A Preliminary Study of Automatic Delineation of Eyes on CT Images Using Ant Colony Optimization

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Abstract Eyes are important organs-at-risk (OARs) that should be protected during the radiation treatment of those head tumors. Correct delineation of the eyes on CT images is one of important issues for treatment planning to protect the eyes as much as possible. In this paper, we propose a new method, named ant colony optimization (ACO), to delineate the eyes automatically. In the proposed algorithm, each ant tries to find a closed path, and some pheromone is deposited on the visited path when the ant finds a path. After all ants finish a circle, the best ant will lay some pheromone to enforce the best path. The proposed algorithm is verified on several CT images, and the preliminary results demonstrate the feasibility of ACO for the delineation problem.

Key words automatic delineation; CT images; ant colony optimization

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The modern radiotherapy techniques try to improve the therapeutic ratio by using optimized beams to produce highly three-dimensionally conformal dose distributions to the target (tumor), while sparing those organs-at-risk (OARs) and normal tissues as much as possible[1]. As for the treatment of head tumors, eyes are important OARs that should be especially protected. Correct delineation of the eyes on CT images is one of important issues for treatment planning to protect the eyes as much as possible.

In the most of clinical cases, the eyes, together with most of other OARs, are contoured manually on two-dimensional (2D) slices using simple drawing tools. The development of fast and robust automated contouring (segmentation) tools has become crucial for OAR protections with the novel high-precisely treatment methods. However, automated segmentation of the image data for planning is a challenging problem. In particular, boundaries between different soft-tissues are vague on CT scans. Moreover, the organ shapes can be highly variable[2-7].

In this paper, we propose a new method, named ant colony optimization (ACO) algorithm, to delineate the eyes automatically. The rest of this paper is organized as follows. In Section 1, the principle of ACO is briefly introduced. Section 2 describes the realization of ACO for the delineation problem. Some results and discussions are presented in Section 3. Conclusions are given in the final section.

1 Principles of ACO

Ant colony optimization (ACO) is based on the cooperative behavior of real ant colonies, which are able to find the shortest path from a food source to their nest. In essence, ACO is an evolutionary approach where several generations of artificial ants search for good solutions[8-9]. Every ant of a generation builds up a solution step by step going through several probabilistic decisions until a solution is found. Ants found a good solution mark their paths through the decision space by putting some amount of pheromone on the edges of the path. The following ants of the next generation are attracted by the pheromone. After a transitory period, the shorter paths will be more frequently visited and pheromone will accumulate faster on them. This in turn causes more ants to select these paths. This positive feedback effect means that all the ants will potentially use the shortest path.

The first ACO algorithm, called ant system (AS), has been applied successfully to different optimization problems, such as the traveling salesman problem (TSP)[8] and quadratic assignment problem (QAP)[10-11]. Subsequently, some modifications were carried out over the original AS. Recently, the ACO meta-heuristic was proposed as a common framework for existing versions[12]. Among those ant colony meta-heuristics, the ant colony system (ACS) is an improvement of the AS algorithm[9]; its performance for the solution of classical optimization problems is favorably compared
with genetic algorithm (GA) and simulated annealing (SA) techniques.

Summarizing, the ants in the ACS are guided to build their tours by both heuristic information and pheromone information according to the state transition rule, the local updating rule, and the global updating rule\(^{[9,12]}\).

### 1.1 State Transition Rule

During the construction of a new solution the state transition rule is the phase where each ant decides which is the next state to move to. In the ACS \(m\) ants are initially positioned on \(n\) cities chosen according to some initialization rule (e.g., randomly). Each ant builds a tour by repeatedly applying a stochastic greedy rule (the state transition rule), called pseudo-random proportional rule, is given by Eqs.(1) and (2), which give the probability with which ant \(k\) in city \(i\) chooses to move to the city \(j\). The best state is chosen with probability \(q_0\) (that is a parameter \(q_0 \in [0,1]\) usually set to 0.8-0.9) according to

\[
p_i(j) = \begin{cases}
1, & \text{if } j = \arg \max_{r \in A_k(i)} \left\{ \tau_{ij} \eta_j^\beta \right\} \\
0, & \text{if } j \neq \arg \max_{r \in A_k(i)} \left\{ \tau_{ij} \eta_j^\beta \right\}
\end{cases}
\]

(1)

and with probability \((1-q_0)\) the next state is chosen randomly with a probability distribution based on \(\tau_{ij}\) and \(\eta_j\) according to

\[
p_i(j) = \begin{cases}
\frac{[\tau_{ij}][\eta_j]^\beta}{\sum_{r \in A_k(i)} [\tau_{ir}][\eta_r]^\beta}, & \text{if } j \in A_k(i) \\
0, & \text{otherwise}
\end{cases}
\]

(2)

where \(\tau_{ij}\) is the pheromone intensity of trail on edge \((i, j)\), \(\eta\) is the heuristic function, \(\eta_j = 1/\delta_j\) is the inverse of the distance \(\delta_j\) of the edge \((i, j)\), \(A_k(i)\) is the set of cities that remain to be visited by ant \(k\) positioned on city \(i\) (to make the solution feasible), and \(\beta > 0\) is a parameter which determines the relative importance of pheromone versus distance.

The state transition rule provides a controlled trade-off scheme between the exploration of new states and exploitation of a priori and accumulated knowledge and the parameter \(q_0\) determines the relative importance of exploitation versus exploration. Eqs.(1) and (2) illustrate that ants prefer to move to cities that are connected by short edges with a high amount of pheromone.

### 1.2 Local Updating Rule

While constructing a feasible solution (i.e., a tour), ants visit edges and change their pheromone level by applying the local updating rule given by

\[
\tau_{ij} \leftarrow (1-\psi)\tau_{ij} + \psi \Delta \tau_{ij}
\]

(3)

where \(0 < \psi < 1\) is a parameter and \(\tau_{ij}\) is the initial pheromone level.

The effect of this rule is to make the desirability of edges change dynamically: every time an ant uses an edge it becomes slightly less desirable (since it loses some of its pheromone). It favors the exploration of other edges, thus avoiding premature convergence.

### 1.3 Global Updating Rule

Once all ants have completed their tours, a cycle is finished and a global pheromone updating rule is applied, and only the globally best ant is allowed to deposit pheromone. This strategy directs the search in a neighborhood of the best tour found up to the current iteration. The global updating rule is given by

\[
\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho \Delta \tau_{ij}
\]

(4)

\[
\Delta \tau_{ij} = \begin{cases}
\frac{1}{L_{\min}}, & \text{if } (i, j) \in \text{global best tour} \\
0, & \text{otherwise}
\end{cases}
\]

(5)

where \(0 < \rho < 1\) is a pheromone decay parameter, \(L_{\min}\) is the length of the globally best tour.

Eqs.(4) and (5) indicate that only those edges belonging to the globally best tour will receive reinforcement. In essence, global updating is intended to provide a greater amount of pheromone to those shorter tours, and hence, intended to increase the attractiveness of those promising routes.

### 2 ACO for the Delineation of Eyes on CT Images

Fig.1 shows a simple scheme of ACO for the delineation of the eye tissues on CT images. First, a rectangle-shaped working area is manually defined by the user. In the working area the whole eye should be included in, and the center of the rectangle is approximately close to the center of the eye on this CT slice. The pheromone on each pixel in the working area is assigned with same values. Then, ants will be placed on each pixel on the cross lines. All the ants will be controlled to approximately move clockwise (or anticlockwise).
Before the ant starts to move, two values of information are computed, i.e., the CT value of the starting point and the gradient value of the neighboring 5×5 area. These two values are represented as a vector \( \mathbf{X}_i = (x_{i1}, x_{i2}) \), where \( i = 1, 2, \cdots, N \) is the index of ants, and \( N \) is the number of total ants, i.e., the pixel number on the cross lines in Fig.1. \( x_{i1} \) and \( x_{i2} \) are the CT value and gradient value of the pixel. To save the computation time and weaken the influence of those random noises, four neighboring pixels can be combined to one pixel by averaging.

Also, two values about the eyes are previously calculated as follows. First, all the CT values at each pixel except the pixels of bones and airs (which CT values are approximately known) are classified into two categories: one for the eye and one for the normal tissue around the eyes. Then, the CT value \( c_{i1} \) and the gradient value \( c_{i2} \) for the eye could be easily found, which are also represented as a vector \( \mathbf{X}_i = (c_{i1}, c_{i2}) \).

When ants move, \( \mathbf{X}_i = (x_{i1}, x_{i2}) \) is calculated for those all neighboring pixels (except the ones that have just been visited) that will be potentially visited, and the heuristic function \( \eta \) is calculated according to

\[
\eta = \frac{1}{\sqrt{(x_{i1} - c_{i1})^2 + (x_{i2} - c_{i2})^2}}
\]  

(6)

Then, the next pixel to be visited is determined according to Eq.(6) and the state transition rule described by Eqs.(1) and (2). For each ant a memory is allocated to save the visited pixels (i.e., the visited path) in a cycle. Also, the sum of the heuristic function value of each pixel on the path is saved to determine which path is the best one after all ants finish its cycle.

While visiting each pixel, the ant changes the pheromone level of the pixel by applying the local updating rule given by Eq.(3). Once all ants have completed their tours, the global updating rule is applied, and only the globally best ant is allowed to deposit pheromone according to Eq.(4) and

\[
\Delta r_{ij} = \begin{cases} 
\frac{1}{\eta^{HF_{min}}}, & \text{if } (i, j) \in \text{global best tour} \\
0, & \text{otherwise}
\end{cases}
\]  

(7)

where \( HF_{min} \) is the sum of the heuristic function value of the global best path.

At the very beginning of the optimization, the initial pheromone values of all pixels in the rectangle area are set to unit. The iteration will be terminated when the global best path is not obviously improved (the improvement is smaller than a specified very small value, such as 0.0001 in this work) during the several successive iteration numbers (10 iterations in this work). The visited path of the global best ant is regarded as the final delineation result.

3 Results and Discussions

Fig.2 shows the delineation results on four CT images. The rectangle-shapes working area are same for all of these CT images, and the number of the ants are 220. To save the computation time and decrease the influence of the random noises, four neighboring pixels are combined to one pixel by averaging before delineating with ACO. The computation time taken by the four cases is 24 s, 19 s, 22 s, and 26 s, respectively.

It can be seen that the results in Fig.2(b) and (c) are perfect, and the results in Fig.2(a) are reasonably acceptable. On the contrary, Fig.2(d) shows poor results, which is mainly because of the non-continuous tissues of the eyeballs on that CT.
eyes are determined using a quite simple statistics method, which is of course not always accurate. Second, it is not easy to determine the number and the initial position of the ants. There is no doubt that better results would be found if more ants are used; however, the computation time would obviously increase. Furthermore, it is not enough for delineation only using the CT values and gradient information.

4 Conclusions

This work proposes an ACO-based algorithm to implement the automatic delineation of eyes on CT images. One of the important usages of our algorithm is to contour the eyes and the OARs that need special protection during the treatment of the tumor in the head with radiation. The preliminary results show the feasibility of the proposed algorithm. This gives confidence to us to improve the algorithm and extend it to the delineation of other OARs and normal tissues, such as the lung, kidney, heart, bladder, and so on, or even the delineation of tumors.

The future works on the propose algorithm are as follows. First, it is necessary to try to find some more useful information that could be available, such as the texture. Second, it is useful to find a more effective mechanism to describe the characteristics of the pixels of the eyes and the surrounding tissues. Finally, it is feasible to find some known models and templates to guide the search progress of the ants. One of the models for the eyes would be a circle on 2-dimensional (2D) plane, or a ball on 3-dimensional (3D) space.

References

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