

Image Segmentation Algorithm Based on Improved Ant Colony Algorithm

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Abstract

In the process of image segmentation, the basic ant colony algorithm has some disadvantages, such as long searching time, large amounts of calculation, and rough image segmentation results. This paper proposes an improved ant colony algorithm. Applying different transfer rules and pheromone update strategies to different regions of an image, including background, target, edge and noise, we develop a highly adaptive image segmentation method with high edge detection accuracy and high algorithm implementation efficiency. In the initial stage of image segmentation, we apply the idea of fuzzy clustering, which enables ants to gather quickly to the edge in the background and the target area of the image. In the later stage of image segmentation, we introduce an edge search strategy in the edge area. A following experiment shows that this developed image segmentation method can split the target more quickly and accurately.

Key words: Ant Colony Algorithm, Image segmentation, Fuzzy Clustering, Edge search strategy

1. Introduction

In image analysis and processing, one is usually interested in regions of an image with some specific or unique properties. These regions of the image are defined as targets, and the rest are defined as backgrounds. In order to identify the target better, these areas need to be separated from the image, calling for image segmentation [1]. The results of image segmentation determine subsequent image analysis, image interpretation and pattern recognition. Influenced by a number of factors, such as the complexity of background images, the differences in goals, and the existence of noise in the background, image segmentation has been a constant interest and challenge in the field of image research. Traditional image segmentation methods, such as edge detection, region growth, and threshold segmentation, have achieved very good results. Nevertheless, these methods are limited given distinct image characteristics. For instance, the edge detection method produces edges that are imprecise or discrete. The region growth method, which overcomes such a problem, can sometimes overcut the image. The threshold segmentation method, though efficient, mistakenly treats noise as image for segmentation.

Ant colony algorithm, as a new intellectual bionic evolutionary algorithm, has been applied in the field of combinatorial optimization, system identification, network routing, function optimization, robot path planning and data mining. The discrete, parallel properties of ant colony algorithm are ideal for digital image processing. As a result, it has been successfully used for image matching, image segmentation and image texture classification [2-6]. However, the algorithm also its limitations (some of which is to be elaborated later) and researchers has been improving the algorithm to overcome some of its disadvantages [7-9].

This paper starts with the basic principles of ant colony algorithm, and continues with

our improvement of the algorithm and its application to image segmentation, a process that clusters pixels of similar characteristics. It takes the gray scale and gradient of each pixel as its segmentation feature. As the ants in the basic model of ant colony algorithm walks randomly and blindly in the searching process, the model produces a large number of redundant search with an unsatisfying accuracy of image segmentation [10]. To address these problems, the paper improves the basic ant colony algorithm by treating the background area, target area, noise points and border area differently with the attempt to improve the execution efficiency and the accuracy of edge detection.

2. Basic ant Colony Algorithm

Ant colony optimization algorithm, a random search algorithm, is also known as artificial ant colony algorithm (ant colony algorithm for short). First proposed by Italian scholar M. Dorigo among others, it solved a series of combinatorial optimization problems. Bionics researchers, after a long observation on ants in nature, find that ants emit a special discharge called pheromone along their moving path to communicate with other ants in the colony [11]. The other ants, which can sense and be influenced by pheromone within a certain range, cooperate with ants that secrete pheromone to complete some complex tasks. As the ants move along, the concentration of the released pheromone increases, which further increases the probability of other ants to choose this path. For other paths with few ants, the amount of pheromone will gradually decrease [12]. In this way, the entire ant colony is able to find the shortest path from the nest to the food source. In the process of finding the shortest path, the ant colony can adapt to changes in the environment and their search for the optimal path is not affected by obstacles on the way. Although a single ant has limited ability to choose the optimal path, the whole ant colony displays a high degree of self-organization with the help of pheromone. In other words, the choice of the optimal path depends on the collaboration of the whole ant colony. Below we present a mathematical description of the algorithm applied in image segmentation.

To split an image, it is necessary to identify the characteristics that reflect the differences between images. The pixel gray value of the target usually varies greatly from that of the background; therefore, the pixel gray value can be used as a clustering feature. In addition, the gray scale often mutates at the boundary points, and the gradient of the point reflects this change. Therefore, it is an important feature to identify the differences between boundary points and background or target area points. If we treat each pixel in the image as an ant, we can build a two-dimensional vector characterized by gray scale and gradient for each ant. We set the two-dimensional vector as the corresponding pixel pheromone. Image segmentation based on the ants' behavior is a process in which these ants with different characteristics search for food sources. In the image, ants roam and look for pixels with similar pheromone features. They do not stop roaming until they move to the border or the pheromone-pixel without similar characteristics. For a given image X , the transition probability of a pixel (ants) X_i choosing to transfer to X_j is,

$$p_{ij}^k = \begin{cases} \frac{\tau_{ij}^\alpha \eta_{ij}^\beta}{\sum_{j \in S} \tau_{ij}^\alpha \eta_{ij}^\beta}, & j \in S \\ 0, & otherwise \end{cases} \quad (1)$$

where τ_{ij} is the pheromone that the ants carry; η_{ij} is the heuristic function; α and β reflect, respectively, the relative importance of the pheromone accumulated while the pixels move to the cluster, and the degree the heuristic function is paid attention to when the cluster is moving. S is the set of feasible paths for the next step. Set the

Euclidean distance (two-dimensional vector) of any pixels from X_i to X_j as d_{ij} ,

$$d_{ij} = \sqrt{(X_{i1} - X_{j1})^2 + (X_{i2} - X_{j2})^2} \quad (2)$$

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (3)$$

Heuristic function can reflect the similarity between the pixels. The greater the heuristic function, the greater the probability of pixels attributed to the same cluster. Ants will take with them new pheromone in each transfer. After one cycle, adjust the pheromone on each path according to the rules of global adjustment:

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \rho \Delta \tau_{ij} \quad (4)$$

In (4) ρ is the pheromone evaporation coefficient, $\Delta \tau_{ij}$ is the pheromone increment of this cycle path.

$$\Delta \tau_{ij} = \sum_{k=1}^m \Delta \tau_{ij}^k \quad (5)$$

$\Delta \tau_{ij}^k$ is the amount of information that the k-th ant leaves in the path ij.

3. Basic Ideas and Strategies of the Improved Algorithm

One idea of the basic ant colony algorithm for image segmentation is equal treatment on all pixels in the image. It uses the same search strategy and pheromone update method when ants move in the image, leading to a long time for the algorithm to execute and a low accuracy of image edge detection. Inspired by the division of labor among ants in nature we improved the basic ant colony algorithm, aiming to achieve better image segmentation and edge detection results. The improved algorithm takes different state transition strategies and information update strategies to guide the actions of the ants, which are distributed among the background, target, edge, and noise area of the image.

To shorten the execution time in the background and the target area in the image, this section introduces a fuzzy clustering idea that allows ants to gather quickly to the edge of the image. The ant colony in the region undertakes a global pheromone update after a complete traversal. In order to improve the accuracy of image edge detection, we introduce an edge compensate search in the edge of the image area. Ants are responsible for searching the edge of the image, conducting edge compensation in the region, and updating the pheromone on the path locally and globally. The inevitable noise of the image needs to undergo special processing. Otherwise, it will be taken as image edge. The improved strategies focus on the following aspects: background, target area, edge, and noise points. Below we elaborate the strategies.

3.1. Background and the Target Area

Due to the randomness and blindness of the ants' searching process in the image, image segmentation methods that are based on basic ant colony algorithm produce a large number of redundant searches, thus lower the efficiency of the algorithm. In order to reduce redundant searches and to improve the efficiency of algorithm execution, we introduce in the background of the image and the target area the idea of fuzzy clustering, which enables the ants to assemble quickly on the edge. Based on the segmentation characteristics, we specify the initial cluster centers in the region to guide the ants. The process of setting the initial cluster centers is as follows.

(1) Set the gray value of the initial cluster centers

The appearing frequency of different gray-scale pixels can be reflected by image histograms. To a certain extent, the frequency can reflect the results of gray clustering. Based on the above analysis, we can from the original image histogram by selecting the number of n-peak points as initial cluster centers, with n meanwhile being the gray feature. Setting the initial cluster centers reduces the execution time of the algorithm, because this method replaces a large number of cycle calculations among all pixels with the comparison between pixels and the n peak values.

(2) Set the gradient value of the initial cluster centers

For most images, the number of pixels in the background and objectives area is large, yet the gradient of the region is normally small. The gradient of the pixels at the image boundary and the noise points are large, and the pixels at the boundary points outnumber those at the noise point. In the n cluster centers, if a gray feature of the cluster center which corresponds to the number of pixels outnumbers the other cluster centers; we set the gradient characteristics of the cluster center to zero. Other gradient values of cluster centers gf can be calculated as follows:

$$gf = \frac{1}{m} \left(\max_{j=1, \dots, n} \left(\sum_{i=1}^m gd(i, j) \right) \right) \quad (6)$$

Where $gd(i, j)$ indicates the gradient value of pixel (i, j) , and the image size is $m \times n$.

(3) Set the neighborhood eigenvalue of the initial cluster centers

For the cluster center of 0 gradient values, set their neighborhood characteristics value as 8. Most of these points are the target pixel or the background pixels in the image. If the number of pixels that gray features correspond to is large, we can deduce that the cluster center is a boundary point. Then set the neighborhood characteristics of the cluster center value as 6, and set the neighborhood features value of the cluster center in the noise as 3.

After the three steps above, the initial cluster centers is $C_i (V; G; Ne)$, where $i = 1, \dots, n$.

In the target and background areas, the heuristic function reflects the similarity of the current search pixels and cluster centers, and it uses the following formula:

$$\eta_{ij} = \frac{r}{d_{ij}} = \frac{r}{\sqrt{\sum_{k=1}^m p_k (x_{ik} - c_{jk})}} \quad (7)$$

We can deduce from the above formula that the larger the cluster radius r is, the greater the value of heuristic function η_{ij} is, hence the greater probability of the pixels in this cluster. On the contrary, the greater distance between the ants and the pixel there is, the smaller the function value is, hence the smaller probability of the pixel assigned in this class. In fact, the heuristic function indicates the degree of which the current search pixel is expected to assign to a class. We use the following formula to calculate the probability that in the target and background areas, ant i at time t transfers to the next pixel j .

$$p_{ij}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{j \in S} [\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}, & \text{if } j \in S \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Where α is the pheromone strength accumulated in the clustering process, β is the desired inspiration factor, and τ_{ij} is the pheromone intensity on the path between pixel i and pixel j . $S=\{X_s|d_{sj}\leq r, s=1, \dots, n\}$ is the set of the feasibility of the path.

Every time the ant colony in the background and the target area complete a cycle, it needs to update globally the pheromone on each path. The pheromone on each path is adjusted following the formula below:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \quad (9)$$

$$\Delta\tau_{ij} = \sum_{k=1}^n \Delta\tau_{ij}^k \quad (10)$$

$\Delta\tau_{ij}^k$ is the amount of pheromone that the k -th ant remains on the path ij in the current cycle.

3.2. The Edge

When ants search for the edge of the image, their movement is based on the differences of the 8-neighborhood pixel value. In the basic ant colony algorithm, when ants search near the real edge, the edge strength nearby can lead them to mistakenly take the nearby area as the real edge. In addition, the global pheromone update strategy can result in fuzzy edge. To further enhance the search performance of the ant colony algorithm in the image edge area, we introduce the largest adjacent difference value and the maximum connection similarity [13] to guide the ants' search on the edge.

The largest adjacent difference value refers to the edge that the ants are able to identify from the high-neighborhood differences.

The maximum connection similarity refers to the situation in which the ants keep searching the possible edge in the image until they find the pixels near the real edge. The edge of the image should have the same strength. The maximum connection similarity is much more important than the largest adjacent difference value.

We modify the heuristic function of the ants on the edge as follows:

$$\eta'_{ij} = \frac{V(p_j)}{\max\{1, |p_j - p_i|\}} \quad (11)$$

Where p_i represents the pixel intensity of i , and p_j is the intensity of pixel j next to pixel i . $\max\{1, |p_j - p_i|\}$ is the maximum connections similarity factor, which guides the ants' searching direction. $V(p_j)$ is the adjacent difference value at p_j . A large value of η'_{ij} indicates the existence of an ideal edge on this path.

$V(p_j)$ is calculated according to formula (12):

$$V(p_j) = \frac{\sum_{i \in NE_j} |p_j - p_i|}{8} \quad (12)$$

Where NE_j is a set of eight pixels in the field. If $V(p_j) = 0$, the ants stop moving.

A single ant communicates with other ants by emitting pheromone on its moving path. If there exists a shorter path, more ants will choose the shorter one, leading to an increase of the concentration of pheromone on the path, and attracting more ants to choose this path. In order to obtain a better image edge, the ants of the edge need to get rid of the attraction of the current maximum information intensity path. We bring in the idea of compensation edge searching. The selection rules of edge path are modified as follows:

$$str = \begin{cases} \arg \max \{ [\tau_{ij}]^\alpha [\eta'_{ij}]^\beta \}, & \text{when } q \leq q_0 \\ J, & \text{when } q > q_0 \end{cases} \quad (13)$$

J is the random selection probability determined by formula (14).

$$p_{ij}^k(t) = \frac{[\tau_{ij}]^\alpha \cdot [\eta'_{ij}]^\beta}{\sum_{j \in NE} [\tau_{ij}]^\alpha \cdot [\eta'_{ij}]^\beta}, \text{ if } j \in NE_i \quad (14)$$

Where η'_{ij} is the heuristic function calculated by the formula (11)? Its role is to determine the visibility of the edge path. τ_{ij} is the pheromone strength on the path between pixel i and pixel j. q is a random variable. q_0 ($0 \leq q_0 \leq 1$) is the maximum impact parameter, and its value affects the ants' path selection for the next step.

According to the definitions in formula (13) and (14), when $q \leq q_0$ the ants on the edge select the path for the next step through the maximum correlation effects. On the contrary, they may be assigned to search new paths according to the related impacts. For the improved algorithm, the random selection on the edge expands the ants' searching space, and prevents the algorithm from falling into a local optimal solution too early. With the adjustable parameter q_0 , not only can the algorithm get a more accurate edge, but improve its execution efficiency.

Every time the ants at the edge take a step, they determine whether edge compensate is needed for the next step. The amount of pheromone for the movement from the pixel i to pixel j at time t is updated using the following formula,

$$\tau_{ij}(t) = (1 - \rho) \tau_{ij}(t-1) + \rho \tau_0 \quad (15)$$

Where ρ is the rate of the evaporation of the local pheromone, whose values satisfy $0 \leq \rho \leq 1$. τ_0 is the concentration of pheromone on the path.

To control the search direction of the ants in the edge, when the ant colony in the region complete a traverse, the pheromone on all the paths need to be updated globally, so that the ants can continue with the boundary compensation. The update rules of pheromone are adjusted in accordance with the following formula,

$$\tau_{ij} = (1 - \rho) \tau_{ij} + \rho \Delta \tau_{ij} \quad (16)$$

$$\Delta \tau_{ij} = \sum_{m=1}^k \frac{avg(S_m)}{\tau_{max}} \quad (17)$$

Where $avg(S_m)$ is the mth ant's average step length, and τ_{max} is the value of the maximum pheromone in the image.

3.3. Noise Point

Noise in an image is inevitable. We need to have special treatment on the noise points so that they will not be mistakenly taken as edge. In the basic ant colony algorithm, a pixel which has similar gray value as a noise point in a 3×3 neighborhood is also taken as a noise point. In the improved algorithm, such noise points should be deleted when ants transfers there[14]. With N denoting a set of noise points, the transfer rule of the ants in the region is given below:

$$p_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_{l \in S} [\tau_{il}(t)]^\alpha \cdot [\eta_{il}(t)]^\beta}, & \text{if } j \notin N \\ 0, & \text{otherwise} \end{cases} \quad (18)$$

The purpose here is to reduce the probability of selecting a noise point. On the other hand, even if a noise point in the image is chosen, we can decrease the pheromone of the noise point, hence increase the evaporation coefficient ρ . At this moment, the rule of updating the pheromone in this region is as follows:

$$\tau_{ij}(t) = (1 - \rho) \tau_{ij}(t) \quad (19)$$

After this special treatment of the noise points in the image, the chance of taking noise points as image edge decreases, thus the efficiency of image segmentation and the accuracy of edge detection are improved.

4. Application of the Improved Ant Colony Algorithm in Image Segmentation

- (1) Initialize the parameters needed in the program. Set cycle times $N_c=0$, time $t=0$. Place M ants in the image randomly, and set the maximum number of iteration $N_{c_{max}}$, as well as other parameters in the program, including α , β , r , ρ and T .
- (2) Start the cycle, $N_c \leftarrow N_c + 1$.
- (3) Determine the region of the ants. Identify the region that the ants are located in through the number of ant k 's pixels that have similar pixel gray as that of k in a 3×3 neighborhood.
- (4) If ant k is in the background and target region, it is transferred to this area first. According to the state transition probability formula in (8), it calculates the probability of selecting the next element and moves forward. It also updates the pheromone on the path based on the formula in (9).
- (5) If ant k is located on the edge, it calculates the probability of selecting the next element and moves forward according to the state transition probability formula (13). In addition, it updates locally and globally the pheromone on the path following the formula in (15) and (16).
- (6) If ant k is in the noise point, it calculates the state transition probability according to formula (18), and updates the pheromone on the path.
- (7) If the cycle satisfies the ending condition, i.e. the number of cycles $N_c \geq N_{c_{max}}$, it ends the loop and put out the results. Otherwise it returns to step (2) and continues.

5. Experiment and Analysis

To verify the effectiveness of this improved algorithm, we use a Gray Pepper Figure of size 256×256 to compare several edge detection methods. The original images used in the experiment are shown in Figure 1(a). The operating environment is Windows XP, matlab7.0 and Visual C++6.0. Because the mathematical basis of the ant colony algorithm is weak to some extent, and there exists no theory of setting various parameters in the algorithm, we determine the parameter values through experimental testing. Figure 1(b) is the image segmentation result of the basic ant colony algorithm, with some crucial parameters set as follows: $T=50$, $\alpha=1$, $\beta=2$, $\rho=0.01$. Figure 1(c) is the image segmentation result of the improved ant colony algorithm, with some crucial parameters set as follows: $\alpha=2$, $\beta=1$, $r=50$, $\tau_0=1$, $m=30$, $q_0=0.9$, $\rho=0.05$, $p'=0.2$, $T=40$.

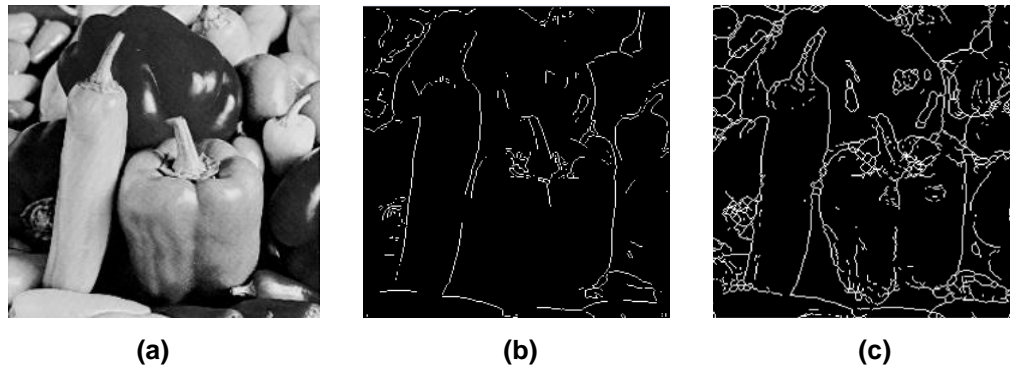


Figure 1. The Original Image and the Segmentation Results

The results of the experiment indicate that when the target and background have similar gray intensity, the basic ant colony algorithm has low continuity (Figure 1(b) below), with severe false and missing detection on the edge.

The improved algorithm proposed in this paper can better detect the image edge (cf. Figure 1(c)). It can effectively compensate the discontinuity of image edges, greatly reduce the running time and improve the execution efficiency of the algorithm.

6. Conclusion

In image segmentation, the basic ant colony algorithm is limited in that it involves a long searching time, a large amount of calculation, and produces rough segmentation results. This paper proposes an improved ant colony algorithm for image segmentation with a higher efficiency and better edge detection effect. Some crucial improvements include: (a) in the initial stage of segmentation, we bring in the idea of fuzzy cluster, enabling the ants to assemble quickly to the edge of the image. (b) In later stage, we introduce an edge search strategy to the edge of the image. A follow-up experiment shows that the improved algorithm is able to segment images in a more efficient manner.

Acknowledgments

This work was supported in part by NSFC under Grant Nos. 61272029.

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