Edge Detection of an Image based on Ant Colony Optimization Technique

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Abstract: ***ACO is introduced to think about the image edge detection issues where the purpose is to evolve the edge information existing in the picture, since it is critical to understand the image's content. The main mechanism of ACO is the discovery of good tours is the positive feedback done through the pheromone update by the ants. Ant colony optimization is inspired by food foraging behaviour exhibited by ant societies to find approximate solutions to the tough issues. An ACO algorithm is the combination of prior information regarding the structure of a solution with the information regarding the structure of previously obtained good solutions. Experimental results show the success of the technique in extracting edges from a digital image.***

Keywords: Ant colony optimization, Feature extraction, Image Edge detection, Mean square error, Peak signal to noise ratio.

1. Introduction

Ant algorithms were inspired by the observation of real ant colonies. Ants are the social insects that reside in colonies. Within the early 1990s, ant colony optimization (ACO) was presented by M. Dorigo and colleagues [1] as a novel nature-inspired meta-heuristic for the solution of exhausting combinatorial optimization (CO) problems. ACO has been widely applied in various problems [2]-[10].

The first ACO algorithm called ant system that was proposed by M. Dorigo et al [11]. In 1991, M. Dorigo suggests the Ant System in his doctoral thesis (which was published in 1992). In 1996, an article on Ant System was published [11]. The Ant Colony System given by Dorigo and Gambardella was published in 1997 [12]. Since then, a variety of ACO algorithms have been developed like ant system Max-Min [13]-[15] and Ant colony system [11], [12], [16]. ACO is exploited to 'directly' extract the edge information in our proposed method, in contrast to that ACO serves as a 'post-processing' in [17] to enhance the edge information that has already been extracted by conventional edge detection algorithms.

In this paper, we tend to study other algorithms [18] and [19] to obtain better result. Ant colony optimization (ACO) is the algorithm that has inspired from natural behaviour of ants life, which the ants deposit pheromone to chase food on the ground [11], [14]. In this algorithm, ants search the appropriate way in order to find the solution space.

Dorigo et al. proposed the first ACO algorithm, ant system (AS) [11], [14]. In this paper, ACO is introduced to confront the image edge detection problem, where the intention is to evolve the edge information presented in the image, since it is critical to understand the image's content [20].

2. Literature Survey

The Previous work on image edge detection performed by various researchers is given below.

2.1 Raman Maini & Dr. Himanshu Aggarwal proposed a comparison of various image edge detection techniques of Gradient and Laplacian based edge detection. Gradient-based algorithms such as Prewitt filter have a major drawback of being very sensitive to noise. The kernel size and coefficients are fixed and cannot be adapted to a given image. Therefore, an adaptive edge detection algorithm is necessary to provide a robust solution that is adaptable to the varying noise levels of these images to help distinguish valid image contents from visual artifacts introduced by noise.

2.2 Marco Dorigo, Gianni Di Caro and Luca M. Gambardella proposed ant algorithms for discrete optimization which introduces the ant colony optimization (ACO) meta-heuristic and the basic biological findings on real ants and their artificial counter parts while in the other part a number of applications to combinatorial optimization and routing in communications networks are described.

2.3 Shweta Agarwal performed Edge detection in Blurred images using Ant Colony Optimization Technique. Edge detection in blurred digital images and prioritized them using different colour values according to their strength and importance. Here algorithm does not consider image deblurring hence eliminating any chances of data loss and a blur image will produce multiple edges in an area of concern is few among these edges will be non-prominent and less useful.

2.4 Anna Veronica Baerina, Carlos Oppus proposed edge detection using ant colony optimization in which they established a pheromone matrix that represents the edge information at each pixel based on the routes formed by the ants dispatched on the image.

Here results are based on at different values of parameter controlling the degree of exploration of the ants. Increase in the parameter value results in smoother edges. The value should be between, but not equal to, 0 and 1 because it causes some significant features to be missed. Therefore, higher values of parameter controlling the degree of exploration of the ants are suitable for images that contain less amount details while lower values are suitable for those that contain more details.

3. Image Edge Detection

Image edge detection refers to the extraction of the edges in a digital image. It is a series of actions whose aim is to identify points in an image where discontinuities or sharp changes in intensity occur. This series of action is crucial to understand the content of an image [19, 21] and these extracted edge points from an image provides an insight into the important details in the field of image analysis and machine vision [22]. It acts as a pre-processing step for feature extraction and object recognition [23]. It is normally applied in initial stages of computer vision applications. The purpose of detecting sharp changes in image intensity is to capture significant events and changes in the physical properties of the world. Under general assumptions about the image formation process, the causes of intensity changes usually correspond to two types of events one is Geometric events and other is Non-geometric events.

Geometric events consist of discontinuities in surface orientation, discontinuities in depth, discontinuities in colour and texture. Non-geometric events consist of changing illumination, shadows and inter-reflections [19, 21]. Conventional approaches to edge detection like SOBEL operator [20], Prewitt operator [24], Robert's operator [25], LoG operator [26] and CANNY operator [27] detection techniques are computationally expensive because each set of operations is conducted for each pixel. In normal courses, the computation time quickly increases with the size of the image. However, most of the existing detection techniques use a huge search space for the image edge detection [28]. Therefore, without optimization the edge detection task is memory and time consuming. An ACO constituent course has the potential of overcoming the limitations of conventional methods.

Several ACO-based approaches to the edge detection problem have been proposed [18, 29]. AS is the first ACO algorithm. Since its development, a number of extensions have emerged. One of the successful ones is ACS.

4. General Behaviour of ACO Algorithm

Artificial ants iterates tour construction loop which is biased with the artificial pheromone trails and the heuristic information. The main mechanism at work in ACO is the discovery of good tours is the positive feedback done through the pheromone update by the ants. The shorter the ant's tour, the more amount of pheromone is deposited by ants. This forces the ants to select the same arcs in the subsequent iterations of the algorithm. The occurrence of arcs with high pheromone values are further reinforced by the mechanism of pheromone evaporation that avoids an unlimited amount of pheromone and decrease the pheromone content from the arcs that rarely receive additional pheromone [30].

5. Ant Colony Optimization

Ant colony optimization is inspired by food foraging behaviour exhibited by ant societies or we can say that it is a nature-inspired optimization algorithm [31], [32]. Ants as individuals are unsophisticated living beings. Through some biologist's point of view, the visual sensory organs of the real world ants are rudimentary by nature and in some cases they are completely blind. The ants communicate using a chemical substance called pheromone. In journey of an ant, it accumulates a constant amount of pheromone that other ants can follow. Each ant initially moves in a somewhat random fashion, but when an ant encounters a pheromone trail, it must settle an issue whether to follow it or not. If it came after the trail, the ant's own pheromone reinforces the current trail, and the growth in pheromone increases the probability of the next ant selecting the path. Therefore, the more the ants travel on a path, the more attractive the path becomes for consecutive ants. Furthermore, an ant using a short route to a food source will return to the nest sooner and, therefore, mark its path twice, before the arrival of other ants. This straight forwardly influences the selection probability for the next ant departing the nest.

Over time, as more ants are capable to complete the shorter route. Therefore on shorter paths pheromone accumulates faster and the longer paths are less reinforced and finally abandoned. On smaller paths Pheromone densities stay high because pheromone is laid down faster. When looking for food, ants tend to follow trails of pheromones whose concentration is higher. These trails are created by individuals looking for food, to guide others toward the same sources of food. The concentration of pheromone is stronger in highly visited places because of the space travelled by ants to reach food sources and return to the nest [33]. This method of positive feedback eventually leads the ants to follow the smaller paths. It is this usual experience that encouraged the development of the ACO meta-heuristic.

6. ACO Based Image Edge Detection

In this proposed method, number of ants move on a 2-D image, stepping from one pixel to another to construct a pheromone matrix, which determine the edge information for each pixel location in the image to extract the edges of the image. The movement of the ants is directed by the local variation of the image's intensity values [34]. Image Edge detection [18, 35] process has the following steps: first is the initialization process. After this pheromone matrix is constructed by the ACO when it further runs for N no. of iterations. Iterative process consists of construction process and update process. The last is decision process by which edge is determined.

6.1 Initialization process

In this process for an image I of size M ×N is taken as input which works as a solution space for the artificial ants. The K numbers of ants are randomly moved over the whole image such that the every pixel of the image is viewed as a node. The constant is assigned to each , which is the initial value of every component of the pheromone matrix.

6.2 Construction Process

In the nth step of construction, one ant being randomly selected from K total ants and this ant will move over the image for L steps. This ant will move from the (l,m) node to (i, j) node which is its neighbouring node or pixel, is specified by the transition probability given by the equation (1).

$$P^{(n)}_{(l,m),(i,j)} = \frac{(\tau^{(n-1)}_{i,j})^{\alpha}(\eta^{\beta}_{i,j})}{\sum_{(i,j)\in\Omega_{(l,m)}}(\tau^{(n-1)}_{i,j})^{\alpha}(\eta^{\beta}_{i,j})} \cdots\cdots\cdots\cdots (1)$$

Here represents the pheromone value at node (i, j), $\Omega_{(l,m)}$ is the neighbourhood of nodes of the node (l, m), heuristic information at node (i, j) is represented by $\eta_{i,j}$. The constants α and β shows the influence of the pheromone matrix and heuristic matrix respectively.

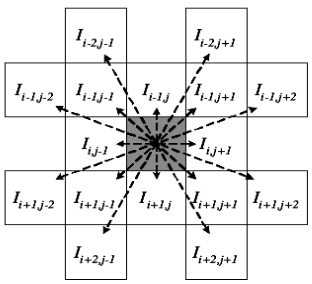


Figure 1: Clique matrix [36]

The process contains two important issues and these are given below:
The first issue is the heuristic $\eta_{i,j}$ information which can be determined by the local statistics of the image which depends on clique c. The local statistics at the pixel location (i, j) is calculated as follows [36].

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

Where Z is a normalization factor $V_c(I_{i,j})$ denotes the function of a local group of pixels c which is called clique [37]. Specifies the intensity value of a pixel at a location (i,j) of an image I and is given by equation below

$$Z = \sum_{i=1:M_1}\sum_{j=1:M_2} V_c(I_{i,j}) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (3)$$

The pixel (i, j) is marked as a grey square and its value rely upon on the variation of the intensity values in the clique c (as shown in figure 1).

$V_c(I_{i,j})$

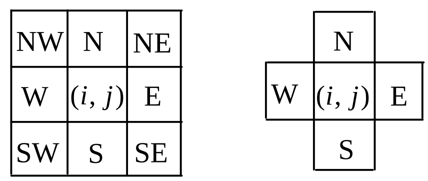
The function can be determined, if the pixel is under consideration

$$\begin{aligned} V_c(I_{i,j}) = f(&|I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}| \\ &+ |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j-1} - I_{i+1,j+1}| \cdots\cdots\cdots\cdots (4) \\ &+ |I_{i-1,j} - I_{i+1,j}| + |I_{i-1,j+1} - I_{i-1,j-1}| \\ &+ |I_{i-1,j+2} - I_{i-1,j-2}| + |I_{i,j-1} - I_{i,j+1}| \end{aligned}$$

The function f(x) is determined by the following equations given below:

$$f(x) = \lambda x, \quad \text{for } x \geq 0,$$
$$f(x) = \lambda x 2, \quad \text{for } x \geq 0,$$
$$f(x) = \begin{cases} \sin\left[\frac{\pi x}{2\lambda}\right] & \text{for } 0 \leq x \leq \lambda \\ 0 & \text{else} \end{cases} \cdots\cdots\cdots\cdots\cdots (5)$$
$$f(x) = \begin{cases} \sin\left[\frac{\pi x}{2\lambda}\right] & \text{for } 0 \leq x \leq \lambda \\ 0 & \text{else} \end{cases}$$

By slightly changing the value of λ, we can determine the function shape. The second issue is to determine the permissible range of ant movements (i.e. Ω(l, m)) in the position (l, m).



(A) (B)

Figure 2: (A) node (i, j) has 8-connective proximity [18], (B) node (i, j) has 4-connective proximity

The ants at any position (l, m) can wander in either any of the 4 directions (E,W,N,S) or in 8 directions (NW, N, NE, W, E, SW, S, SE) which is shown in the Figure2.

Ant's memory length is a parameter that needs some highlight. The locations in ant's memory are non-admissible. Therefore, its choice is a crucial one. Small length may cause the algorithm idle whereas large length might miss the details. It is empirically chosen [37] in the interval [0.85 A, 1.15 A] where A is 40 for image of size 128 × 128.

6.3 Update Process

The pheromone matrix is updated in the update process after the two update operations. The first update is accomplished after the movement of each ant in each construction-step. Each building block of pheromone matrix is modified as given in equation (6):

$$\tau_{i,j}^{(n-1)} = \begin{cases} (1-\rho)*\tau_{i,j}^{(n-1)} + \rho*\Delta_{i,j}^{(k)}, & \text{if (i, j) belongs to the best tour;} \\ \tau_{i,j}^{(n-1)}, & \text{otherwise} \end{cases} \qquad (6)$$

Here ρ is defined as evaporation rate of pheromone that depends on the value of user choice, is determined by the heuristic matrix.

The second update is performed after the movement of the entire ants in all construction-step as given in equation (7):

$$\tau_{i,j}^{(n)} = (1-\psi)\tau_{i,j}^{(n)} + \psi * \tau_0 \cdots\cdots\cdots\cdots (7)$$

Here ψ is the pheromone decay coefficient. The local update broadens the search for the subsequent ants by reducing the pheromone level on the traversed edges. This way it provides an opportunity for the subsequent ants to produce necessary solutions. Therefore, the chance of repetition becomes less likely in the same iteration [38].

6.4 Decision process

The solution is based on the values in the final pheromone matrix. The literature applies a threshold technique, also known as the Otsu threshold technique [39] or by the method developed in [40] to reduce the resulting grey scale image to a binary image with only two possible values for each pixel. This is done to be able to classify each pixel as either an edge or a non-edge. Though, when it comes to analysing the work carried out by the ant collective in image edge detection, a result showing various degrees in intensity values is just as good as a black and white declaration. Hence, in an ant's image edge detection, the solution is a direct result of the values in the final pheromone matrix

In this step, a binary decision is made at each pixel location to determine whether it is edge or not. The decision is made by applying a threshold τ on the final pheromone matrix. Here the threshold value τ chosen to be adaptively computed.

6.5 Visualize Process

In this step, different values of the Si (ψ) parameter are applied to the above algorithm. Smaller the value of the phi parameter more edges the algorithm detects in the image. As we go on decreasing the value of the phi parameter, output of the given image becomes clearer [34] but it should not be zero.

Table 1: Experimental parameter and their value

Parameter	*Value*
K (total number of ants)	√M1 ×M2
ρ (evaporation rate)	0.0009
λ (constant)	1
τ_{init} (initial value of each element of pheromone matrix)	0.0001
α (weighing factor of pheromone information)	2
β (weighing factor of heuristic information)	0.009
L (No. of ants movement steps within each construction step)	300
ψ (pheromone decay coefficient)	0.0009
N (total no. of construction steps)	40
∈ (denotes the user-defined tolerance value used in the decision process)	0.1
Ω (implies the tolerable ant's movement range)	8 connectivity neighbourhood

7. Proposed Methodology

The proposed image edge detection based on ACO is applied on a 2D image to generate a pheromone matrix. Each entry of that pheromone matrix represents the intensity change in the original image influenced by the edge location. A heuristic matrix [36] is also giving guidance to the algorithm to attain the optimum point easily and consuming less computation time.

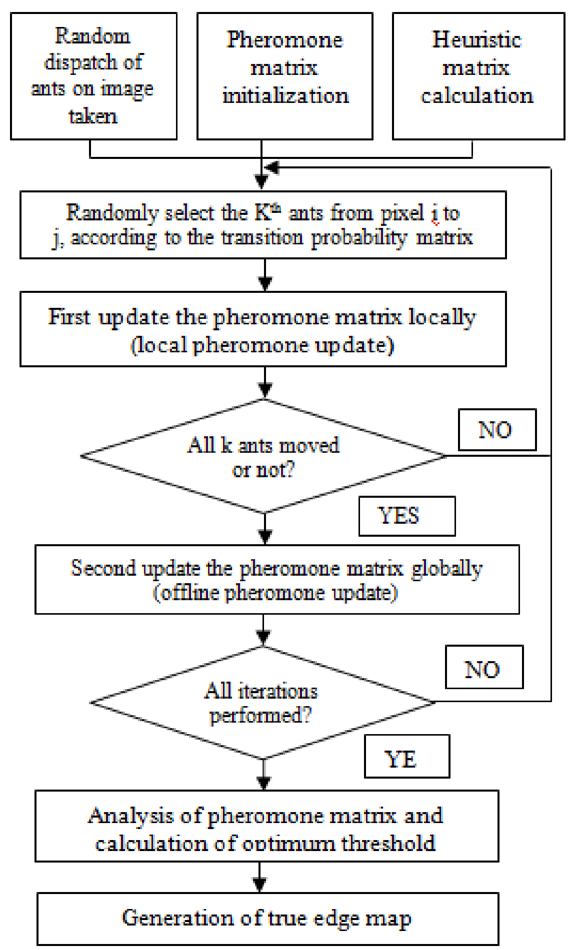


Figure3: The proposed ACO-based image edge detection approach.

8. Experimental Results

Experiments are conducted to evaluate the performance of the proposed approach (with the experimental parametric values are given in Table1) on the basis of peak signal to noise ratio and mean square error are shown in Table 2 and 3 using seven experiment images, Tomato, ship, Lotus temple, Butterfly, Rose, Birds and Taj-Mahal, are shown in Figure 4-10.

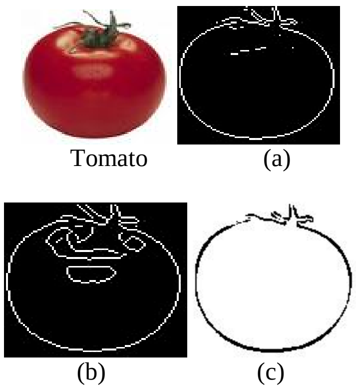


Figure 4: Tomato: (a) Sobel edges (b) Canny edges (c) proposed method

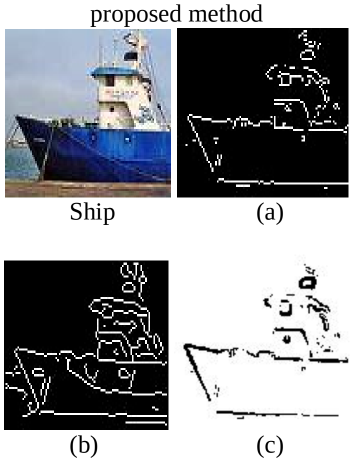


Figure 5: Ship: (a) Sobel edges (b) Canny edges (c) proposed method

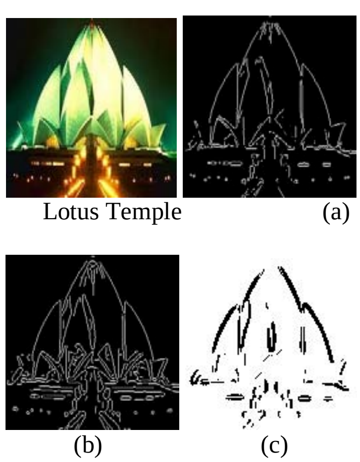


Figure 6: Lotus temple (a) Sobel edges (b) Canny edges (c) proposed method

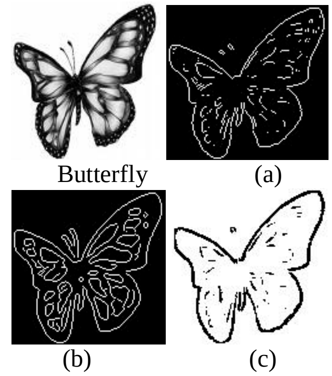


Figure 7: Butterfly (a) Sobel edges (b) Canny edges (c) proposed method

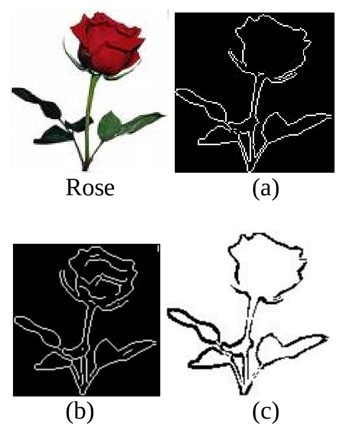


Figure 8: Rose (a) Sobel edges (b) Canny edges (c) proposed method

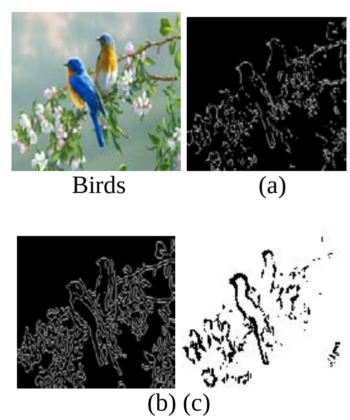
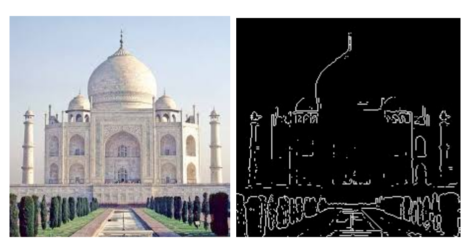


Figure 9: Birds (a) Sobel edges (b) Canny edges (c) proposed method



The Taj Mahal (a) Sobel edges

(b) (c)

Figure 10: (b) Canny edges (c) proposed method

Table 2: Experimental values of Peak signal to noise ratio

S.No.	*Images*	*Psnr Sobel*	*Psnr Canny*	*Psnr Ant*
1.	Tomato	4.0069	4.0075	9.8835
2.	Ship	4.6750	4.6764	9.8821
3.	Lotus temple	6.0590	6.0606	9.9795
4.	Butterfly	1.8888	1.8900	10.0783
5.	Rose	1.2509	1.2510	10.0456
6.	Birds	4.0712	4.0733	10.0232
7.	The Tajmahal	2.7145	2.7167	9.9851

Table 3: Experimental values of mean square error

S.No.	*Images*	*Mse Sobel*	*Mse Canny*	*Mse Ant*
1.	Tomato	129.2296	129.2098	13.3586
2.	Ship	110.8033	110.7676	13.3630
3	Lotus temple	80.5651	80.5361	13.0667
4	Butterfly	210.4625	210.4038	12.7728
5.	Rose	243.7597	243.7515	12.8693
6.	Birds	127.3306	127.2677	12.9356
7.	The Tajmahal	174.0223	173.9334	13.0498

9. Conclusions

An ACO-based image edge detection formula that takes advantage of the improvements introduced in ACS has been successfully obtained and tested. Experimental results show the possibility of the approach in identifying edges in an image and mean square error of proposed algorithm is 6% to 19% lower in comparison to that of sobel and canny algorithm which leads to 2 to 5% increase in Peak signal to noise ratio of proposed algorithm in comparison to that of sobel and canny algorithm.

With appropriate parameter values, the formula was able to determine the edges with success in the test images. It should be noted that the suitable parameter values rely on the character of the image, and thus, could vary per application. In recent studies, techniques that might enhance the performance of ACS are explored. In [41], ants are assigned a different pheromone sensitivity level, which makes some ants more sensitive to pheromone than the others. In [42], multiple ant colonies with new communication strategies were utilized. The proposed ACS methodology for edge detection could be extended and possibly be improved by making use of such techniques.

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