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Edge detection in digital images using Ant Colony Optimization

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Abstract

Ant Colony Optimization (ACO) is an optimization algorithm inspired by the behavior of real ant colonies to approximate the solutions of difficult optimization problems. In this paper, ACO is introduced to tackle the image edge detection problem. The proposed approach is based on the distribution of ants on an image; ants try to find possible edges by using a state transition function. Experimental results show that the proposed method compared to standard edge detectors is less sensitive to Gaussian noise and gives finer details and thinner edges when compared to earlier ant-based approaches.

Keywords: Ant Colony Optimization (ACO), Digital image processing, Edge detection, Noisy images.

1 Introduction

Edge detection is by far the most common approach for detecting meaningful discontinuities in gray level. It is an important problem in pattern recognition, computer vision and image processing. Conventional image edge detection algorithms usually perform a linear filtering operation (or with a smoothing pre-processing operation to remove noise from the image) on the image [1], such as Sobel, Prewitt [2] and Canny operators [3].

Ant Colony Optimization (ACO) is an optimization algorithm inspired by the behavior of real ant colonies [4, 5]. Ants deposit pheromone on the ground to mark their favorable paths, which can be followed by the ants of the colony. The first ACO algorithm, called the ant system, was proposed by Dorigo et al. [4]. Since then, a number of ACO algorithms have been developed, such as the Max-Min ant system [6]. ACO has been widely applied in various problems [7, 8, 9, 10, 11]. Besides, ACO algorithms has been used to solve many complex problems successfully such as quadratic assignment problem [12], data clustering [13], image retrieval [14], too used to image thresholding [15], and image segmentation [16, 17].

Zhuang [18] proposed to utilize the perceptual graph to represent the relationship among neighboring image pixels, then use the ant colony system to build up the perceptual graph. Nezamabadi-Pour et al. [19] proposed to use the ant system to detect edges from images by formulating the image as a directed graph. Lu and Chen [20] proposed to use the ACO technique as a post-processing to compensate broken edges, which are usually incurred in the conventional image edge detection algorithms. Alikhani et al. [21] use a Fuzzy Inference System (FIS) with 4 simple rules to identify the probable edge pixels in 4 main directions, then the ACO is applied for assigning a higher pheromone value for the probable edge pixels. Finally, by using an intelligent thresholding technique which is provided by training a neural network, the edges from the final pheromone matrix are extracted. Davoodianidaliki et al. [22] proposed usage of traditional edge detectors for initial pheromone and distribution matrixes that previously were equal and random. Koner and Acharyya [23] have applied the variants for detection of edges in binary images. Contreras et al. [24] propose an approach based on a paradigm that arises from artificial life; more specifically ant colonies foraging behavior. Ari et al. [25] proposed a novel algorithm for image edge detection using ant colony optimization and Fisher ratio (Fratio)-based techniques. Ming and Xianghong [26] used ant colony system algorithm (ACSA) to detect the edge of gray scale images. The novelty of the proposed method is that the artificial ants used for detecting the edges of images have global memory capacity. Method proposed by Agrawal et al. [27] gives a pheromone matrix and memory stored positions that are followed by leading ant. The memory based positions are stored on the basis of intensity values with reference with a threshold value. Tian et al. [28]

proposed to establish a pheromone matrix that represents the edge presented at each pixel position of the image, according to the movements of ants on the image.

In this paper, we propose an improved ant-based edge detector that provides finer details and thinner edges on both noisy and clean images. This method uses pheromone information to detect the edges of image.

The remainder of the paper is organized as follows; the next section describes Ant Colony Optimization. In Section 3, we discuss Ant-Based our edge detection approach in details. Experimental results and analysis are presented in Section 4. Finally, Section 5 concludes this paper.

2 Ant Colony Optimization (ACO)

In the natural world, ants (initially) wander 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. Over time, however, 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 more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.

Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to all the ants' following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve. The ant colony optimization algorithm is a probabilistic technique for solving computational problems which can be reduced to finding better paths through graphs. This algorithm is a member of the ant colony algorithms family, in swarm intelligence methods, and it constitutes some metaheuristic optimizations. Initially proposed by Marco Dorigo in 1992 in his PhD thesis [4]; the first algorithm was aiming to search for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behavior of ants.

The goal of this article is to introduce an ant-based algorithm for edge detection.

3 The proposed Ant-Based Approach

In this approach, the value of visibility is determined using the maximum variation of gray level of the image intensity. Edge pixels are expected to have a greater value of visibility. Therefore, the ants' movements are driven by the local variation of the image intensity values. That is, the ants prefer to move towards positions with larger variations [12].

The proposed approach works as follows:

Step1: At first, k ants are placed on the randomly chosen nodes (pixel position) on an image I with a size of $M1 \times M2$. Therefore, one ant is assigned to each pixel position (called a node) of the image. The proposed approach sets the initial value of each component of the pheromone matrix $\tau^{(0)}$ to be a constant τ_{init}.

Step2: At the n-th construction-step, each ant probabilistically selects a new neighbor pixel to visit according to Eq. (1). The probability of displacing k-th ant from node (l,m) to its neighboring node (i,j) is determined by:

$$P^{(n)}_{(l,m),(i,j)} = \frac{(T^{(n-1)}_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum_{(s,q)\in\Omega(l,m)}(T^{(n-1)}_{s,q})^{\alpha}(\eta_{s,q})^{\beta}}, \tag{1}$$

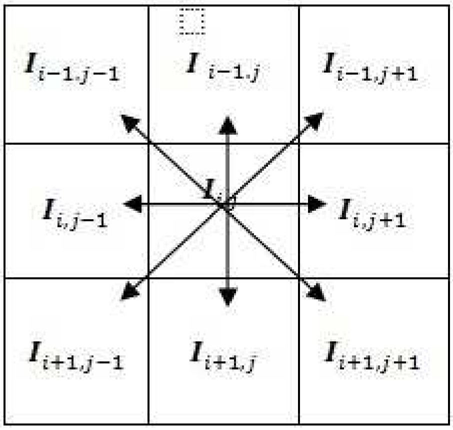

Figure 1. A local configuration at the pixel position $I_{i,j}$ for computing the variation $V_c(I_{i,j})$ defined in (3).

where $\Omega(l,m)$ is the neighborhood nodes of the node (l,m); $\eta_{i,j}$ and $T_{i,j}^{(n-1)}$ are the heuristic information which belongs to pixel (i,j) and the pheromone intensity of the pixel (i,j), respectively; and, the parameters α and β control the relative importance of the pheromone matrix versus the heuristic information $\eta_{i,j}$ used in [28], which is given by:

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

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 and function $V_c(I_{i,j})$ is a function of a local group of pixels c, and its value depends on the variation of image's intensity values on the clique c (as shown in Figure 1). The function $V_c(I_{i,j})$ is determined by:

$$\begin{aligned} V_c(I_{i,j}) = f(&|I_{i-1,j-1} - I_{i+1,j+1}| + |I_{i-1,j} - I_{i+1,j}| + \\ &|I_{i-1,j+1} - I_{i+1,j-1}| + |I_{i,j-1} - I_{i,j+1}|). \end{aligned} \tag{3}$$

To determine the function f (.), the following four functions are considered [8]; they are mathematically expressed as follows:

$$f(x) = \lambda x \qquad x \geq 0; \tag{4}$$

$$f(x) = \lambda x^2 \qquad x \geq 0; \tag{5}$$

$$f(x) = \begin{cases} sin(\frac{\pi x}{2\lambda}) & 0 \leq x \leq \lambda \\ 0 & else \end{cases} ; \tag{6}$$

$$f(x) = \begin{cases} sin(\frac{\pi x \; sin(\frac{\pi x}{\lambda})}{\lambda}) & 0 \leq x \leq \lambda \\ 0 & else \end{cases} . \tag{7}$$

We select f (.) which is defined by (8), because this function shows better results.

$$f(x) = \begin{cases} sin(\frac{\pi x}{2\lambda}) & 0 \leq x \leq \lambda \\ 0 & else \end{cases} . \tag{8}$$

The parameter λ determines the function's shape.

Step3: After every step, the pheromone values are updated after the movement of each ant within each construction-step according to:

$$\tau_{i,j}^{(n-1)} \leftarrow \begin{cases} (1-\rho).\tau_{i,j}^{(n-1)} + \rho.\Delta_{i,j}^{(k)} & if\ (i,j)\ is\ visited\ by\ the\ current \\ & k-th\ ant; \\ \tau_{i,j}^{(n-1)} & Otherwise \end{cases} , \tag{9}$$

where ρ is evaporation rate, it controls the degree of the updating of $\tau_{i,j}^{(n-1)}$; $\Delta_{i,j}^{(k)}$ is determined by the heuristic matrix; that is, $\Delta_{i,j}^{(k)} = \eta_{i,j}$. Secondly, after the movement of all ants, the pheromone matrix is updated as:

$$\tau^{(n)} = (1-\Psi).\tau^{(n-1)} + \Psi.\tau^{(0)}, \tag{10}$$

where Ψ is the pheromone decay coefficient, and $\tau^{(0)}$ is the initial value of the pheromone. Steps 2 and 3 iteratively run for N iterations. Finally, the pheromone matrix $\tau^{(n)}$ can be obtained to represent the saliency of the image.

Step4: Finally, 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, we use thresholding based on the method developed in [1] as follows:

1. Select an initial estimate for T (average of the values for the points).
2. Produce two groups of values: G_1 consisting of all values $> T$ and G_2 consisting of values $< T$.
3. Compute the average values μ_1 and μ_2 for the values in G_1 and G_2.
4. Compute a new threshold value: $T = \frac{\mu_1+\mu_2}{2}$.
5. Repeat steps 2 through 4 until the difference in T in successive iterations is smaller than a predefined parameter ε.

4 Experimental Results

Experiments were conducted to demonstrate the performance of the proposed approach using two test images, Camera and House, which are shown in Figure 2.

4.1 Parameters Setting

Suitable algorithm parameters are determined based on trial and error. The parameters of the proposed approach were experimentally set as follows:

K is the number of ants. It could be chosen proportionally to the root of pixel numbers $M1 \times M2$. Total number of ant's movement-steps within each construction-step and total number of construction-steps

(a) (b)

Figure 2. Test images used in this paper: (a) Camera (256×256); (b) House (600×600).

are selected to be L= 50 and N= 4, respectively. τ_{init}, the initial value of each component of the pheromone matrix is set to be 0.0001; α and β control the relative importance of intensity of pheromone versus the heuristic information, they are set to be $\alpha = 6$ and $\beta = 0.001$, respectively [4]. The permissible ant's movement range at the position (l,m) could be either the 4-connectivity neighborhood or the 8-connectivity neighborhood. It is selected to be 8-connectivity neighborhood. λ is the adjusting factor of the functions, it is set to be 10. Evaporation rate and the pheromone decay coefficient are set to be $\rho = 0.1$ and $\Psi = 0.005$, respectively. Parameter ε is set to be 0.01.

4.2 Experimental Results and Discussions

Experimental results are provided to compare the proposed approach with Tian et al.'s edge detection method [28]. Figures 3 and 4 show the proposed approach that always outperforms Tian et al.'s method, in terms of visual quality of the extracted edge information. Therefore

Figure 3. Results of edge detectors for Cameraman image. (a) The original image; (b) Tian et al.'s edge detection algorithm [28]; (c) The proposed ACO-based image algorithm.

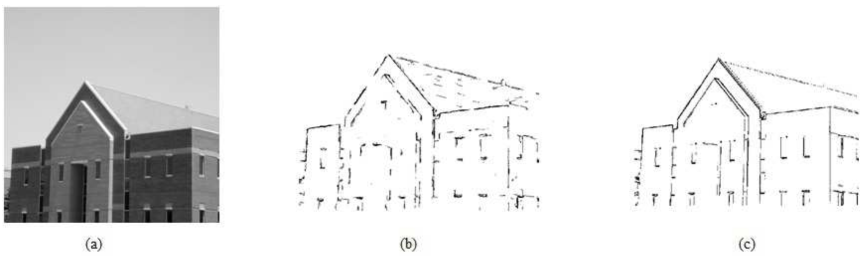

Figure 4. Results of edge detectors for House image. (a) The original image; (b) Tian et al.'s edge detection algorithm [28]; (c) The proposed ACO-based image algorithm.

the determination of parameters is critical to the performance of the proposed approach. Figures 5 and 7 show the results of Canny, Sobel, Log, Roberts and the proposed ACO-based edge detectors respectively on clear images. Furthermore we added Gaussian noise (see Figures 6 and 8) to test images. As we can see in the figures, our proposed method gives better results than the others, both in clean and noisy images.

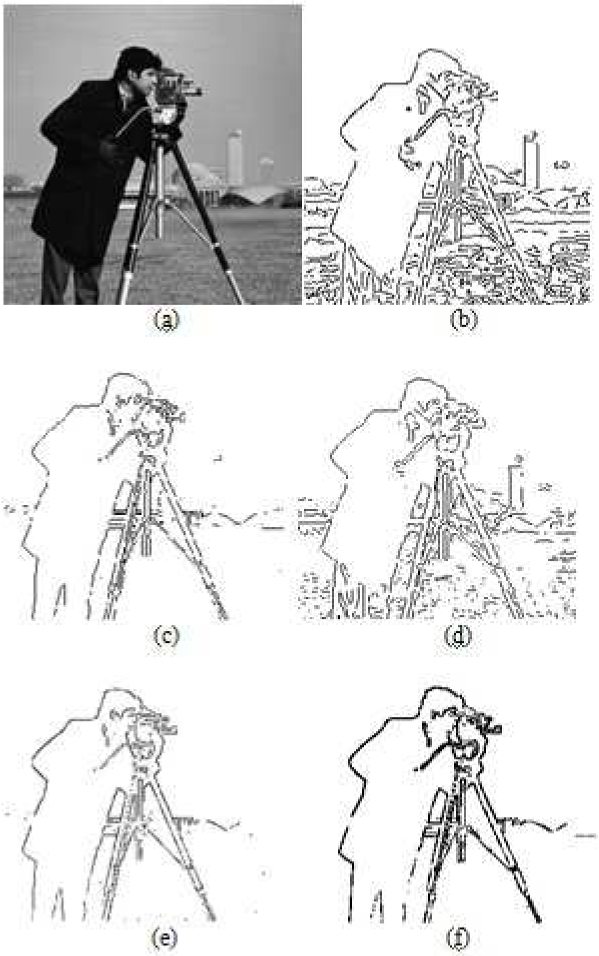

Figure 5. Comparison of ant-based edge detection algorithms. (a) The original image; (b) Canny edge detector; (c) Sobel edge detector; (d) Log edge detector; (e) Roberts edge detector (f) The proposed ACO-based edge detector.

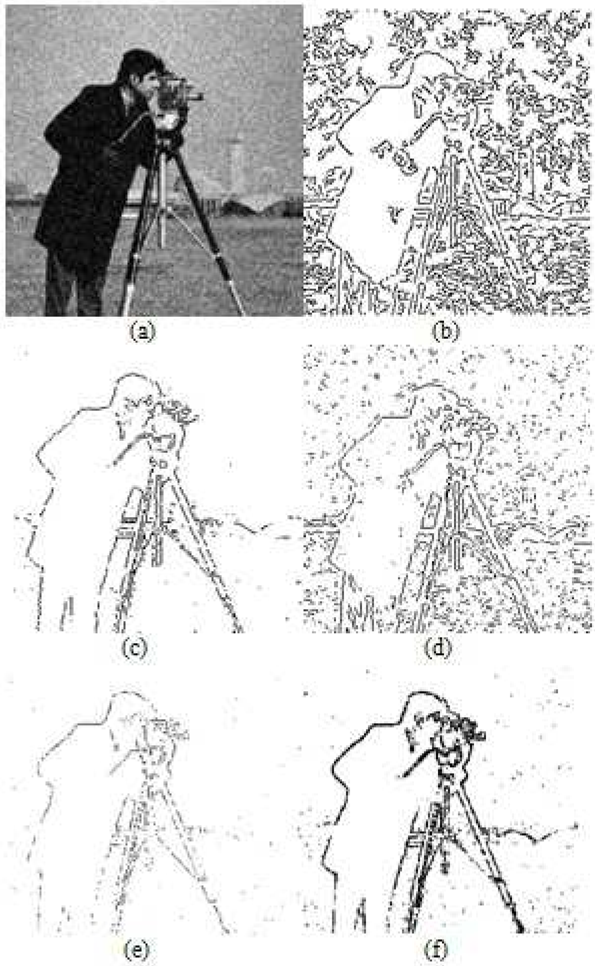

Figure 6. Comparison of ant-based edge detection algorithms. (a) The noisy image; (b) Canny edge detector; (c) Sobel edge detector; (d) Log edge detector; (e) Roberts edge detector (f) The proposed ACO-based edge detector.

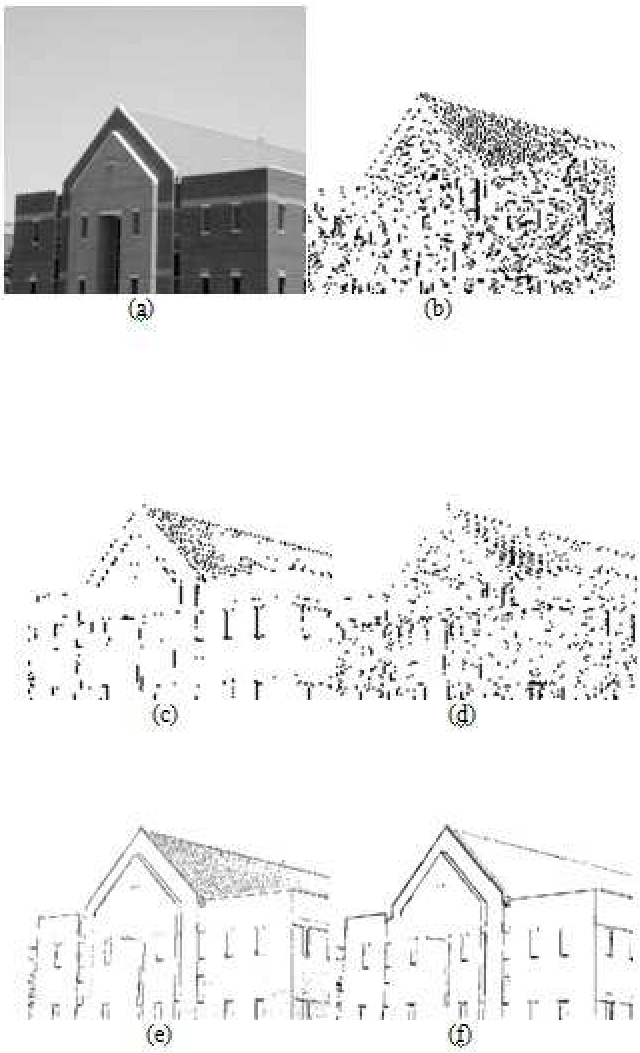

Figure 7. Comparison of ant-based edge detection algorithms. (a) The original image; (b) Canny edge detector; (c) Sobel edge detector; (d) Log edge detector; (e) Roberts edge detector (f) The proposed ACO-based edge detector.

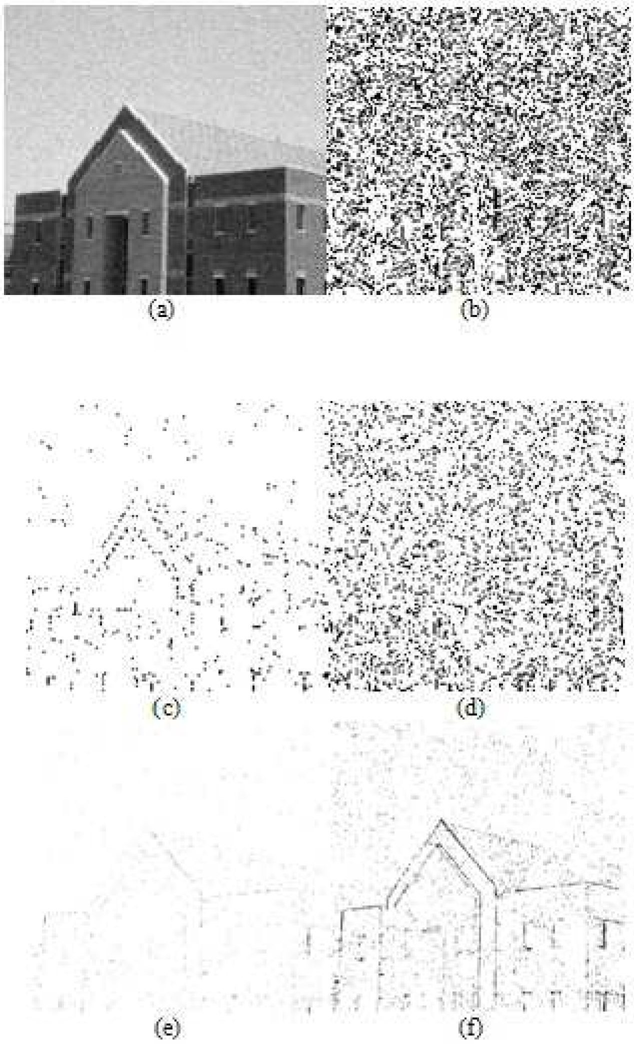

Figure 8. Comparison of ant-based edge detection algorithms. (a) The noisy image; (b) Canny edge detector; (c) Sobel edge detector; (d) Log edge detector; (e) Roberts edge detector (f) The proposed ACO-based edge detector.

5 Conclusions

This paper introduces an efficient ant-based edge detector that gives satisfactory results both in clean and noisy images. This approach uses a pheromone matrix that represents the edge presented at each pixel position of the image, according to the movements of ants on the image and updates the pheromone matrix using the initial pheromone value [28]. Suitable values of the algorithm parameters were determined through empirical studies. When we compare our proposed edge detector with other ant-based approaches, our edge detector gives finer details and thinner edges. Experimental results show that the proposed method compared to standard edge detectors is less sensitive to Gaussian noise.

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