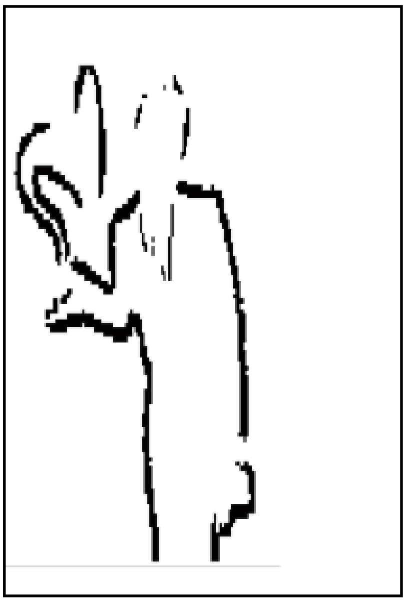

Fig 1 d) β=0.6,α=0.02

Fig 1 e) β= 0.8, α=0.02

Fig 2 a): β=0.2, α = 0.02

Fig 2 b): β=0.2 α = 0.04,

ISSN : 2394-2975 (Online)
ISSN : 2394-6814 (Print)

Fig 2c): β=0.2, α = 0.06

Fig 3: β=0.1 α = 0.09,

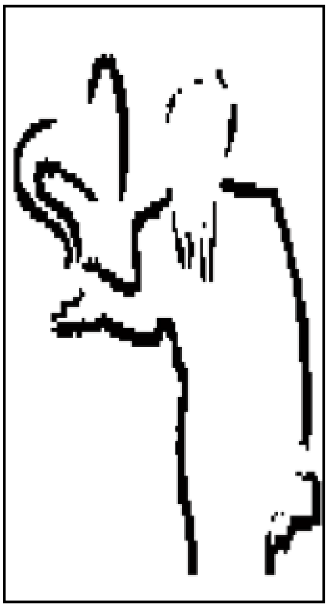

Fig 4: β=0.9, α = 0.01

VII. Conclusion

In this paper, an ACO-based image edge detection approach has been successfully developed. The proposed approach yields superior subjective performance to that of the existing edge detection algorithm [16], as verified in our experiments. The parallel ACO algorithm [17] can be exploited to further reduce the computational load of the proposed algorithm, for future research work. Furthermore, image becomes more sharper as we go on decreasing the value of the parameter α & increasing the value of the parameter β by visualizing the output.

References

[1] *M.Dorigo and S.Thomas, Ant Colony Optimization .Cambridge :MIT Press,2004.*

[2] *Jing Tian, Weiyu Yu, and Shengli Xie, "An Ant Colony Optimization Algorithm For Image Edge Detection", in Proc. of the IEEE International, pp.751-756,2008.*

[3] *Hossein Nezamabadi-pour· Saeid Saryazdi Esmat Rashedi, "Edge detection using ant algorithms", inproc. Of Springer-Verlag, pp.623-628,2005.*

[4] *Aleksandar Jevti´c, Joel Quintanilla-Dominguez, M.G. Cortina-Januchs and Diego Andina, "Edge Detection Using Ant Colony Search Algorithm and Multiscale Contrast Enhancement", in the Proceedings of the 2009 IEEE International Conference on systems, man, and cybernetics, pp.2193-2198,2009.*

[5] *X. Zhuang, "Edge Feature Extraction in Digital Images with the Ant Colony System ", inproc. Of the IEEE international Conference an computational intelligence for Measurement Systems and Applications, pp.133-136,2004.*

[6] *Alirezae Rezaee," Extracting edge of images with ant colony ", in the Journal of ELECTRICAL ENGINEERING, pp.57–59,2008.*

[7] *X.Zhuang," Image Feature Extraction with the perceptual graph based on the ant colony system ", inproc. Of the IEEE International conference on systems, man and cybernetics, pp.6354-6359,2004.*

[8] *X.Zhuang," Image Feature Extraction with the Perceptual Graph Based on the Ant Colony System ", in the IEEE International Conference on Systems, Manand Cybernetics, pp.6354-6359,2004.*

[9] *M.Dorigo and L.M.Gambardella," Antcolonysystem: A cooperative learning approach to the traveling salesman problem,"in the proc. of IEEE Trans. On Evolutionary Computation, pp.53–66,1997.*

[10] *M.Dorigo, M.Birattari, and T.Stutzle," Ant colony optimization,"in the proc. of the IEEE Computational Intelligence Magazine, pp.28–39,2006.*

[11] *H.-B. Duan ,Ant Colony Algorithms :Theory and Applications. Beijing: Science Press, 2005.*

[12] *M.Dorigo, V.Maniezzo, and A.Colorni," Antsystem: Optimization by a colony of cooperating agents," IEEE Trans .on Systems, Manand Cybernetics, PartB, vol.26,pp.29–41,Feb.1996.*

[13] *M.Dorigo, M.Birattari, and T.Stutzle," Ant colony optimization," IEEE Computational Intelligence Magazine, vol.1,pp.28–39,Nov.2006.*

[14] *T.Stutzle and H.Holger," Max-Min ant system," Future Generation Computer Systems, vol.16,pp.889–914,Jun.2000.*

[15] *M.Dorigo, G.D.Caro, and T.Stutzle, Special Issue on*

Ant Algorithms, Future Generation Computer Systems, vol.16,Jun.2000.

[16] *H.Nezamabadi-Pour, S.Saryazdi, and E.Rashedi,“ Edge detection using ant algorithms,” Soft Computing, vol.10,pp.623–628,May2006.*

[17] *M.Randall and A.Lewis,“ A parallel implementation of ant colony optimization,” Journal of Parallel and Distributed Computing, vol.62,pp.1421–1432,Sep.2002s*

Author’s Profile

Name- Abhishek Sharma
E-Mail Id- kitmfnds@gmail.com