Modified Ant Colony Optimization Based Approach for Edge Detection in Images

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Abstract

Various methods based on Ant Colony Optimization (ACO) are used to detect edges in digital images. Such techniques generate a pheromone matrix that represents the edge information at each pixel position on the routes formed by ants dispatched on the image. In this paper a modified ACO-based approach for edge detection in images is proposed. In this paper we propose to determine the heuristic information based edge magnitude obtained using Laplacian operator. This information is used by the ants to find possible edges. Moreover, the proposed ACO-based approach takes advantage of the fuzzy clustering to determine whether a pixel is edge or not. Experimental results show the superior performance of the proposed approach.

1. Introduction

Edge detection in images is the process of extracting edges. Edge detection helps in identifying the pixels where sharp changes in intensity occur and this helps in determining the object boundaries in images. Hence edge detection plays a very important role in pattern recognition, image analysis, computer vision and image processing. There are various approaches to detect edges in images based on gradients [1]. But there are some limitations of these conventional approaches. Firstly, the computation time of these approaches increase with the increase in the size of the image [2]. Secondly, the edges detected using these approaches are discontinuous [3].

Ant Colony Optimization (ACO) is one of the bio-inspired algorithms [4-7], which is based on the natural foraging behavior of ant species. Ants deposit pheromone on the ground to mark some favorable path between a food source and their colony which should be followed by other members of the colony. ACO has been used to solve a number of optimization problems. Several ACO-based approaches have been proposed for edge detection [8-13,2]. The approaches given in [8-9] are used to enhance the edge information obtained using conventional techniques. The pure ACO-based methods proposed in [10-13,2] describe that ACO-based approaches based on Ant System [4-6] and Ant Colony System [4-5,7] can be used to directly detect edges in images. These works clearly indicate that more research work is needed to improve the quality of the edges detected using these methods and to decrease the time complexity. ACO-based approach has the potential of overcoming the limitations of conventional methods. Moreover it can be readily parallelized thus making the algorithm suitable for distributed environments.

In this paper, we propose a modified ACO-based approach to detect edges that edge magnitude obtained using Laplacian operator and thresholding based on fuzzy c-means clustering to determine whether a pixel is an edge or not.

2. Ant Colony Optimization

ACO is a nature-inspired technique that is designed based on ant colonies. Ant colonies have trail-laying and trail-following behavior during foraging for their food. Ants deposit pheromone on the ground to mark the path between a food source and their colony. During the course of time, the pheromone evaporates. The shorter or favorable paths are travelled by the ants faster and thus receive greater compensation for pheromone evaporation. As pheromones are laid down faster pheromone densities are high on shorter paths. It is this positive feedback mechanism that helps in finding good solutions and is the basic idea behind ACO-based algorithms.

In an ACO algorithm, ants move through a search space, the graph, which consists of nodes and edges. The movement of an ant in the graph is determined by the transition probabilities. Heuristic information and pheromone information determine the transition probability. The construction of a solution to a problem contains a certain number of construction steps. Each ant tries to find a good solution simultaneously and individually at every construction step.

According to the ant system [7] at the nth construction step, the kth ant moves from node i to node j according to the transition probability

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

where $\tau_{i,j}^{(n-1)}$ is the quantity of pheromone between state i and $j, \eta_{i,j}$ is the heuristic information for going from node i and to node to j, Ω is the set of unvisited states and α and β are constants that control the influence of the pheromone and heuristic information respectively. The Ant Colony System (ACS) [7] allows for exploration by slightly modifying the rule based on equation 1 as follows:

$$j \begin{cases} \arg\max \{[\tau(i,j)].[\eta(i,j)]^{\beta}\} & if q \leq q_0 \\ J & otherwise \end{cases}$$

$$(2)$$

where q is a random number, q_0 is a parameter $(0 \leq q_0 \leq 1)$ and J is a random variable selected according to the previous probability distribution function given in equation (1). At every step, based on the value of q generated an ant moves from state i and to state j. If $q \leq q_0$ then the best edge is chosen (exploitation), otherwise an arbitrary edge is chosen according to equation (1) (biased exploration).

The best-so-far solution for every construction step or for the entire algorithm is recorded. Pheromone deposit by ant provides a positive feedback and thus reinforces the probability of finding new good solutions. Similarly evaporation of pheromone acts as a negative feedback which prevents the algorithm to stop at local optima. The pheromone is updated twice during the algorithm. The first update is performed after the movement of each ant in each construction step as [14]:

$$\tau_{i,j}^{(n)} = \begin{cases} (1-p).\tau_{i,j}^{(n-1)} + \rho.\Delta_{i,j}^{(k)} & \text{if (i,j)belongs to best} \\ \tau_{i,j}^{(n-1)} & \text{otherwise} \end{cases}$$

$$(3)$$

where ρ is the evaporation rate and

$$\Delta \tau^k(i,j) = \begin{cases} 1/f_k & \text{if ant k used edge (i,j)} \\ 0 & \text{otherwise} \end{cases} \quad \text{-- (4)}$$

where f_k is the tour length of the kth ant. This tour length depends on the nature of the problem to be solved. Its value is chosen in such a way that desirable routes have smaller tour lengths.

The second update is performed after all K ants have moved within each construction step as [14]:

$$\tau^{(n)} = (1-\Phi).\tau^{(n-1)} + \Phi.\tau^{(0)} \quad \text{-------------- (5)}$$

where Φ is the pheromone decay coefficient.

3. Ant Colony based Approach for Edge Detection

At the beginning of every iteration, ants are randomly placed on the image. A gray level image is considered as a two-dimensional (2-D) graph where the pixels are nodes. The edges of the graph connect adjacent pixels together. The ants wander on the 2-D graph pixel by pixel in fixed number of steps (ant memory) and deposit pheromone on the graph according to the quality of the path and a pheromone matrix is constructed. The path quality determines the quality of the edge.

The algorithm consists of three main steps

1. Initialization process

Let K ants be randomly assigned on an image I whose size is RXC. The initial value of each component of the pheromone matrix $\tau^{(0)}$ is set to be a constant τ_{init}. The heuristic information $\eta_{i,j}$ is determined based on the variation of image's intensity values in the neighborhood.

2. Iterative Construction and Update Process

Let the algorithm be executed for N iterations. At the nth iteration, one ant is randomly selected from the K ants. This ant moves on the image for L movement steps. At every step the ant moves from node (l,m) to its neighboring node (i,j) according to the transition probability given in equation (1). The neighborhood of

the ant is considered to be 8-connectivity neighborhood in this implementation. An ant can move to any adjacent pixel with a condition that an ant moves only to a node that it has not recently visited to avoid ants visiting the same set of nodes repeatedly. The first update of the pheromone matrix is done after the movement of each ant in each construction step according to equation 3. The second update is done after the movement of all ants in each construction step according to equation 5. The deposited amount of pheromone $\Delta_{i,j}^{(k)}$ is equal to the heuristic information associated with the pixels that belong to the tour of the kth ant if pixel (i,j) was visited by the kth ant in its current tour; 0 otherwise.

In ACO-based edge detection method all the visited pixels are updated. The aim of each ant is to produce only a partial edge piece in the image. The collective interaction of the ants produces a pheromone matrix from which all the edges are extracted.

3. Decision Process

The goal of the ant's movement is to construct a final pheromone matrix that reflects the edge information. Each element in the pheromone matrix corresponds to a pixel in the image and specifies whether that pixel is an edge or not. Finally by applying a threshold T on the final pheromone matrix $\tau^{(N)}$ a binary decision is made at each pixel location to determine whether it is edge or not.

4. Proposed Modifications to ACO based approach for Edge Detection
4.1. Determination of Heuristic Information

The movement of ants from one state to another is determined by the transition probabilities. The transition probability depends on the combination of a) the heuristic information or the attractiveness $\eta_{(i,j)}$ which is problem specific and is calculated a priori and b) the trail level $\tau(i,j)$ which indicates how proficient it has been in the past to make such a move and this value is updated by the ants depending on the quality of the path.

In [12], $\eta_{(i,j)}$ is a function of local group of pixels called clique. Its value depends on the variation of the image's intensity values on the clique. In [15], $\eta_{(i,j)}$ is

determined using structures of 3x3 ideal edge images based on [16, 17].

In this paper, we have determined $\eta_{(i,j)}$ based on the edge magnitude obtained using Laplacian operator [18]. The areas in images which are smooth have the gradient value as zero. The edge regions have positive values on one side of the edge, a positive value on the other side of the edge and zero at a point between these regions. Thus the movement of the ants are steered by the edge magnitude obtained using Laplacian operator. Desirable routes are the routes that pass along pixels with higher edge magnitude. The Laplacian function is given by

$$L(x,y) = -\frac{1}{\pi\sigma^2}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \quad \text{----------- (6)}$$

We consider a 3x3 neighborhood. The 3x3 digital filter obtained from the equation 6 is used to convolve with the 3x3 neighborhood in the image. The result obtained is the edge magnitude, i.e. $\eta_{(i,j)}$, obtained and is used as the heuristic information.

4.2. Thresholding based on Fuzzy C-Means Clustering

The final pheromone matrix is used to determine whether each pixel is an edge or not. The decision is made by applying a threshold on the final pheromone matrix $\tau^{(N)}$. In [12, 2], the thresholding is done based on the method developed in [19].

In this paper, the threshold T is computed based on fuzzy c-means clustering method developed in [20]. Let x denote the 1-D representation of the final pheromone matrix p. The algorithm is based on the minimization of the following objective function:

$$J_m = \sum_{i=1}^{RxC}\sum_{j=1}^{L} u_{ij}^m \parallel x_i - c_j \parallel^2 \quad \text{-------------------- (7)}$$

where m is any integer value greater than or equal to 1, u_{ij} is the degree of membership of x_i in cluster j, x_i is the i-th pheromone element, c_j is the center of the cluster j, L is the maximum number of clusters i.e. $(2 \le j < L)$ and $\parallel * \parallel$ is any norm representing the similarity between data and the center. In our problem the number of clusters, $L = 2$. The algorithm consists of the following steps:

1. Initialize $U = [u_{ij}]$ matrix, $U^{(0)}$, $k = 1$.

2. Calculate the centers $C^{(k)} = [c_j]$ using

$$c_j = \frac{\sum\limits_{i=1}^{RxC} u_{ij}^m . x_i}{\sum\limits_{i=1}^{RxC} u_{ij}^m} \qquad \text{-------------------- (8)}$$

3. Calculate $U^{(k+1)}$ using

$$u_{ij} = \frac{1}{\sum\limits_{k=1}^{L}(\frac{\| x_i - c_j \|}{\| x_i - c_k \|})^{\frac{2}{m-1}}} \qquad \text{-------------------- (9)}$$

4. If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then stop; otherwise set $k = k+1$ and return to step 2.

After the completion of the iterative process, the threshold is calculated as

$$T = \frac{c_1 + c_2}{2} \qquad \text{-------------------- (10)}$$

where c_i is the center of cluster i.

5. Results and Discussion

The various parameters of the proposed algorithm are determined by experiments. A suitable set of parameters are given in table 1.

Table 1. Suitable parameters of the proposed algorithm

Parameter	Value
ρ (evaporation rate)	0.85
τ_{init} (initial value of each element of pheromone matrix)	0.001
α (weighting factor of pheromone information)	1
β (weighting factor of heuristic information)	0.1
L (total number of ant's movement-steps within each construction step)	40
ψ (pheromone decay coefficient)	0.05
N (total number of construction steps)	4

Experiments are conducted based on four test images, camera, boat, house and polygons. The size of

the images is 128x128. The results are compared with Sobel, Prewitt, Canny and ACO-based edge detection technique given in [12]. Figures 1, 2, 3 and 4 present the results of test images camera, boat, house and polygons respectively. As seen from the figures, the proposed approach gives better results compared to other methods except Canny's method, in terms of visual quality of the extracted edge information.
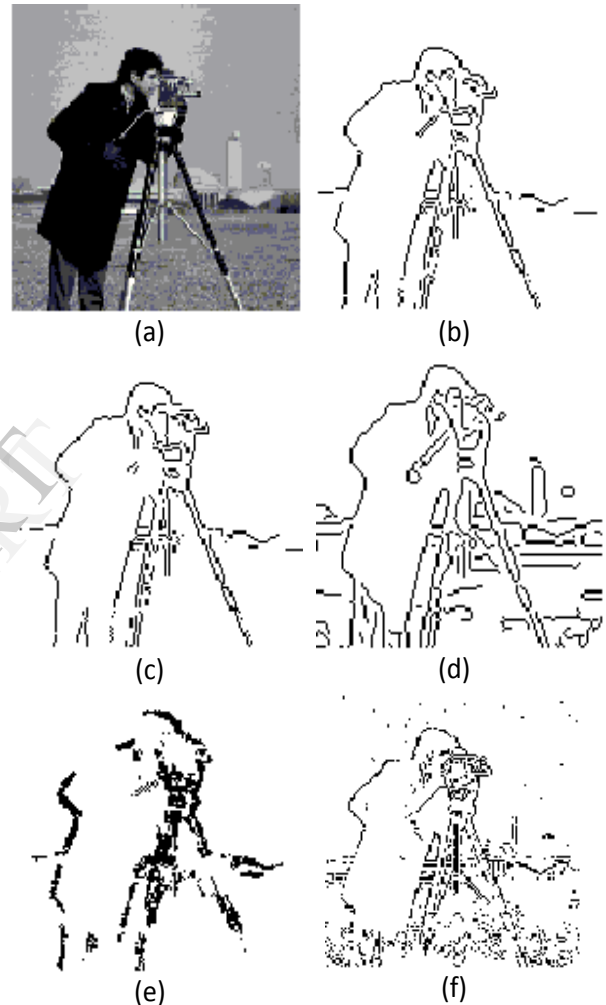

Figure 1. Extracted edges for the test image camera a) original image b) Sobel operator c) Prewitt operator d) Canny's method e) Method proposed in [12] without thinning and f) Proposed method (without thinning)
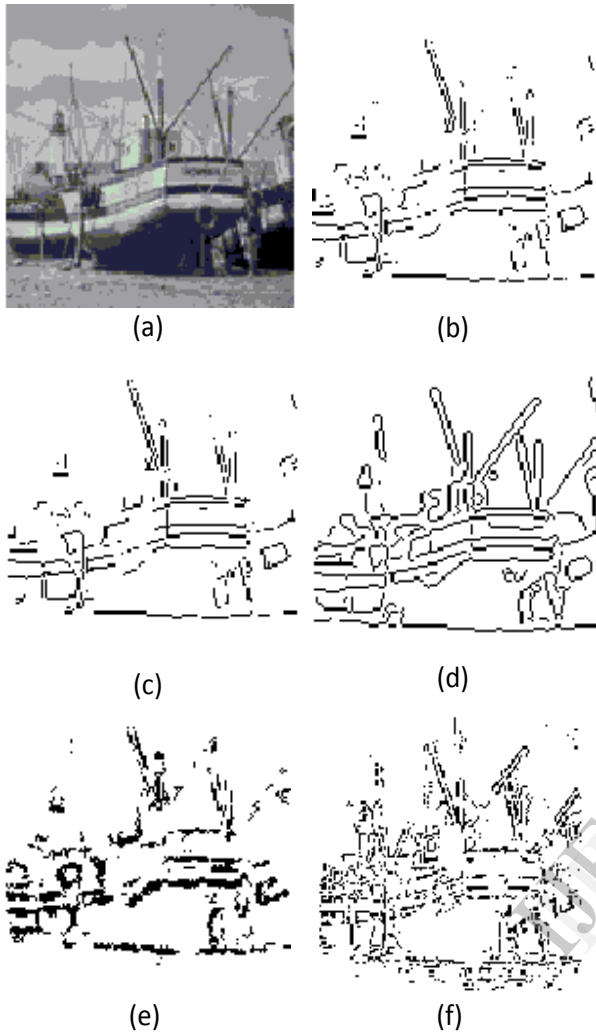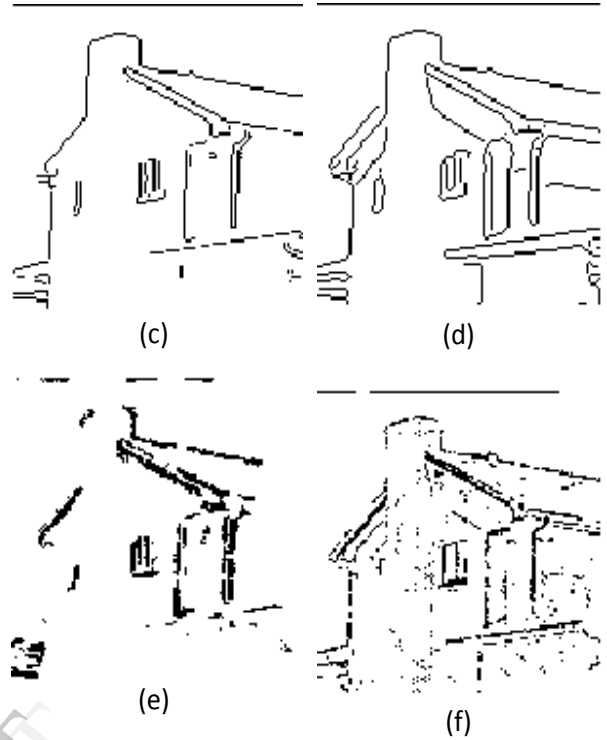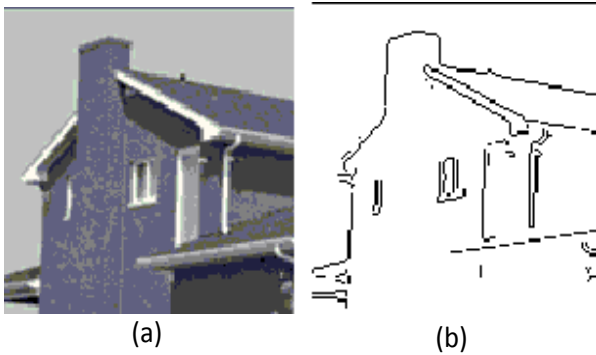
Figure 2. Extracted edges for the test image boat a) original image b) Sobel operator c) Prewitt operator d) Canny's method e) Method proposed in [12] without thinning and f) Proposed method (without thinning)
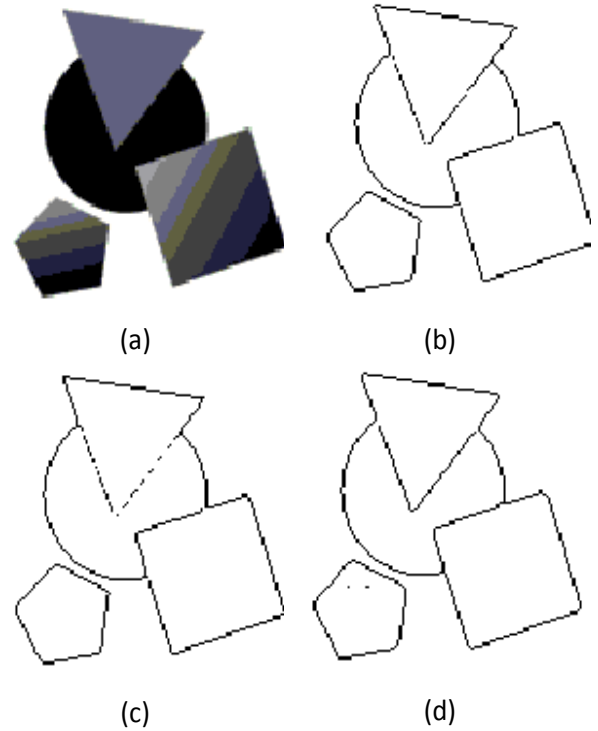

Figure 3. Extracted edges for the test image house a) original image b) Sobel operator c) Prewitt operator d) Canny's method e) Method proposed in [12] without thinning and f) Proposed method (without thinning)
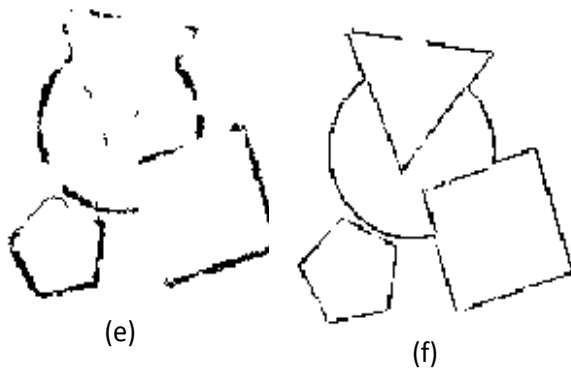
Figure 4. Extracted edges for the test image polygons a) original image b) Sobel operator c) Prewitt operator d) Canny's method e) Method proposed in [12] without thinning and f) Proposed method (without thinning)

6. Conclusion

This paper presents a modified ACO-based edge detection technique. Heuristic function is determined based on the edge magnitude obtained using Laplacian operator. Fuzzy c-means clustering based thresholding is used to determine whether a pixel is edge pixel or not. Experimental results show that the proposed technique gives better results.

7. References

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