

Multi-threshold Image Segmentation based on K-means and Firefly Algorithm

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Abstract. This paper presents multi-threshold image segmentation method based on K-means and firefly algorithm. This method use the firefly algorithm to obtain threshold as K-means initial clustering center. It could effectively overcome the problem that K-means algorithm is sensitive to the initial center. Compared with the K-means algorithm, the experiment results show that the proposed approach has faster run time and higher efficiency. Moreover, the proposed method also had better segmentation result and get a better peak signal-to-noise ratio (PSNR) than the traditional FFCM and PSO-FFCM.

Keywords: Firefly algorithm; K-Means; multi-threshold; image segmentation

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1 Introduction

Image segmentation is the preliminary task of image understanding and analysis. Due to different gray, texture, and color, shape, image is divided into different region with consistent characteristics. At present, there are lots of literatures on image segmentation. There are four major methods of image segmentation, such as threshold segmentation [1], edge detection [2], region extraction [3] and clustering method [4].

Threshold is the most common method in image segmentation. It is especially suitable for the image whose object and background occupy different gray-scale. Due to the need to search for the optimal threshold at the gray-scale range of the image, the complexity and time-consuming of the traditional search algorithm is difficult to meet image understanding and analysis. Many researchers use swarm intelligence algorithm for searching for threshold. Currently, more kinds of bionics algorithm such as particle swarm algorithm (PSO) [5], shuffled frog leaping algorithm (SFL) [6] and artificial bee colony algorithm (ABC) [7] is successfully applied to the multi-threshold image segmentation. This paper attempts to explore more bionic optimization algorithm in the multi-threshold image segmentation. [10]

K-means algorithm is one of the most popular used clustering methods. But the difficult problem is the need to determine the number of clusters and the initial value. The wrong initial value often makes the algorithm into a local optimum. This paper will combine the firefly algorithm. Firstly, initialize the fireflies groups n and take entropy as the objective function. Secondly, search the firefly n' whose value of the objective function is minimum as threshold, and take it as the initial value of K-means. The fewer parameters and the robustness of firefly algorithm could avoid local extremum, and overcome the problem which is sensitive to initial value effectively to achieve a higher quality of image segmentation.

This paper takes entropy as the objective function of the firefly algorithm. The maximum entropy method is one of the better approaches of image threshold segmentation. It can produce good segmentation results for the image with different target size and signal-to-noise ratio.

2 Firefly Algorithm

Inspired by social behavior of fireflies, firefly algorithm (FA) is developed as a novel bionic swarm intelligence optimization [8]. Most of fireflies produced short and rhythmic flashes. Fireflies use these flashes for communication and attracting the potential prey.

(1) Firefly algorithm has two parameters: brightness and attractiveness . Firefly groups moved toward the firefly with high brightness. The brightness is given as follow:

$$I = I_0 \times e^{-\gamma r_{ij}} \quad (2.1)$$

(I_0 is the maximum brightness of the firefly. γ is the absorption coefficient for the light intensity. r_{ij} is the distance between the firefly i and j.)

(2) The attractiveness β represents the moving distance of the firefly. Firefly has its unique attractiveness β . It means that it is attractive for other individuals in the group. β is given as follow:

$$\beta = \beta_0 e^{-\gamma r_{ij}^2} \quad (2.2)$$

(Wherein β_0 is the maximum attractive. γ is the absorption coefficient.)

β_0 is described as the attractiveness in $\gamma_j = 0$. It means that β_0 is the attractiveness when two fireflies is in the same point. Usually, the value range of β_0 is [0,1]. Firefly is distributed randomly when $\beta_0 = 0$; When $\beta_0 = 1$, the firefly make a cooperative search with other fireflies which have more intense luster, in particular in its position near the firefly.

$\gamma = 0$ means the attractive does not change. $\gamma \rightarrow \infty$ means that the attractiveness approaches zero. In a general way, γ is set to $\gamma \in [0,10]$.

(3) Firefly location update is decided by the formula(3)

$$x_i = x_i + \beta \times (x_j - x_i) + \alpha \times (rand - 0.5) \quad (2.3)$$

In the formula(2.3), α is the step factor and rand is the random factor uniformly distributed on [0,1].

The optimization process of firefly algorithm is given as follow: The first firefly groups are randomly distributed in the solution space. Firefly with higher brightness can attract a lower brightness one (according to formula (2.1)). Their moving distance depends on the attraction β (according to the formula (2.2)). In

order to increase the search area and to avoid premature into local optimum, the disturbance term $(\alpha \times (\text{rand} - 0.5))$ increase in the location update procedure. And then calculate the updated position according to formula (3). After several moving, all individuals will gather to the position of the firefly with the highest brightness to achieve optimization [9].

3 K-means Clustering

K-means algorithm is widely used in image segmentation because of its effectiveness and simplicity. The basic idea is given as follow:

- (1) Initialize K cluster centers c_1, c_2, \dots, c_k randomly,
- (2) Repeat
 - a. For each data point, allocate the point to the cluster with the less Euclidean distance to centroid vector, where the distance is determined as followed

$$\text{Dis}(X_p Z_j) = \sqrt{\sum_{i=1}^d (X_{pi} - Z_{ji})^2} \quad (3.1)$$

where, X_p denotes the pth data vector, Z_j denotes the centroid vector of cluster j, and d subscripts the number of features of each centroid vector.

- b. Refine the cluster centroid vectors, using

$$Z_j = \frac{1}{n_j} \left[\sum_{\forall X_p \in C_j} X_p \right] \quad (3.2)$$

where, n_j is the number of data vectors in cluster j and C_j is the subset of data vectors that form cluster j. The K-means algorithm will be terminates when any one of the following criteria is satisfied: when the maximum number of iterations has been exceeded, when there is little change in the centroid vectors, or when there are no cluster membership changes.

4 Proposed Approach

The initial value of K-Means is more sensitive and the selected threshold greatly impact on image segmentation. Meanwhile the firefly algorithm is a global search method because of its robustness and its advantage that is easy to escape from local optima. The main steps are as follows:

- (1) Initial parameters: Set the number of fireflies $n = 60$, the search space $S(r \times c)$, the maximum degree of attraction $\beta_0 = 0.2$, the attract coefficient of the light intensity to $\gamma = 1$ and the compensation factor $\alpha = 0.5$ and the objective function is

$$f(x) = 1/\sum_{i=0}^k S_i \quad (4.1)$$

Wherein $S_i = \sum_{j \in [C_i]} \left[-\frac{p_{ij}}{p_i} \times \ln \left(\frac{p_{ij}}{p_i} \right) \right]$, p_{ij} means the probability of occurrence of the pixel values of j in class C_i , and p_i is the probability of occurrence of all the pixel values in class C_i . S_i is the entropy of the class C_i . Calculate the value of the target function according to the formula (4.1). $\sum_{i=0}^k S_i$ is the entropy of the class i after threshold image segmentation. When the maximum entropy satisfies, the value of the target function $f(x)$ reaches the minimum. The fireflies move towards the optimal position with minimum value.

- (2) Calculate the firefly attractiveness according to the formula (2.2), and then update the location of the fireflies according to formula (2.3), and recalculate the objective function value of the fireflies.
- (3) When the search accuracy (the update location of the firefly ≤ 0 or ≥ 255) satisfied or reached the maximum number of iterations ($N_{\max} = 200$), the firefly which make the objective function reach the minimum in the last calculation is the best individual value. Otherwise go to (1) and continue to be calculated.
- (4) Take the threshold value determined by the firefly algorithm as the initial value of K-Means algorithm and begin to cluster.
- (5) Continue to iterate in accordance with the basic steps of the K-Means algorithm. When the new cluster centers meet the desired range, the iteration finish. Give the average gray to each area to achieve image segmentation.

5 Experiment Results

In experiment, we used test image such as Lena, Cameraman. Software is Matlab 2010, 2.0GHz CPU, and 2.0GHz Memory computer. We compared to other optimization algorithms, such as K-means, traditional fast FCM algorithm (T-FFCM) and FCM algorithm based on particle swarm optimization (PSO-FFCM) according to the running time and PSNR.

Table 1 the comparisons of K-means and the proposed method

| Lena | | k | Cluster center | Iterations | time /s |
|---------------------------------------|-----------------|----------|---------------------------|-------------------|----------------|
| (256 × 256) | K-means | 3 | 68,134,187 | 12 | 0.2909 |
| | Proposed method | 3 | 64,130,184 | 8 | 0.2761 |
| | K-means | 4 | 54,102,145,192 | 15 | 0.3900 |
| | proposed method | 4 | 56,105,147,193 | 10 | 0.3574 |
| | K-means | 7 | 52,94,123,146,165,188,209 | 30 | 1.6759 |
| | proposed method | 7 | 48,74,101,127,151,175,205 | 12 | 0.7313 |
| Cameraman (256 × 256) | K-means | 3 | 20,120,168 | 13 | 0.3280 |
| | proposed method | 3 | 20,120,168 | 8 | 0.2142 |
| | K-means | 4 | 19,113,155,180 | 16 | 0.3765 |
| | proposed method | 4 | 19,110,151,178 | 7 | 0.2338 |
| | K-means | 7 | 14,58,109,138,162,180,223 | 30 | 1.5063 |
| | proposed method | 7 | 14,56,104,130,154,171,193 | 15 | 0.8307 |

Table 2 the PSNR of different approaches

| PSNR | k | K-means | T - FFCM | PSO-F FCM | proposed method |
|--------------------------|---|---------|----------|--------------|-----------------|
| Lena (256 × 256) | 3 | 22.8320 | 22.8987 | 22.8987 | 22.9265 |
| | 4 | 25.9344 | 25.9122 | 25.9347 | 25.9429 |
| | 7 | 30.7808 | 30.8189 | 30.8377 | 30.8189 |
| Cameraman (256 × 256) | 3 | 24.3969 | 24.3922 | 24.3922 | 24.3969 |
| | 4 | 25.9677 | 25.9853 | 25.9853 | 26.0458 |
| | 7 | 30.6820 | 30.3592 | 30.3592 | 30.7522 |

Here, peak signal to noise ratio (PSNR) is used to evaluate the segmentation results. PSNR is defined as

$$\text{PSNR} = 10\log_{10} \left(\frac{255}{\text{RMSE}} \right)^2 \quad (5.1)$$

Where RMSE is the root mean-squared error, defined as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^M \sum_{j=1}^N [I(i,j) - \hat{I}(i,j)]^2}{MN}} \quad (5.2)$$

Here I and \hat{I} are original and segmented images of size $M \times N$, respectively.

From table 1 and 2, it's obvious that the proposed method reduces the running time and the number of iterations compared with the K-means algorithm. It improves the efficiency of the K-means algorithm. As can be seen from the table 2, the PSNR obtained by the proposed method is relatively large compared to the K-means, T-FFCM and PSO-FFCM, especially in the "cameraman" image. The larger value of PSNR, the better quality of the segmentation results.



Fig. 1 original image

Fig. 2 the segmentation results using T-FFCM



Fig. 3 the segmentation result using PSO-FFCM **Fig. 4** the segmentation results using K-means

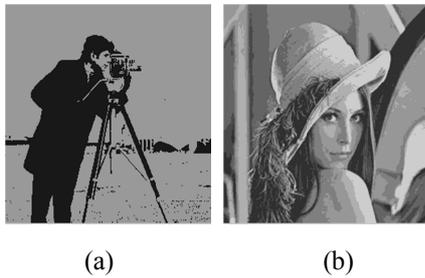


Fig. 5 the segmentation results using the proposed method

6 Conclusion

This paper presents multi-threshold image segmentation approach based on K-means and the firefly algorithm. Experimental result show that proposed approach could effectively overcome the problem which the K-Means algorithm is sensitive to initial value. And the running time of approach method is faster and it can have good segmentation results. It's obvious that the combination of firefly algorithm with K-means could be effectively applied to image segmentation.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (Grant No. 60972133), Provincial Key Laboratory for Computer Information Processing Technology, Soochow University, (Grant No. KJS0922. the fund for Higher-level Talent in Guangdong Province (No. X2DX-N9101070).

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