Implementation of Ant Colony Optimization for Digital Image Edge Detection

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ABSTRACT

Edge detection is one of the important issues in image processing. a new concept for improving digital image edge detection using *Ant colony optimization* (ACO) has been used. It was used to find better solutions to combinatorial optimization problems. ACO, inspired by the searching behavior of ants, it has been used for addressing this problem. ACO has different variants which differ in either the way in which way is constructed or the pheromone is updated on the ants. This proposed work can be an ideal template and ready reference for a novice researcher in the field of image processing to use a typical ACO algorithm out of the different ACO algorithms for his problem. Experimental results are provided to show the existence of the superior performance of the proposed approach.

Index Terms-*Edge detection, Ant colony optimization,image processing, Feature extraction.*

I. Introduction

Edge is one of the most important and the simplest features of image particularly in the fields of feature detection and feature extraction, which main aim at searching points in a digital image. Edges in images are place where strong intensity contrasts present – a jump in intensity from one pixel to the next. The main aim of detecting sharp changes in image brightness is to capture important events and changes in properties of the world.

Ant colony optimization (ACO) is a nature-inspired optimization algorithm [1], motivated by the natural phenomenon that ants sediment pheromone on the ground in order to mark some favorable path that should be followed by other members of the colony. Ant colony optimization (ACO) is a typical example inspired by the intelligence of real ants, for finding solutions to combinatorial optimization problems.

2. Edge Detection

Edges frequently carry important information about an object, when shown as large gradient magnitude. Edge detection strategies attempt to find out obvious edges in an image. Traditional edge filtering methods often result in some drawbacks like broken edges. Therefore, many methods have been put forward to link these broken edges in order to become better edge detection. An edge can be of almost arbitrary shape, and may include junctions. In practice, edges are usually described exactly as sets of points in the image which have a strong gradient magnitude. These algorithms (AS, ACS) usually place some restriction on the properties of an edge, such as shape, smoothness, and gradient value. Image edge detection alludes to the extraction of the edges in a digital image. It is a series of actions whose aim is to recognize points in an image where discontinuities or sharp changes in intensity occur.

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III Problem Definition

Edge detection is used to establish the identity of the edges in an image, i.e., a technique for marking 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 explain the meaning of the information contents in the original image may be essentially simplified. In the proposed work, point at target to find out the edges of the images by using the ant colony optimization algorithm.

IV. Ant Colony Optimization

The ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. ACO is inspired by searching widely for food or provisions behaviour exhibited by ant societies. In the natural world, ants walk randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but to instead follow the trail, returning and reinforcing it if they eventually find food. The pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over faster, and thus the pheromone density remains high as it is laid on the path as fast as it can evaporate. Thus, when one ant finds a good path from the colony to a food source, other ants are more likely to follow that path. 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 route randomly on their way to food. However, the subsequent ants follow a probability-based route construction scheme.

Pheromone update: This step involves two important phenomenon's. 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 phenomenon's.

V. Proposed ACO-Based Image Edge Detection 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 $\hat{o}^{(0)}$ is set to be a constant $\hat{o}_{init}$.

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

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

where $\tau_{ij}^{(n-1)}$ 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 heuristic information for going from node i to node j, which is fixed to be same for each construction-step.

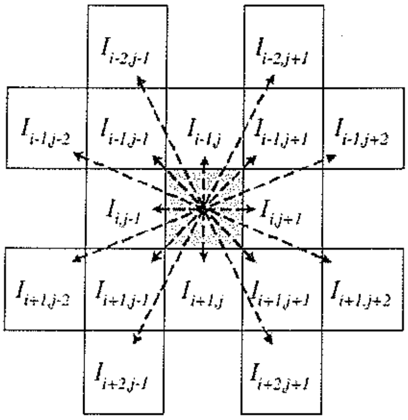


Fig. 1. A local configuration at the pixel position $I_{i,j}$ for computing the variation Vc($I_{i,j}$) The pixel $I_{i,j}$ is marked as gray square.

There is a crucial issues in the construction process. The first issue is the determination of the heuristic information $\varsigma_{(i,j)}$ in (1). In this paper, it is proposed to be determined by the local statistics at the pixel position (i, j) as

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

$I_{(i,j)}$ is the intensity value of the pixel at the position (i, j) of the image I, the function Vc(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's intensity values on the clique c (as shown in Figure 1). More specifically, for the pixel $I_{i,j}$ under consideration, the function Vc(Ii,j) is

$$V_c(I_{i,j}) = f(|I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}| + |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j-1} - I_{i+1,j+1}| + |I_{i-1,j} - I_{i+1,j}| + |I_{i-1,j+1} - I_{i-1,j-1}| + |I_{i-1,j+2} - I_{i-1,j-2}| + |I_{i,j-1} - I_{i,j+1}|) \qquad (3)$$

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

$$f(x)= \lambda x, \text{ for } x \geq 0, \qquad (4)$$

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

$$f(x) = \begin{cases} \sin(\pi x/2\lambda) & 0 \leq x \leq \lambda; \\ 0 & \text{else.} \end{cases} \qquad (6)$$

$$f(x) = \begin{cases} \pi x \sin((\pi x/\lambda))/\lambda & 0 \leq x \leq \lambda; \\ 0 & \text{else} \end{cases} \qquad (7)$$

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

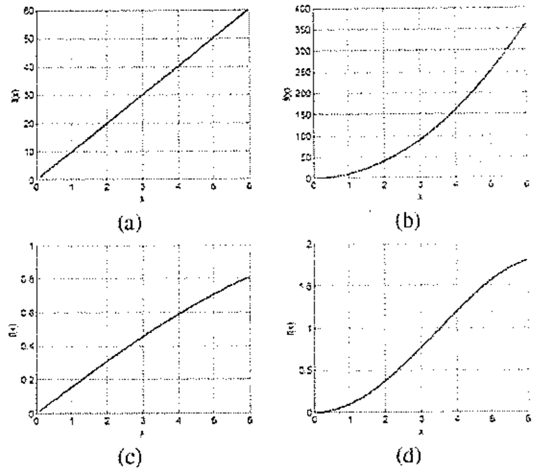
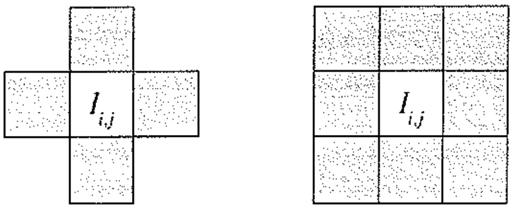


Fig. 2. Various functions with the parameter λ = 10: (a) the function defined in (4); (b) the function defined in (5); (c) the function defined in (6); and (d) the function defined in (7).



(a) (b)

Fig. 3. Various neighborhoods (marked as gray regions) of the pixel $I_{i,j}$: (a) 4-connectivity neighborhood; and (b) 8-connectivity neighborhood.

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

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

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

• The second update is carried out after the movement of all ants within each construction-step according to

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

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 $ô_{(N)}$. In this paper, the above-mentioned T is proposed to be adaptively computed based on the method developed in [8].

VI. Experimental Results

Experiments are conducted to evaluate the performance of the proposed approach using three test images, Aish, Baboon, and tanker, which are shown in Figure 5. Furthermore, various parameters of the proposed approach are set as follows.

K = √M1 ×M2 : the total number of ants, where the function[x] represents the highest integer value that is smaller than or equals to x.

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

$\alpha = 1$: the weighting factor of the pheromone information in (1).

$\beta = 0.1$: the weighting factor of the heuristic information in (1).

Ω = 8-connectivity neighborhood: the permissable ant s movement range in (1)

$\lambda = 10$: adjusting factor of the functions in (4-7).

$\rho = 0.1$: the evaporation rate in (8).

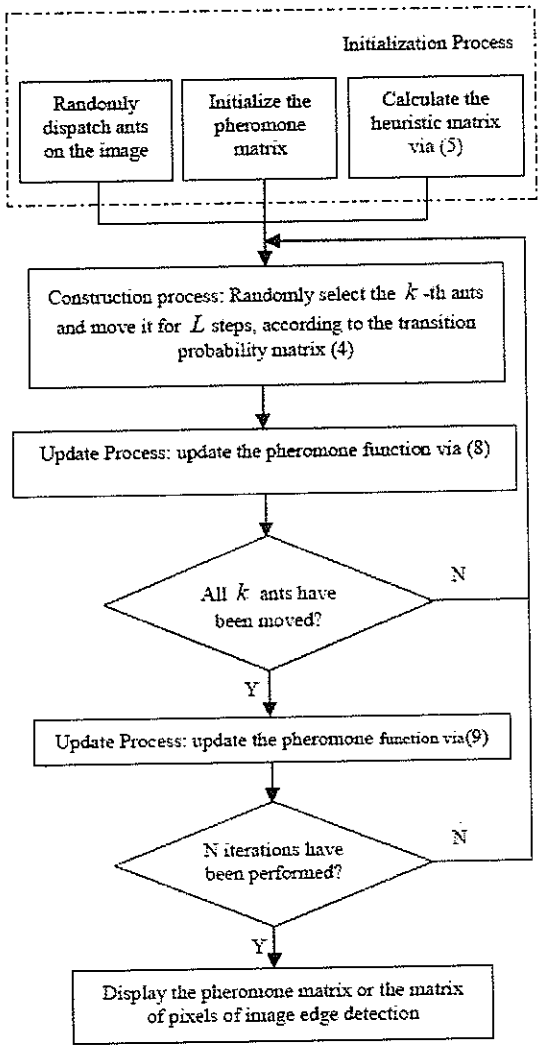
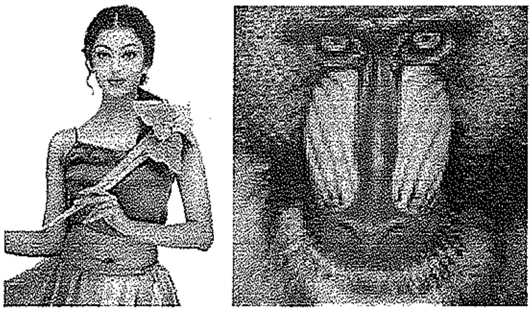


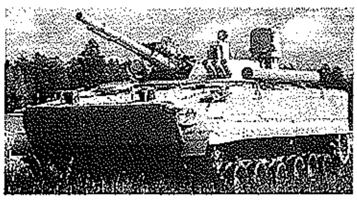
Fig. 4. A summary of the implementation of the proposed ACO-based image edge detection approach.

7. 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 [6], as verified in our experiments. Experimental results show the possible and practical to achieve easily for identifying edges in an image. The parallel ACO algorithm [7] can be making use of and derive benefit for further reduce the computational load of the proposed algorithm, for future research work.



(a) (b)



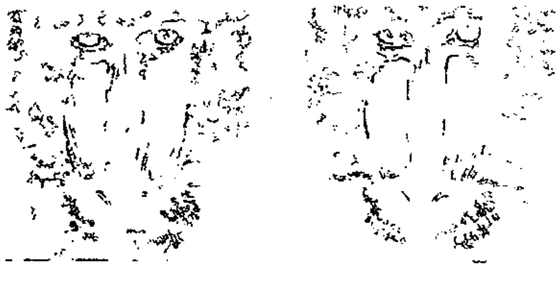
(c)

Figure 5 : Test images used in this paper: (a) Aish (256 × 256); (b) Baboon (256×256); (c) Tanker (256×256);

(a) (b)

(c) (d)

Fig. 6. Various extracted edge information of the test image Camera:(a) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (4); (b) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (5); (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (6); and (d) the proposed ACO based image edge detection algorithm with the incorporation of the function defined in (7).

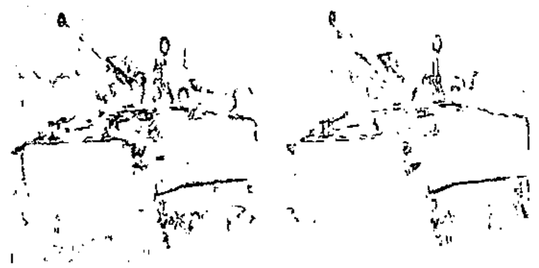


(a) (b)

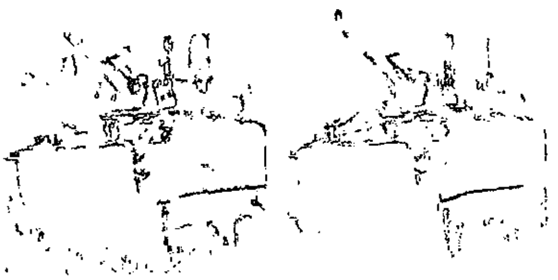
(c) (d)

Fig. 7. Various extracted edge information of the test image Camera:(a) the proposed ACO-based image edge

detection algorithm with the incorporation of the function defined in (4); (b) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (5); (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (6); and (d) the proposed ACO based image edge detection algorithm with the incorporation of the function defined in (7).



(a) (b)



(c) (d)

Fig. 8. Various extracted edge information of the test image Camera:(a) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (4); (b) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (5); (c) the proposed ACO-based image edge detection algorithm with the incorporation of the function defined in (6); and (d) the proposed ACO based image edge detection algorithm with the incorporation of the function defined in (7).

VIII. References

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