COMMUNICATIONS

EXTRACTING EDGE OF IMAGES WITH ANT COLONY

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This paper provides the ant colony system for edge detections. The edge of images can be considered as food for ants. It seems that ant colony structure and implementation to image processing need more research. To process images of still increasing size is an challenge and a need to decreases the computation time is of great importance.

K e y w o r d s: ant colony, image processing, edge detection

1 INTRODUCTION TO ANT COLONY

Research on a new meta-heuristic for optimization is often initially focused on proof-of-concept applications [1]. In the early 1990s, ant colony optimization (ACO) [2] was introduced by M. Dorigo and colleagues as a novel nature-inspired meta-heuristic for the solution of hard combinatorial optimization (CO) problems.

According to Papadimitriou and Steiglitz [3], a CO problem $P = (S, f)$ is an optimization problem in which, given a finite set of solutions S (also called search space) and an objective function $f : S \to R^+$ that assigns a positive cost value to each of the solutions, the goal is either to find a solution of minimum cost value, or — as in the case of approximate solution techniques — a good enough solution in a reasonable amount of time. The ACO algorithms belong to the class of meta-heuristics and therefore follow the latter goal. The central component of an ACO algorithm is a parameterized probabilistic model, which is called the pheromone model. The pheromone model consists of a vector of model parameters T called pheromone trail parameters. The pheromone trail parameters $T_i \in T$, which are usually associated to components of solutions, have values τ_i, called pheromone values [1].

The ACO approach attempts to solve an optimization problem by repeating the following two steps:

- Candidate solutions are constructed using a pheromone model, that is, a parameterized probability distribution over the solution space;
- The candidate solutions are used to modify the pheromone values in a way that is deemed to bias future sampling toward high quality solutions.

2 ANT COLONY SYSTEM

The ant colony system has been applied in optimization, which is the Ant Colony Optimization (ACO) algorithm [1]. In ACO, the solution to a problem corresponds to a state transfer sequence, *ie* a path, from the starting state to the goal state in the discrete state space. The optimal solution corresponds to the shortest path. The ants move randomly between neighboring states from the starting state until the goal state is reached. The state-transfer probability is calculated according to the trial intensity (pheromone). On the other hand, each ant also increases the trial intensity on the way it has passed according to the quality of the solution found. This is a kind of positive feedback mechanism, which leads to fast solution searching by ACO [4]. The probability defined to move from state s_i to s_j given by [1]:

$$p_{ij}(t) = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum\limits_{s_j \in \text{Allowed}} [\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}, & \text{if: } s_j \in A \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Where $\tau_{ij}(t)$ is the trial intensity between s_i and s_j at time t. Further, α and β are two parameters having positive values. η_{ij} is the reciprocal of the distance between s_i and s_j, which is the heuristic information. A is the set of neighboring states that have not been experienced by the current ant.

3 THE ANT COLONY AND APPROACH TO IMAGE PROCESSING

The edge of images can be considered as food for ants. As we know the aim is to get edge of images so another implementation considered as food for ant to reach and that is difference between the median grey-levels of previous cell and its neighbours, and current cell and its neighbours. In the swarm model designed to evolve on digital image habitats [5] a certain number of ants distributed randomly on zero image in the same size of digital image where the image pixel values are between 0 and 255 in grey value (8 bit visualization). On each generation, each ant moves to an adjacent cell and reinforces the pheromone level on that spot. The model has two different policies: one cell may be occupied by one and only one ant, or ants are allowed to share the same cell. In the first,

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an ant will not move if it finds itself totally surrounded by others ants. Here we do not allow more than one ant occupy a pixel. An ant chooses which cell to move according to its current direction and the pheromone intensity on the eight surrounding cells. That is, if an ant comes from south, and the eight cells have no pheromone, the chance of going north is higher, followed by the chance of going northeast or northwest, an so on, until the likelihood of returning south, which is very low [6] this policy will lead us to encounter whole pixel of images. Figure 1 shows the chance of moving an ant to other of the surrounding cells.

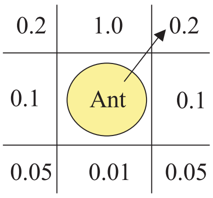

Fig. 1. Chance for moving to adjacent cells

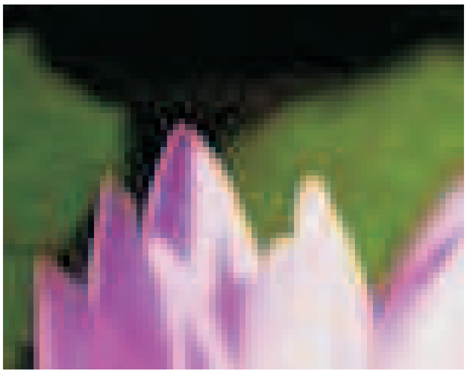

Fig. 2. Original colour image.

The following mask is known as reciprocal η_{ij} in equation 1 where shows the chance of transition from states i to state j. Probability of transition is considered in equation (1). As we knew $\tau_{ij}(t)$ is the trial intensity between s_i and s_j at time t. The trial intensity can be defined be equation (2):

$$\tau_{ij} = \left(\kappa_1 + \frac{\sigma}{\kappa_2 + \delta\sigma}\right) \qquad (2)$$

Where σ implements pheromone released by an ant in transition from state i to j. Here k_1 and k_2 are constant factors, $1/\delta$ implements sensory capacity, which describes the fact that each ant's ability to sense pheromone decreases somewhat at high concentrations.

Of course in the beginning of searching for food, the intensity trial $\tau_{ij}(t)$ will be less and at the end of simulation will be high at the food regions. The pheromone is updated at each iteration by equation (3):

$$Pheromone^{new} = Pheromone^{old} + \rho\,\Delta \qquad (3)$$

Here Δ represents the difference between the median grey-levels of previous cell and its neighbours, and current cell and its neighbours, ρ is the rate of efficiency of Δ in pheromone. Another phenomenon that has to be considered to extract better edge and that is pheromone can evaporate and if pixels have not met more by ants, pheromone will disappear.

3.1 Energy State

Every ant will move on image and release pheromone by itself. If a region that does not consist of pheromone, in that case if some ant exist there, they will reinforce pheromone without any aim to reach and pheromones will detect in that place will conflict with real edges (see Fig. 1). Evaporation of pheromone will not able alone to solve the problem. In that case we consider an energy state for every ant to alive. Equation (4) implements energy state for each ant in every iteration:

$$Energy^{new}_{ant} = Energy^{old}_{ant} - \zeta\,(1 - \Delta) \qquad (4)$$

where ξ is rate of decreasing energy. If trail intensity remains high enough, in the next iteration the energy state of ant decrease less and remain in meaning full condition. We consider fixed coefficient for energy and if the energy state loses down and get less than that, ant will die and disappear.

To elucidate the discussed, let us considered an example with $k_1 = 1.2$, $k_2 = 0.5$, $\delta = 0.62$, $\rho = 5$ with the results shown in Fig. 3. The first row shows Red, Green and Blue image of the original in Fig. 2 and the second row shows the pheromone reinforcement.

As we can see in Fig. 3, edges are detected but it is still not the best extraction, may be it will be improved by fixing the parameters but it will not be capable of further enhancement. Figure 4 shows the starting and the final positions of ants in the image. Existence of ants in middle of the image confirms the existence of some food that can not be ignored.

4 DISTRIBUTING ANT INTELLIGENTLY

By considering Fig. 3 we see that there are extractions near the edges. In the next step this can help us to distribute ants near these edges (as detected in Fig. 3) and to guarantee not to lose another part, we distribute some other ants randomly either. Figure 4 shows the efficiency of this treatment. According the positions of ants in Fig. 4 as can be seen the edges are detected more smoothly than those in Fig. 3.

4 CONCLUSION

We enhanced the equation of calculating energy of state and the released method led us to less iteration at all. In the next step we introduced improved treatment of distributing ants intelligently and results showed the efficiency of this modification and edges of the images were extracted better than using the first step only. As a conclusion it seems that ant colony structure and implementation to image processing need more research.

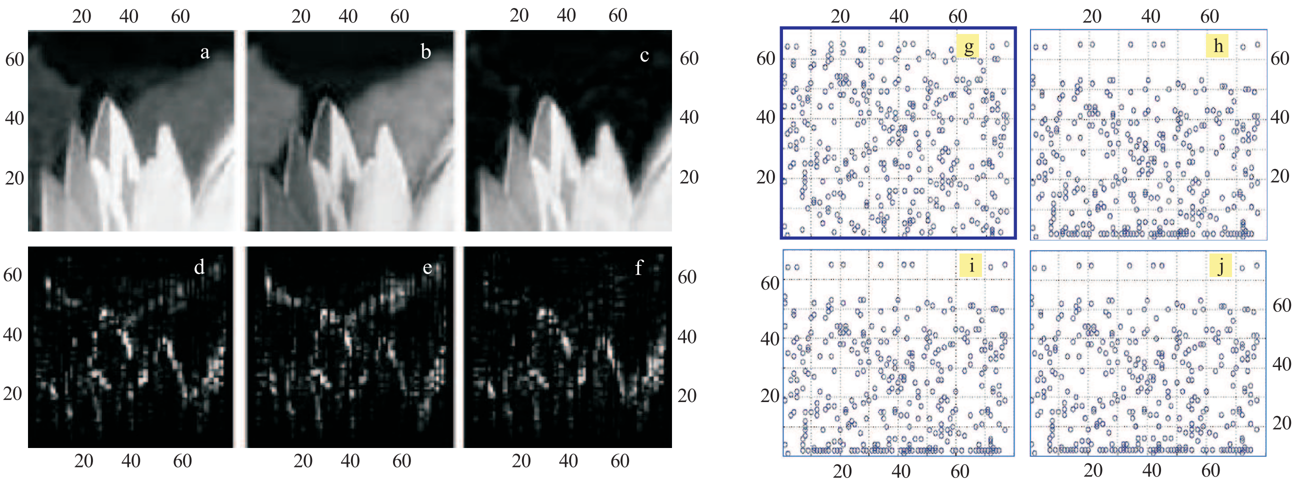

Fig. 3. Left: Images, a – red, b – green, c – blue and pheromone in images d – red, e – green, f – blue. Right: Position of ants, g – starting, and final for images h – red, i – green, j – blue.

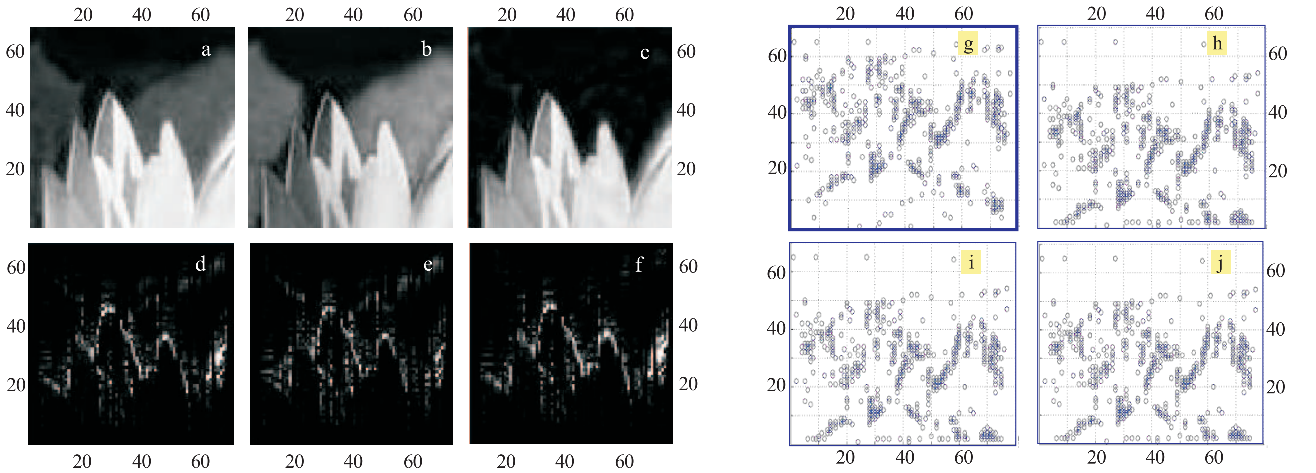

Fig. 4. Left: Images, a – red, b – green, c – blue and pheromone in images d – red, e – green, f – blue. Right: Position of ants, g – starting, and final for images h – red, i – green, j – blue.

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