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IMAGE SEGMENTATION USING ANT COLONY OPTIMIZATION

Abstract

This article provides a detailed segmentation algorithm which uses an ant colony optimization algorithm (ACO) in conjunction with the clustering algorithm of k-means. Results of the images processing with different parameters (the number of ants, the number of clusters and numerical coefficients of the algorithm parameters) are presented. In the conclusion the quality of the proposed algorithm is discussed.

General formulation of the problem

The success of image analysis depends heavily on the accuracy of segmentation algorithms. Algorithms for image segmentation divide the image into private areas, the number of regions depends on the solving problem [1]. Robust automatic segmentation requires the integration and intelligent use of data of the subject area. However, the variability of the background, a variety of properties of different parts of the image and the presence of noise in the images makes it difficult to solve this problem. We often use a variety of methods in the segmentation process, taking into account the subject area. Widely used in image segmentation methods of sprawling areas. In general, these methods have several advantages over gradient methods, including greater reliability. Location of the initial region strongly influences on result of segmentation. Uncontrolled fuzzy clustering, especially k-means algorithm is widely used in image segmentation. Based on the minimal squared error, k-means algorithm can perform classification, without the necessary density estimation of the pixels in the image. But when used in image segmentation, k-means algorithm has a major limitation: it does not exclude any superfluous information. As a result, it is sensitive to noise and interference on the image. In this article, we explore a new approach to image segmentation based on ant colonies [2].

Description of the ACO algorithm for image segmentation

To obtain an efficient algorithm for image segmentation we developed a method in which all the advantages of k-means and ACO algorithms are used.

On the first step we need to set the amount of clusters and randomly initialize their centers. Now, according to a clustering algorithm k-means, we need to determine the memberships of each cluster. At this stage, the most important role plays ACO algorithm. It determines the relationship between each pixel and cluster on the image. This is done according to the probability, which is inversely proportional to the distance between the pixel and the variable cluster center τ, which represents the level of the pheromone. Pheromone level is determined in proportion to the minimum distance between each pair of cluster centers and inversely proportional to the distance between each pixel and its center. Thus, the importance level of pheromone increases with the distance between the centers of clusters and compactness of the pixels in the cluster. Under these conditions increases probability of involving the pixel to the cluster.

The evaporation of the pheromone is calculated in order to reduce the impact of previously selected solutions that are less of a priority. Similarly to k-means algorithm, in a distributed state, cluster centers updating occurs by recalculating the average value of pixels in each cluster. This continues as long as the cluster center value change does not significantly change. In contrast to the k-means algorithm, developed method does not stop at this stage. The process continues to perform clustering of m ants, each of which ultimately finds a solution. Criterion for finding the best solutions and the updated pheromone level, respectively are prior for the next group of m ants. When the stopping criterion is reached the clustering is completed and the best solution is found [3].

Software implementation of the algorithm starts with determining the level of pheromone τ and setting of heuristic information η for each pixel. Then, each ant determines belonging pixel to the cluster with probability P, which is calculated from the expression (1) :

$$P_i(X_n) = \frac{[\tau_i(X_n)]^{\alpha}[\eta_i(X_n)]^{\beta}}{\sum_{j=0}^{K}[\tau_j(X_n)]^{\alpha}[\eta_j(X_n)]^{\beta}}, \quad (1)$$

where:

- $P_i(X_n)$ - probability of belonging pixel (X_n) to the cluster *i;*
- $\tau_i(X_n)$ and $\eta_i(X_n)$ - information about pheromone and heuristic variable of belonging pixel (X_n) to the cluster *i* respectively;
- α и β - constant parameters, that determine the influence of pheromone and heuristic information
- *K* – amount of clusters.

Heuristic information $\eta_i(X_n)$ could be obtained according to expression (2):

$$\eta_i(X_n) = \frac{k}{CDist(X_n, CC_i) * PDist(X_n, PC_i)}, \quad (2)$$

где:

- X_n – pixel number *n;*
- CC_i – i-th spectral cluster center;
- PC_i – i-th spatial cluster center;
- $CDist(X_n, CC_i)$ – distance between (X_n, CC_i) according to the color characteristics of pixels
- $PDist(X_n, PC_i)$ – Euclidean distance between (X_n, PC_i), according to the pixel location;
- k – constant, which is used for balancing values of η and τ.

Amount of the pheromone level at the initial stage is set equal to 1, so the first iteration does not affect the probability of the transition.

Suppose, that m is the number of ants selected for image clustering. Each ant finds its own individual solution. Once m ants have segmented image, the best solution for current iteration is obtained. Then pheromone level is updated and all centers of the clusters are recalculated according to the obtained best solution. Next iteration is initialized by the previous ants experience. At each iteration, each of m ants has his own individual decision, which is adjusted by his own heuristic knowledge and the best general solution, found by other ants. It is repeated until a solution, that satisfies all the given conditions, would be found.

The general solution of the m individual solutions chosen according to 2 parameters:

1. Analysis of the Euclidean distance between the cluster centers based on the color characteristics. It characterizes the partition in terms of clusters isolation.

2. Analysis of the sum of the Euclidean distance between the center of the cluster and each pixel according to its color and spatial characteristics. This is a characteristic of the partition according to the criterion of clusters similarity and density.

In order to choose the best solution of all the local need to satisfy the following conditions:

1. Euclidean distance between clusters, in terms of color characteristics must be large, respectively clusters will be different from each other.

2. The sum of the Euclidean distances between the center of the cluster and its each pixel, according to color characteristics, should be small, respectively, the cluster will be more uniform.

3. The sum of the Euclidean distances between the center of the cluster and its each pixel, according to spatial characteristics, should be small, respectively clusters will be more compact.

In order to meet the first condition, we calculate for each ant the distance between each pair of cluster centers and sort the values in ascending order. Then we select the minimum among all ants, and compare it by choosing the maximum [MinMax (k)].

For the implementation of paragraphs 2 and 3, we need following:

1. Calculate the sum of the distances between the cluster centers and their pixels.

2. Sort the values in ascending order.

3. Select the maximum and minimum for each ant.

Each time selected value gets additional priority and highest priority is the best. Once best solution found, the pheromone value is updated according to (3)

$$\tau_i(X_n) \leftarrow (1-\rho)\tau_i(X_n) + \sum_i \Delta\tau_i(X_n). \quad (3)$$

where ρ – evaporation rate $(0 \le \rho \le 1)$, which acts on the previously established level of pheromone. Due to this factor, increases the influence of the later priority decisions and decreases of the earlier. Parameter $\Delta\tau_i(X_n)$ in expression(3) – difference in level of pheromone, which is added to the previous successful ant. It is calculated according to the expression:

$$\Delta\tau_i(X_n) = \begin{cases} \dfrac{Q * Min(k')}{AvgCDist(k',i) * AvgPDist(k',i)}, & \text{if } X_n \subset \text{cluster } i \\ 0, & \text{in other case} \end{cases} \quad (4)$$

Where Q –positive constant, which is connected with the pheromone level, $Min(k')$ - minimum of the color distances between each cluster center, found by ant *k'* (most successful ant). *AvgCDist*(*k'*,*i*) – average color distance and *AvgPDist*(*k'*,*i*) – average spatial Euclidean distance between each pixel and the centers (color and spatial) for most succesful ant.

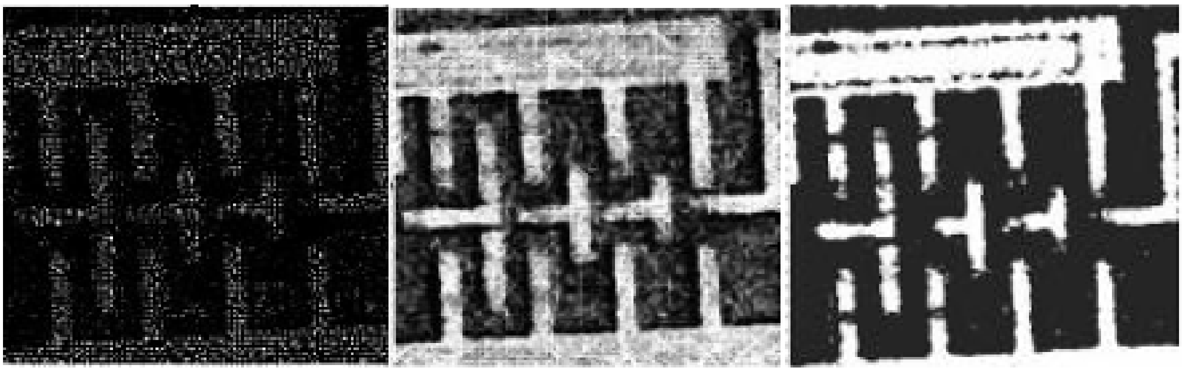
Min(*k'*) – reason for the increase of pheromone in larger cluster's remoteness. *AvgCDist*(*k'*,*i*) and *AvgPDist*(*k'*,*i*) – reasons for the increased levels of pheromone in greater uniformity and compactness of the cluster.

Mixed ant colony algorithm and k-means is presented step by step:

1. Initialize the basic parameters of the algorithm: the value of the pheromone level at the first stage is set equal to 1, the number of clusters is set to K and the number of ants is set to m.
2. Initialize m ants randomly selected for the K cluster centers.
3. Let each ant associates each pixel X_n with one of the clusters *i* randomly with probability $P_i(X_n)$ from expression (1).
4. Compute the new cluster centers. If the new centers coincide with the previous, then go to the next step, if not, go to step 3.
5. Save the best solution of all found by m ants.
6. Update the pheromone level for each pixel according to the 3 and 4
7. Adjust the overall best solution found from individual solutions of each ant.
8. If the stopping criterion is reached, then go to the next step, otherwise – go to step 3.
9. Found the best solution.

Results

Described algorithm has been tested on practice. The results showed, that the minimum number of ants to produce positive results should be at least 10. In this case more iterations are done, than when the number of ants is lower. Parameters α, β, k are chosen heuristically for each ant, proper selection of these parameters is also making a significant contribution to the quality of the result (fig. 1).



(a) – t = 10 (b) – t = 50 (c) – t = 100

Figure 1 – Image segmentation results m=20,K=2, amount of iterations is set to t

As seen from the results, the quality of the result depends on the number of iterations. In case of algorithm working with prescribed accuracy for presented image, it finishes working, when the number of iterations is equal to 100.

Conclusions

In this article has been described an approach for digital image segmentation using ant colonies. We used the distributed algorithm based on ants populations. Each ant builds own decision, using pheromone information deposited by other ants of the population. The feature of this algorithm is its robustness to noise. Algorithm is efficient and to determine the optimal values of the constants, it is necessary to continue further research.

References

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