

Applications of Improved Ant Colony Optimization Clustering Algorithm in Image Segmentation

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Abstract

When expressing the data feature extraction of the interesting objectives, image segmentation is to transform the data set of the features of the original image into more tight and general data set. This paper explores the image segmentation technology based on ant colony optimization clustering algorithm and proposes an improved ant colony clustering algorithm (ACCA). It improves and analyzes the computational formula of the similarity function and improves parameter selection and setting by setting ant clustering rules. Through this algorithm, it can not only accelerate the clustering speed, but it can also have a better clustering partitioning result. The experimental result shows that the method of this paper is better than the original OTSU image segmentation method in accuracy, rapidity and stability.

Keywords: ant colony optimization, clustering algorithm, image segmentation

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1. Introduction

The idea of image segmentation is to map the pixel points to the corresponding feature space according to the features of different interesting blocks of area in the image such as gray scale and texture and then classify them according to certain reasonable similarity criterion. It has been mentioned in the previous paragraph that image segmentation is the key step in image processing and image analysis; therefore, the image segmentation effect will directly affect the accuracy of the subsequent image analysis [1].

Previously, Kapur has published the theory of necessary optimal matching degree value in image segmentation by using the optimal entropy. The P-tile method proposed by Doyle is the early method of automatic threshold selection based on gray histogram [2]. The computation of this theory has low requirements on hardware and it can process different kinds of images, however, its shortcomings are also very obvious and it requires humans to measure the necessary ratio of the image blocks to the source image in advance, resulting in a low repeated utilization factor [3]. Dunn has raised an applied theory. This theory extracts all pixel information of the entire image and then performs overall computation. With the computational result, it seeks the variance and then the optimal matching value [4]. Otsu seeks the optimal solution by using the maximum variance ratio of the pixel information of the entire image, which is the famous OTSU method. This theory has played a far-reaching influence on image processing. It is not only used in the image block segmentation with threshold, but also used in many relevant fields. The biggest advantage of this theory is that it optimizes the setting of the threshold correlation coefficient which hasn't been processed perfectly and it is more accurate in seeking this coefficient than the previous grayscale difference hist method. However, most of the histograms obtained from the images are not simple monopolar-value images and OTSU criterion is weak in segmenting these images, making it difficult for segmentation to reach a satisfactory objective [5]. At present, with the in-depth development of the research in this field, it begins to see the threshold segmentation in the image block segmentation as the traversal algorithm solution of certain problems and it starts to apply swarm intelligence algorithm into the processing of such problems.

In order to solve the above-mentioned problems, this paper has introduced ant colony optimization clustering algorithm into image segmentation. It firstly introduces the characteristics

of image segmentation and then proposes an improved ant colony optimization clustering algorithm based on the basic ant colony algorithm, which improves the parameter setting and fitness function of ACCA; accelerates the segmentation process and finds the optimal threshold of the image to be segmented with ACCA as the threshold search strategy. Finally, it compares the performances of ACCA and OTSU in the segmentation result and convergence.

2. Image Segmentation

When expressing the data feature extraction of the interesting objectives, image segmentation is to transform the data set of the features of the original image into more tight and general data set. If the variance generated in the image segmentation is transferred to a higher link of image processing, the image segmentation will have a bigger variance and it will have a bigger influence on the final image processing; therefore, image segmentation effect plays an obvious role in the entire image processing. Basically, image segmentation can be divided into the following four steps:

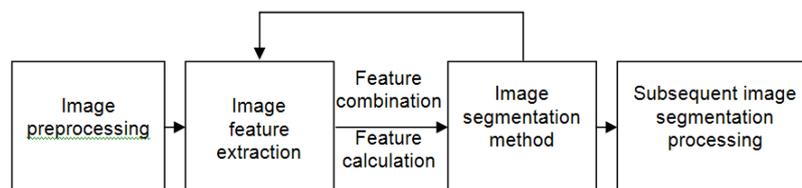


Figure 1. Process chart of image segmentation

What has been used more frequently at present is an image segmentation definition formed from the concept of set in mathematics. Express an entire image with set Q ; segment this image and form N blocks of area, namely divide set Q into N subsets. Every sub-set is non-empty and every subset should meet the following conditions:

- (1) All i and j ($i \neq j$) should meet that $Q_i \cap Q_j = \phi$;
- (2) $\sum_{i=1}^N Q_{(i)} = I$, $Q_{(i)} \cap Q_{(j)} = \phi$, $\forall i, j, i \neq j$;
- (3) When $i \neq j$, $P(Q_i \cup Q_j) = \text{False}$;
- (4) When $i=1, 2, \dots, N$, $P(Q_i) = \text{True}$;
- (5) When $i=1, 2, \dots, N$, Q_i is the connected region.

Here, symbol ϕ is the concept of empty set in mathematical set while $P(Q_i)$ is the logical predicate of the elements in all subsets Q_i and it has specific meaning. Detailed illustration will be made about the five conditions in the following passage [6].

Condition (1) indicates that all the blocks of area after image segmentation can't have the same pixel point; in other words, a pixel point can only belong to a point and a class. In mathematics, it means that the segmented subsets can't have intersection. Condition (2) shows that after the image segmentation, all pixel points shall be allocated to their own corresponding subsets, namely that every pixel point shall have its own class and that there is no unclassified pixel point. Condition (3) demonstrates that after image segmentation is finished, the pixel points in different sub-block of area definitely have different characteristics, that is to say that different sub-blocks of area have no same pixel points. Condition (4) manifests that after image segmentation is completed, every segmented sub-block of area has its own characteristics, which are different from other sub-blocks of area, namely that all the pixel points of the same sub-block of area have certain same or similar characteristics. Condition (5) states that after image segmentation is completed, all pixel points of the same sub-block of area are connected.

By analyzing the above five conditions, it can be known that the foundation of image segmentation is the discontinuity and similarity of the image pixels. Discontinuity means that the

characteristics of the pixels in different sub-blocks of area are different to a certain extent and they form incoherent pixel characteristics in different sub-blocks of area before it forms discontinuity. Similarity refers to that the pixels of the same sub-block of area have certain pixel characteristics with high similarity such as the grayscale value and color feature of the pixel. In practice, the practical applications of both image processing and image analysis are the applications for certain specific occasions. Therefore, most of the image segmentation in practical applications doesn't need to meet all the above conditions; instead, they only need to satisfy one or several conditions according to specific application requirements [7].

OTSU image segmentation method extracts gray histogram of all pixel points in the source image to perform the first-step processing. Its second step is to compare and get the maximum value from the histogram information calculated in the last step and then determine the threshold of the image segmentation according to the maximum variance. This is the method of self-adaptive threshold selection. The segmentation principle of OTSU image segmentation method is to seek 0- and 1-order moments defined on the basis of the gray histogram of the image and its advantage is that it doesn't require any prior information, saving some manpower supervision, therefore, it can be applied in many practical fields and it has become an important theory in image segmentation. At the same time, the shortcomings of OTSU segmentation method are also very obvious. Its optimal solution, namely to seek the maximum matching degree value requires to traverse all information. Besides, after deeply investigating OTSU method and promoting it to two-dimension, its principle is to define the comparison between the data to be extracted in the source image and other impure data as the trace of a matrix. The change of this computational equation is determined by $w_0(s,t)$, $\mu_1(s,t)$ and $\mu_j(s,t)$. Additionally:

$$w_0(s,t) = \sum_{i=0}^s \sum_{j=0}^t p_{ij} \quad (1)$$

$$\mu_1(s,t) = \sum_{i=0}^s \sum_{j=0}^t ip_i \quad (2)$$

$$\mu_j(s,t) = \sum_{i=0}^s \sum_{j=0}^t jp_j \quad (3)$$

Here, perform accumulative summation on $w_0(s,t)$, $\mu_1(s,t)$ and $\mu_j(s,t)$ and their results need to be incorporated in all (s,t) . The complexity of this computation has reached $O(L^4)$ and it can't meet the real-time requirement in practical applications since it is very time-consuming. OTSU image segmentation method reduces its time complexity by adopting special calculation principle, however, this method requires excessive investment and it is not applicable as well [8].

Ant colony optimization has the characteristics of self-organization, parallel and positive feedback and it has strong robustness. In the search process, every ant is independent from each other and they communicate only through pheromone. Therefore, ant colony algorithm can be seen as a distributed multi-agent system and it performs independent solution search in many points of the problem space at the same time. It not only increases the reliability of the algorithm, but is also makes the algorithm have stronger global searching ability. At the beginning of the algorithm, a single artificial ant searches the solution disorderly. After some-time evolution, the artificial ants spontaneously search some solutions close to the optimal solution through the pheromone. This is a process from disorder to order. The optimal matching degree value is the optimal solution [9].

3. Improved Ant Colony Clustering Algorithm

3.1. Principle of Ant Colony System Optimization

Every ant in the ant colony here is an autonomous entity. It continuously interacts with the environment; it has intelligence, dynamics and movability and it can provide technical support for data clustering. In this algorithm, every ant stands for a data object and its next

moving position is determined according to the similarity function and probability transfer function between itself and the ant in the neighborhood space. In the mean while, it dynamically updates its class number according to clustering rule sets. The movement of ant makes it affect itself and its object in the neighborhood. It can form a faster and better cluster after certain iterations through little local neighborhood information. In the following paragraph, the ant routing sketch of Figure 2 vividly indicates the principle of ant colony system optimization [10].

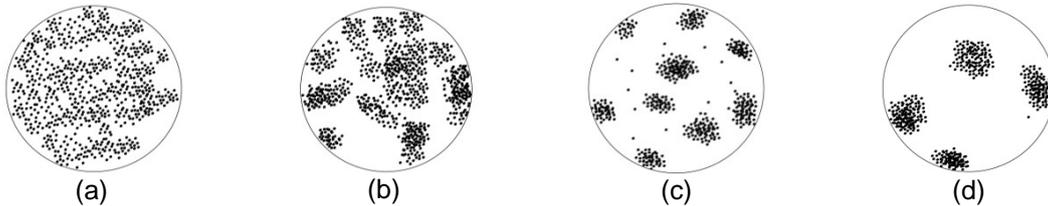


Figure 2. Ant colony clustering sketch

In Figure 2, 5000 objects are randomly distributed in a circular region with the same 200-unit radius and 10 artificial ants cluster these objects. (a), (b), (c) and (d) in Figure 2 show the result of ant clustering in different iterations. The randomly distributed objects are firstly clustered into several small classes within a short time and then gradually clustered into big classes repeating the above process; the pheromone intensity in the path presents a bigger and bigger difference. Finally, all the ants choose the path with high pheromone intensity [11].

3.2. Algorithm Description

3.2.1. Ant Expression

The algorithm simulates the behavior of the agent ant to “search proper swarm” in the movements. Its basic idea is to randomly project the objects to be clustered in a two-dimensional grid and every subject has a randomly initial position. Every ant can move in the grids. Measure the swarm similarity of the current object in the local environment. Transfer the swarm similarity to the probability of the moving object through probability transfer function and pick up or put down the subjects at this probability. The joint action of multi-agent ant makes the objects of the same class in the same spatial domain cluster together [12].

An ant agent refers to a data object; in this way, it can reduce the computation time and the storage space. Its behaviors are simple: when it doesn't find a proper colony, it keeps on searching; when it has found the relatively proper colony, it stops moving. It repeats this process until all the agent ants have found the proper positions. We use the following quintuple to describe the state of every ant:

$$(x_i, y_i, c_i, s_i, v_i), 1 \leq i \leq n$$

Here, n is the number of data, x_i and y_i are the coordinates of where the i th ant is located, c_i is the class number of the ant, s_i reflects whether the ant is in the movement state or the stability state and v_i is the speed of the ant in its movement [13].

3.2.2. Calculation of Similarity

Assuming there is an ant a_i in the place r at the moment t , define the average similarity of a_i and its neighbour object a_j as:

$$f(a_i) = \frac{1}{\sigma} \sum_{a_j \in N(a_i)} \left[1 - \frac{d(a_i, a_j)}{a(1 + (v_i - 1) / v_{\max})} \right] \quad (4)$$

In this formula, $N(a_i)$ is the neighbourhood of a_i . In the grid, every agent ant will have 8 blanks in its neighborhood if this ant is located anywhere but the boundary; if the ant is in the

boundary of the grid, there are only 3 grids in its neighbourhood [14]. v_{\max} is the maximum speed and v_i is the movement speed. Take a decreasing random number here to make the ant move fast at the beginning in order to form a cluster fast and roughly. Then the speed reduces randomly to refine the clustering result.

$d(a_i, a_j)$ is the distance between ant a_i and a_j , which can be calculated in the preprocessing phase of the clustering and its definition is as follows:

$$d(a_i, a_j) = \sqrt{\sum_{k=1}^m (a_{ik} - a_{jk})^2} \quad (5)$$

In the formula, m is the number of properties, α is the coefficient to adjust the similarity between the data objects and it determines the clustering number and convergence speed, making the value of α gradually decrease in the clustering process.

The change of parameter σ directly affects the value range of the similarity function and the value of σ is the number of ants in the neighbourhood [15].

3.2.3. Calculation of Movement Probability

Probability transfer function is the function of $f(a_i)$ and it transfers the average similarity of the data objects as the movement probability P_m of the agent ants. If $f(a_i)$ is very small; then P_m is very high; otherwise, P_m is very low. We select Sigmoid function as the probability transfer function because Sigmoid function has non-linearity. Only one parameter is needed to be adjusted in the movement and it has faster convergence speed.

Define the movement probability P_m of a_i which hasn't found proper colony in the random movement as:

$$P_m = 1 - \text{Sigmoid}(f(a_i)) \quad (6)$$

In this formula, $\text{Sigmoid}(x) = \frac{1 - e^{-cx}}{1 + e^{-cx}}$ is the natural exponential form. If the parameter c is big, the curve saturates fast and the convergence speed is also fast [16].

3.2.4. Description of Clustering Rules

Clustering Rule: the class information c_i of a_i is updated according to the following rules:

- (a) If a_i finds a proper classification and stops moving, its class number will be changed by the class number of the agent ant with the minimum similarity in its neighborhood;
- (b) If a_i changes from halt state to movement state, its class number will also be changed by its mark number during its movement;
- (c) If a_i keeps its movement state unchanged, its class number will also remain the same.

The clustering rules are very simple and the agent ants can update their state with local information and form clustering dynamically. The clustering result will be given directly by the class number of the agent ant [17].

3.2.5. Description of the Algorithm Process

Through the above analysis, the process of multi-agent ant clustering algorithm is described as Figure 3.

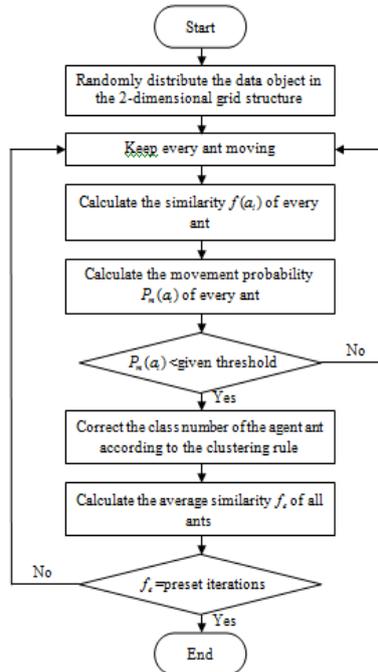


Figure 3. The process of ant clustering algorithm

4. Analysis of Experimental Results

This paper compares the segmentation efficiency by using OTSU and ACCA segmentation methods on the standard test image Coins. In this experiment, the hardware memory is 2.5G and the run-time environment is Matlab2012. The comparison result of the matching value and the processing time by these two segmentation methods is indicated in Table 1. The segmented experimental results are shown in Figure 4. Figure 4(a) is the original image; Figure 4(b) is the image segmented by OTSU segmentation method and Figure 4(c) is the image segmented by ACCA segmentation method. We can get the standard of the practical applications from these obvious comparisons.

Table 1. Comparison of Matching Degree Value and Processing Time after Calculation

Experiment No.	OTSU image segmentation method		ACCA image segmentation method	
	Image threshold	Time (ms)	Image threshold	Time (ms)
1	103	24.97	121	18.37
2	103	25.05	128	17.93
3	103	24.38	136	17.34
4	103	24.72	133	17.61
5	103	25.02	123	18.02

It can be seen from Table 1 that ACCA meets the practical application requirements and it greatly reduces the processing time and the computational time of the threshold.

From the analysis of the comparison of the above figures, it can be seen that ACCA can search the optimal threshold fast and quickly. The method of this paper has certain effectiveness in segmentation effect, segmentation speed and convergence and it has better segmentation effects and clear texture compared with OTSU image segmentation method.

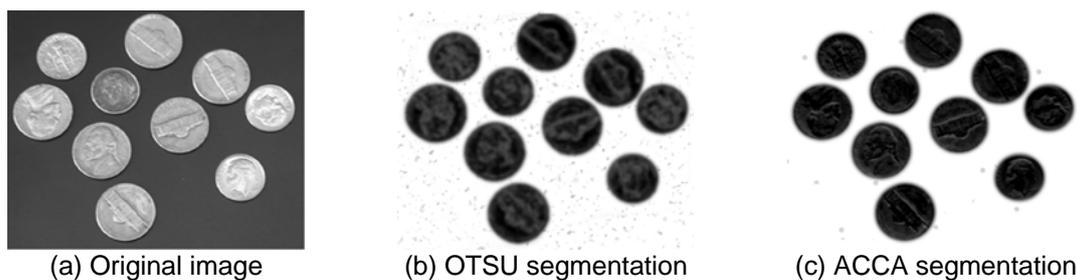


Figure 4. Comparison of image segmentation effects by different methods

5. Conclusion

This paper has realized ant colony optimization clustering algorithm in image segmentation, simulated the behavior of “searching the appropriate swarm” in the movement; dynamically updates its class-mark according to certain clustering rules and guides the ant individuals to find the optimal segmentation threshold quickly. By comparing the performances of the standard image test and the traditional image segmentation methods, the experimental result has demonstrated that for the same image to be segmented, the colony intelligence optimization clustering algorithm has a fast optimization speed and high optimization quality.

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References

- [1] Naosheng Qiao, Ping Sun. Study of Improved Otsu Algorithm and Its Ration Evaluation Analysis for PCB Photoelectric Image Segmentation. *Optik-International Journal for Light and Electron Optics*. 2014; 125(17): 4784-4787.
- [2] Xinsong Wang, Guofeng Qin. Pavement Image Segmentation Based on FCM Algorithm Using Neighborhood Information. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(7): 1610-1614.
- [3] Dirk Holz, Sven Behnke. Approximate Triangulation and Region Growing for Efficient Segmentation and Smoothing of Range Images. *Robotics and Autonomous Systems*. 2014; 62(9): 1282-1293.
- [4] Shibai Yin, et al. Efficient Multilevel Image Segmentation through Fuzzy Entropy Maximization and Graph Cut Optimization. *Pattern Recognition*. 2014; 47(9): 2894-2907.
- [5] Sebastian T Gollmer, et al. Using image Segmentation for Evaluating 3D Statistical Shape Models Built with Groupwise Correspondence Optimization. *Computer Vision and Image Understanding*. 2014; 125: 283-303.
- [6] Sijie Niu, et al. Automated Retinal Layers Segmentation in SD-OCT Images Using Dual-Gradient and Spatial Correlation Smoothness Constraint. *Computers in Biology and Medicine*. 2014; 54(1): 116-128.
- [7] Sung Ha Kang, Riccardo March. Multiphase Image Segmentation via Equally Distanced Multiple Well Potential. *Journal of Visual Communication and Image Representation*. 2014; 25(6): 1446-1459.
- [8] Ozge Oztimur Karadag, Fatos T Yarman Vural. Image Segmentation by Fusion of Low Level and Domain Specific Information via Markov Random Fields. *Pattern Recognition Letters*. 2014; 46(1): 75-82.
- [9] Nan Geng, Dongjian He, Yanshuang Song. Camera Image Mosaicing Based on an Optimized SURF Algorithm. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(8): 2183-2193.
- [10] Sina Tabakhi, Parham Moradi, Fardin Akhlaghian. An Unsupervised Feature Selection Algorithm Based on Ant Colony Optimization. *Engineering Applications of Artificial Intelligence*. 2014; 32: 12-123.
- [11] Aritra Chowdhury, Swagatam Das. Automatic Shape Independent Clustering Inspired by Ant Dynamics. *Swarm and Evolutionary Computatio*. 2012; 3: 33-45.
- [12] Salabat Khan, Abdul Rauf Baig, Waseem Shahzad. A Novel Ant Colony Optimization Based Single Path Hierarchical Classification Algorithm for Predicting Gene Ontology. *Applied Soft Computing*. 2014; 16: 34-49.

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- [13] Aboul Ella Hassanien, et al. MRI Breast Cancer Diagnosis Hybrid Approach Using Adaptive Ant-Based Segmentation and Multilayer Perceptron Neural Networks Classifier. *Applied Soft Computing*. 2014; 14(A): 62-71.
- [14] Arash Ghanbari, et al. A Cooperative Ant Colony Optimization-Genetic Algorithm Approach for Construction of Energy Demand Forecasting Knowledge-Based Expert Systems. *Knowledge-Based Systems*. 2013; 39: 194-206.
- [15] Md Monirul Kabir, Md Shahjahan, Kazuyuki Murase. A New Hybrid Ant Colony Optimization Algorithm for Feature Selection. *Expert Systems with Applications*. 2012; 39(3): 3747-3763.
- [16] Amioy Kumar, Madasu Hanmandlu, HM Gupta. Ant Colony Optimization Based Fuzzy Binary Decision Tree for Bimodal Hand Knuckle Verification System. *Expert Systems with Applications*. 2013; 40(2): 439-449.
- [17] RJ Kuo, et al. Automatic Kernel Clustering with Bee Colony Optimization Algorithm. *Information Sciences*. 2014; 283(1): 107-122.
- [18] Pablo Loyola, et al. Predicting Web User Behavior using Learning-Based Ant Colony Optimization. *Engineering Applications of Artificial Intelligence*. 2012; 25(5): 889-897.