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ORIGINAL ARTICLE

Ant colony optimization technique for edge detection using fuzzy triangular membership function

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Abstract Edge recognition is one of the fastest growing image segmentation process. It is reported existing edge detection process shows low performance high time complexity, if the volume of image is enlarged. Furthermore, condition becomes more revered in the existence of gaps between the edge's pixels. Therefore in this work one of the bio inspired technique Ant Colony Optimization based approach is used to identify edges of a ship in ocean water. To reduced time complexity triangular fuzzy member ship function is used. The results of proposed work confirm clear edges of small and partial objects.

Keywords Image segmentation · Edge detection · Membership function

1 Introduction

Edge recognition is one of the growing image segmentation process to detect object in a given image. Edges of objects are detected on the basis of rapid transition in intensity. Therefore the primary objective is to recognize the pixels that may be the likely candidates of interest i.e. part of edge. The attribute of edge pixel is abrupt transition in intensity of pixel as compare to adjacent pixels i.e. non edge pixels.

Ant Colony Optimization (ACO) is one of the bio inspired technique that utilized the above said feature of pixel. The first step is to select set of pixels as candidates for edge formulation. Thereafter outputs edges by using a suitable heuristic measure.

As the size of the image increases the computation time for conventional edge detection increases quickly (Touzi et al. 2001), as well as result in edges have discontinuities (Slade 2009; Cumming and Wong 2005). The above said heuristic membership function based ACO shows better performance in terms of quality of edges as well as computation time. ACO, the main features of its improvement involve mechanisms to intensify the search involving high-quality solutions and preserve a sufficient search space (Lopez-Ibanez et al. 2015). The ACO has been applied to solve numerous complex combinatorial optimization problems, Mazidi et al. (2016) and Zhang and Lu (2012). Hence, in proposed work ACO is used to find out edges of ship in a sea water. Fuzzy triangular membership function estimate degree of edginess or heuristic information to reduce computation time.

There are five sections in this; Sect. 2 gives a brief introduction to the essential concepts of ACO. Section 3 explains the proposed ACO edge detection process. Practical work and outcomes are shown in Sect. 4. Section 5 consists of the conclusion and future directions (Fig. 1).

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Fig. 1 Picture of ship in sea environment

2 Ant colony optimization bio-inspired technique

This technique is based on property of natural ant in selecting the shortest path. Ant selects to follow a route rich in pheromone which is conserve by ants as they pass through from that route. The capability of ants to discover shortest path is primarily due to this pheromone. The pheromone decay as the time passes which results in much fewer pheromones on less used paths. As the time passes, the shortest route will have the highest rate of ant traversal, this path will be reinforced and the others diminished until all ants follow the same, shortest path. It is also possible that there are many equally short paths—this situation can be handled by ACO as well. In this situation the rates of ant traversal over the short paths will be roughly the same, resulting in these paths being maintained while others are ignored. Additionally, the system responds to this and will eventually converge to a new solution if a sudden change to the environment occurs (e.g., a large obstacle appears on the shortest path).

2.1 Application of ACO algorithms

In common, an ACO technique can be useful to any combinational problem as far as it is possible to define:

Appropriate problem representation The problem can be described as a graph with a set of nodes and edges between nodes.

Heuristic desirability of edges: A suitable heuristic measure of the "goodness" of paths from one node to every other connected node in the graph.

Construction of feasible solutions: A mechanism must be in place whereby possible solutions are efficiently created. This requires the definition of a suitable traversal stopping criterion to stop route construction when a solution has been reached.

Pheromone updating rule: A suitable method of updating the pheromone levels on edges is required with a corresponding evaporation rule, typically involving the selection of the n best ants and updating the paths they chose.

Probabilistic transition rule: The rule that determines the probability of an ant traversing from one node in the graph to the next.

The natural ants work in a team as they come out from the nest in search of rations. To correspond with each other a chemical acknowledged as pheromone is evaporated by each ant on the route, which is going to be followed by that particular ant. If any obstacle appears on the path ants can choose a new path as shown in Fig. 2. The amount of pheromone is reduced as time passes. This results in the amount of pheromone on the most followed route is deposited is higher than on the less familiar one, hence the chance with which any single ant chooses the path to follow is quickly biased towards the lesser one. The final result is that very quickly all ants will choose the path with higher amount of pheromone.

The selection of edge pixels task may be reformulated into an ACO-suitable problem. ACO requires a problem to be represented as a graph—here nodes represent pixels of images, with the edges between them denoting the choice of the next pixel. To search for the potential candidates for pixels an ant traversal through the graph where a minimum number of nodes are visited or move of ants satisfy the traversal stopping criterion.

Figure 3 illustrates this setup—the ant is currently at node a and has a choice of which pixel to add next to its pixel (dotted lines).

It chooses pixel b next based on the transition rule, then c and then d. Upon arrival at d, the current set of pixels are {a, b, c, d}, and four numbers of move is sufficient to satisfy the stopping criterion. The ant terminates its movement and outputs this traversal is a set of pixels candidate for edge formation.

2.2 Explanation of ant system

The ant colony system is derived from the study of real ant colonies. But artificial ants have some major differences with a real (natural) one (Ferro-Famil and Pottier 2007).

- Non-natural ants will have some memory,
- Simulated ant will not be completely blind,
- Artificial ant will live in an environment where time is discrete.

The movement of an ant in the graph is determined by the transition probabilities. This transition probability is influenced by two factors namely, the heuristic information and pheromone information. The construction of a solution to a problem contains a certain number of construction steps. Each ant tries to obtain a good solution simultaneously and individually at every construction step (Gonzalez and Wood 2002).

According to the Souyris et al. (2003), Ouchi and Wang (2005), Johnsen and Larsen (2006), Ouchi et al. (2004) and

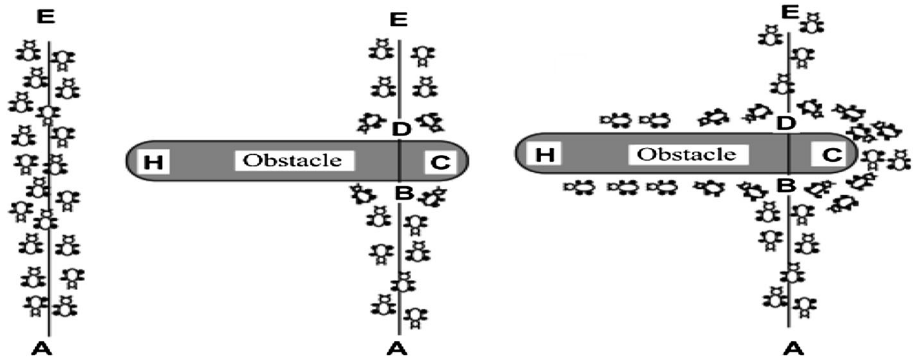

Fig. 2 Movement of natural ants

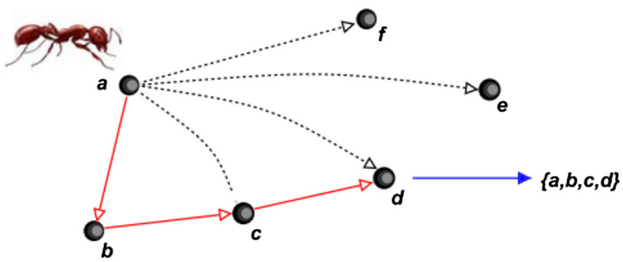

Fig. 3 Ant colony for edge pixels selection

Greidanus (2006), at the nth construction step, the kth ant moves from node i to j according to transition probability. The transition Probability $(n)_{p_{ij}}$ is estimated as Eq. (1).

$$(n)_{p_{ij}} = \frac{\left((n-1)_{\tau_{i,j}}\right)^{\alpha} \cdot (\eta_{i,j})^{\beta}}{\sum_j \in \Omega_j \left((n-1)_{\tau_{i,j}}\right)^{\alpha} (\eta_{i,j})^{\beta}} \tag{1}$$

where Ω is set of unvisited states α and β are constant to control influence of pheromone Heuristic information η is based on degree of edginess because movement of ant are trigger by greater degree of edginess it is neighborhood.

The ant colony system allows for exploration by Eq. 2

$$j = \begin{cases} argmax[\tau(i,j) * \eta(i,j)] & if\ q \le q_0 \\ j & otherwise \end{cases} \tag{2}$$

where q is a random number, q_0 is a parameter ($0 \le q_0$-< 1), and J is the random variable selected according to the previous probability distribution in Eq. 1.

At every step, based on the value of q generated an ant is moves from state I to state j, if q $\le q_0$ the best edge is chosen according to (1). The best so far solution for every construction step for entire algorithm is recorded.

If, pheromone deposited by an ant provides a positive feedback and thus reinforce the probability to find new good solution. Otherwise evaporation of pheromone acts as a negative feedback, which prevent algorithm to stop at local maxima (Tomiyasu 1976).

The pheromone is updated twice during algorithm. The first update is performed after movement of each ant in each construction step (Ferro-Famil and Pottier 2007).

$$(n)_{\tau_{ij}} = \begin{cases} (1-\rho) * \left((n-1)_{\tau_{ij}}\right)^{\alpha} + \rho * (\Delta_{ij})^{\beta} & if\ i,j\ belongs\ to\ best\ tour \\ (n-1)_{\tau_{ij}} & otherwise \end{cases} \tag{3}$$

where ρ is evaporation rate.

$$(n)_{\Delta\tau(i,j)} = \begin{cases} {}^{1}/_{f_k} & if\ ant\ k\ edges\ (i,j) \\ 0, & otherwise \end{cases} \tag{4}$$

where f_k, is the tour length of 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 length (Oliver and Quegan 2004).

The second update is performed after all K ants have moves within each construction steps (Olsen et al. 2009).

$${}^{(n)}\tau = (1-\varphi) \cdot ({}^{(n-1)}\tau) + \varphi \cdot ({}^{(0)}\tau) \tag{5}$$

here φ is the pheromone decay coefficient.

3 Proposed ACO based approach for edge detection

In proposed algorithm fuzzy membership function is used for edge finding. The heuristic information gathered by ants is very essential for assessment of transition probability. The value of transition probability is used to make a decision over the choice of ant to move or select a particular pixel. For segmentation of object from ground edginess property is used as heuristic information. As a final step pheromone matrix is used to determine whether a pixel is edge or not. For this purpose threshold of intensity is used. Algorithm consists of four main Steps:

1. Read Image

First step is to read image 'I', and convert it into gray level image. Further, image is converted into is 2-D image matrix 'G'.

2. Initialization Process

This process consists of two steps initialization element of pheromone matrix and estimation of degree of edginess for each pixel.

(a) The initial value of each element of pheromone matrix $\tau_{int} = 0.001$.
(b) Heuristic information η_{ij} is estimated on the basis of variation of image's intensity values in neighborhood by Eq. (6).

$$\eta = \Delta/(c - b) \tag{6}$$

Heuristic information η is based on degree of edginess because movement of ant is trigger by greater degree of edginess it is neighborhood. A '3 × 3' neighborhood considered η is given by triangular fuzzy membership function as shown in Fig. 4.

$$\Delta = G(i,j) - \left(\sum_{k=-1 \text{ to } 1} G(i+k, j+k)/8 \right) \tag{7}$$

here G(i, j) is intensity of pixel at ith row and jth column, c = max(G(i, j)) and b = min(G(i, j)).

3. Iterative Construction and Update Process

This construction step is twofold update process, in first step each ant moves individually and update pheromone matrix. The second update is performed after all K ants moved within each construction step.

(a) Let, in first construction step kth ant move L times. Then transition probability ${}^{(n)}p_{ij}$ is estimated by Eq. (1). On the basis of estimated transition probability amount of pheromone is determine by Eqs. (2) and (3).

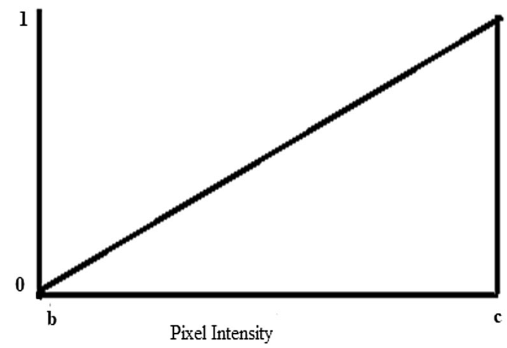

Fig. 4 Triangular membership function

(b) The second update is performed in each construction step after all k ants moved within each construction step by Eq. (4).

4. *Decision Process* A final pheromone matrix constructed to reflect the edge information. Each element of matrix corresponds to a pixel in image and specifies whether that pixel is an edge or not on the basis of threshold T.

4 Experimental work and results

Proposed method is based on algorithm given below.

4.1 Proposed algorithm

START
STEP 1: Read Infrared Image
STEP 2: Convert into gray level image
STEP 3: Estimation of pheromone matrix
(a) Initialize values of quantity of pheromone (τ), evaporation rate (ρ), and pheromone decay coefficient(φ) .
τ= 0.001, ρ=0.01 , and φ=0.001
(b)**)** Measure Heuristic information η_{ij} by equation (5).
(c) Estimate Transition Probability ${}^{(n)}p_{ij}$ and pheromone quantity for first construction step by equations (1) and (3) .
(d) Performed second update after all K ants moved within each construction step by equation (4).

STEP 4: Construct final pheromone matrix reflects the edge information by pixel by pixel analysis of gray level for the Threshold T=0.7
(a)If f(x,y) >T
Then g(x,y)=f(x,y)
(c) Else
f(x,y)==0

END

On the basis of proposed methodology experiments are carried out and results along with experimental work are discussed in now onwards.

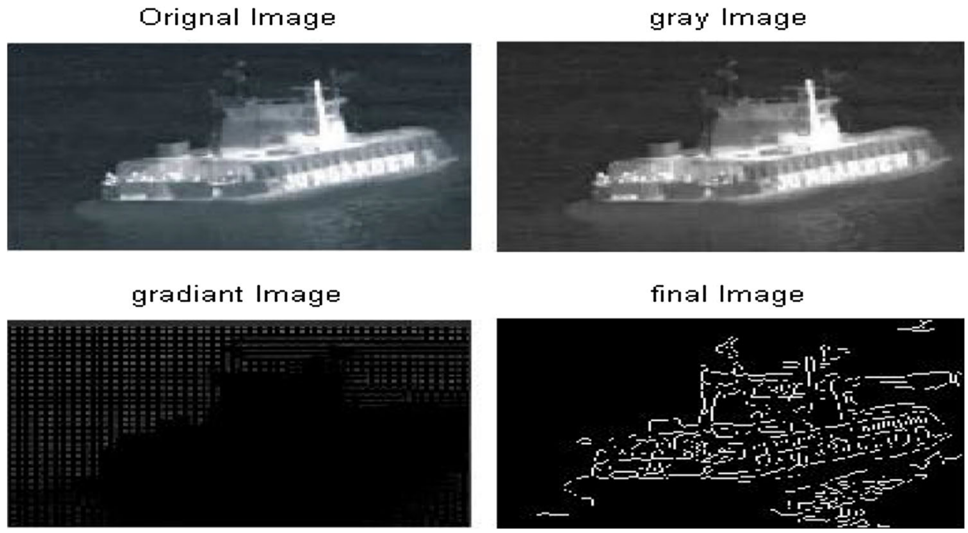

Fig. 5 Extracted edge information by using proposed method

The experimental work is carried out by taking infrared image of ship as shown in Fig. 1. The resolution of image is 256 × 256 pixels. Number of ants, K = 4; Each ant moves N = 40 construction steps. The threshold value is taken T = 0.7. In first step all the values initialized as follows $\tau = 0.001$, $\rho = 0.01$, $\varphi = 0.001$.9- Pixels (3 by 3) neighborhood considered, to determine degree of edginess η, by applying triangular fuzzy membership function. The outcomes of experimental work are shown in Fig. 5.

To check the performance of algorithm works is to imagine each ant, if isolated would move with local maxima. This local guarantee only locally optimal moves and will practically always lead to formation of discontinues edges. If we now consider the effect of the simultaneous presence of many ants, then each one contributes to the trail distribution. Good parts of paths will be followed by many ants and therefore they receive a great amount of trail. On the contrary, bad parts of paths are chosen by ants only when they are obliged by constraint satisfaction these edges will therefore receive trail from only a few ants. To verify the performance of proposed algorithm some more images are considered as shown in Figs. 6, 7 and 8. Figures 6 and 7 display edges of small ship and partial ship respectively. Where as in Fig. 8 an edge of a girl face is shown very clearly, which are generated by proposed algorithm.

Performance of proposed triangular fuzzy membership function based ACO is compared with well-established Fuzzy C-Means ACO algorithm. The threshold value is taken T = 0.7. Following parameter are taken $\tau = 0.001$, $\rho = 0.01$, $\varphi = 0.001$ with 8- neighborhood is considered to

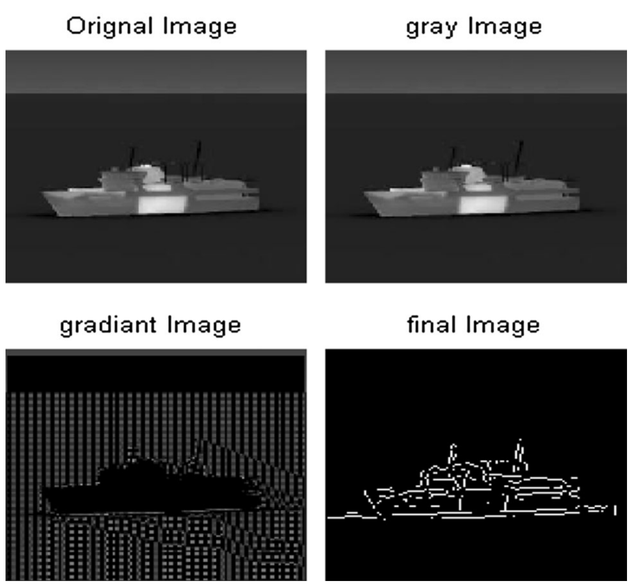

Fig. 6 Outcomes of ACO based edge detection of small ship

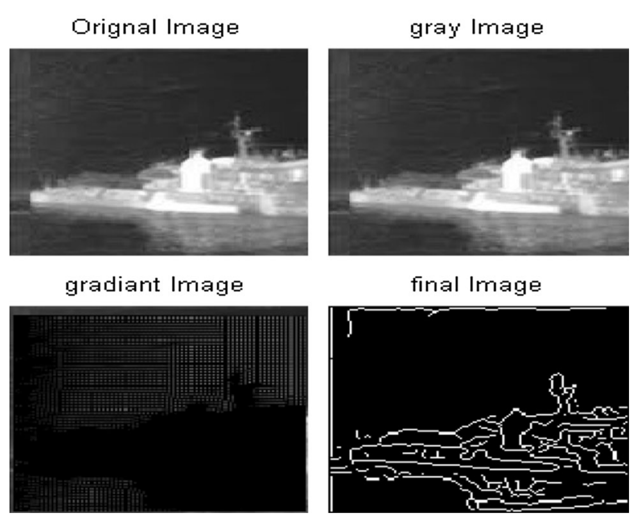

Fig. 7 Outcomes of ACO based edge detection of partial ship

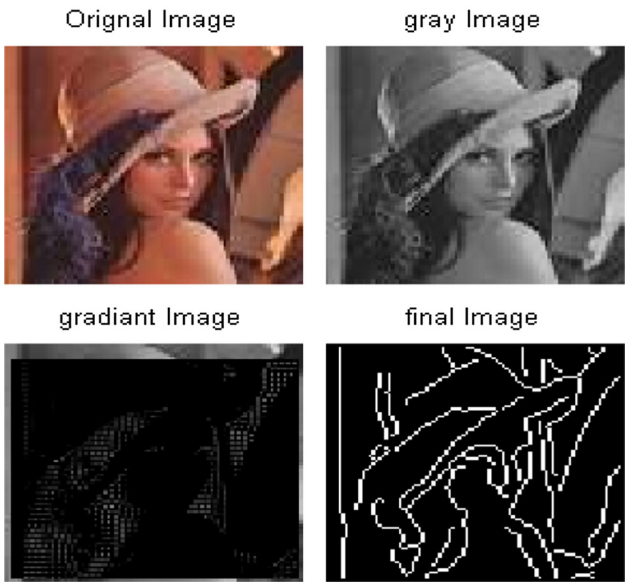

Fig. 8 Outcomes of ACO based edge detection of Girl's image

Table 1 Performance of proposed algorithm

Dimension of image	Number of ants	Time required to find all the participating pixels to draw edge	
		Fuzzy membership function based ACO (s)	Fuzzy C-means ACO algorithm (s)
256 × 256	4	13	14
256 × 256	8	6	7
256 × 256	16	2.57	3

draw the edge's pixel, ant moves N = 40 construction steps.

After analyzing Table 1, it is found that performance of proposed algorithm time complexity is better than well know Fuzzy C-Means ACO algorithm.

5 Conclusion and future directions

This paper is presented a naive search tactic based on a triangular membership function based heuristic to identify edges of ship under sea water. The common proposal underlying the Ant Colony System pattern is that ants are heading for by amount of pheromone on the various path. Higher amount of pheromone on any path from source to destination is representing that, it was followed by a higher number of ants and may leads to edge pixel. To construct final pheromone matrix threshold of 0.7 is used. Proposed work gives better results as compared to other conventional methods of edge detection.

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