Multi-threshold Image Segmentation by Improved Lion Swarm Optimization Algorithm

Xiaogang Li and Mingyan Jiang
School of Information Science and Engineering, Shandong University, Qingdao, 266237, China
Email: jiangmingyan@sdu.edu.cn

Abstract. In this paper we propose an improved Lion Swarm Optimization (ILSO) algorithm for multi-threshold image segmentation. We introduce the global search method of Artificial Bee Colony optimization (ABC) algorithm and revise the updating function of LSO algorithm to improve the global and local search performance of LSO algorithm. We introduce a sign to record the number of times an individual falls into the local optimum, and attenuate it so that the algorithm can jump out of the local optimum more quickly in the early stage and accelerate the convergence speed in the later stage. The maximum inter-class variance criterion is selected as the fitness function to solve the Multi-threshold image segmentation problem by ILSO. Experiment results show this algorithm can obtain ideal image segmentation result. And when the dimension of the problem is higher, the advantage of the improved Lion Swarm Optimization algorithm proposed in this paper is more obvious.

1. Introduction
Image segmentation is an important technology of computer vision. At present, there are several different methods of image segmentation such as threshold-based approaches [1], edge detections-based [2] approaches, clustering-based [3-4] approaches, region-based [5-6] approaches, and other methods [7]. Maximum inter-class variance [8] and maximum entropy [9] are two the most common methods of threshold-based approaches with the advantages of simple theory, stable performance and easy imply. However these two methods can not segment complex images very well, and their computational complexity is large.

In response to the above problems, some researchers have applied the optimization algorithm to threshold-based image segmentation. Wei [10] use PSO for image segmentation to reduce calculation time. Horng [11] use the maximum entropy as fitness function proposed a threshold-based image segmentation optimized with ABC, and obtain well result.

In order to adapt to more social needs, multi-threshold image segmentation is more and more worth studying. We propose an improved LSO algorithm for multi-threshold image segmentation in this paper. We combine the global search method of ABC [12] algorithm and revise the updating function of LSO algorithm to improve the global and local search performance of LSO [13] algorithm. The maximum inter-class variance criterion is selected as fitness function. PSO [14], ABC and LSO algorithm will be compared with the ILSO algorithm proposed in this paper on multi-threshold image segmentation.
2. The Basic Theory of Lion Swarm Optimization

The LSO algorithm divides the lion group into three classes: king, lioness and cub according to the real living conditions of lions in nature. Due to the different classes among the lion group, the king, lioness and cub simulate the three behaviors of king guarding, lioness hunting and cub following.

Assume the number of lions is \( N \), the dimensions of fitness function solution is \( D \). The quantity of adult lions is \( n_{\text{Leader}} \beta \leq \frac{N}{2} \). Each member in the lion group is defined as follows

\[
X = (x_1, x_2, ..., x_D)
\]

where \( x_i = (x_{i1}, x_{i2}, ..., x_{ID}) \) \( 1 \leq i \leq N \).

The king occupies the optimal position of the group, maintains the superiority of his own position and looks for a better position in the moving process, the position updating function of the king is

\[
x_{k_i}^{k+1} = g_k^k (1 + \gamma) \bigg[ g_k^k - p_i^k \bigg]
\]

where \( g_k^k \) represents the optimal position of the group, \( p_i^k \) represents the history optimal position of the \( i^{th} \) member in \( k^{th} \) generation, \( \gamma \) is a random number generated by normal distribution \( N(0,1) \).

There is only one king among the lions, the quantity of all lionesses is \( n_{\text{Leader}} - 1 \). The lioness cooperate with each other in hunting, conducting local searches, the position updating function of the lioness is

\[
x_{c_i}^{k+1} = \frac{p_i^k + p_j^k}{2} (1 + \alpha_f) \quad \alpha_f = \text{step} \times e^{-\left(\frac{3t}{T}\right)^{\alpha}}
\]

where \( p_i^k \) is the history optimal position of a lioness other than itself, \( \alpha_f \) is perturbation factor, \( \text{step} \) is step length, \( \text{High} \) and \( \text{Low} \) respectively represent the mean of the minimums and maximums of each dimension in the feasible region, \( T \) is the Maximum number of iterations, \( t \) is Current number of iterations.

There are three main behaviors of cub. When hungry, they approach the king, learn to hunt with the lioness, and when they grow up, they keep away from the group. The position updating function of the cub is

\[
x_{c_j}^{k+1} = \begin{cases} 
\frac{g_k^k + p_i^k}{2} (1 + \alpha_c) & q < \frac{1}{3} \\
\frac{p_i^k + p_j^k}{2} \big(1 + \alpha_c\big) & \frac{1}{3} \leq q < \frac{2}{3} \\
\frac{g_k^k + p_i^k}{2} \big(1 + \alpha_c\big) & q \geq \frac{2}{3}
\end{cases}
\]

where \( p_i^k \) is the history optimal position of lioness, \( \alpha_c \) is perturbation factor, \( g_k^k = \text{High} + \text{Low} - g_k^k \) is the position where cub stay away from the king. \( q \) is a random number generated by Uniform distribution \( U(0,1) \).

3. The Improved Lion Swarm Optimization

We combine the ABC algorithm with LSO algorithm to improve the global search performance. When a member of group fall into local optimal position for limited times, let the lion execute random search. As the same time, revise the position updating function of LSO algorithm to improve the local
search performance, and strengthen the connection between different kinds of the lion group to use the position information efficiently.

Assume the quantity of the lion group is \( N \), the dimensions of fitness function solution is \( D \). The number of adult lions is equation (1), we increase the proportion factor of adult lions \( \beta \) to let more lion for local search.

The king’s position updating function is still equation (3), set the king search better position around the group optimal position.

In order to strengthen the connection of the lion group, set the lioness cooperate with adult lions. Add the communication of group history optimal position and lioness history optimal position with lioness for effective utilization of high quality information to improve the convergence speed of the algorithm as well. The position updating function of lioness is

\[
x_{i}^{k+1} = \begin{cases} 
    p_{i}^{k} + \text{rand} \times (p_{i}^{k} - p_{c}^{k}) \times \alpha_{c}, & q < \frac{1}{3} \\
    p_{i}^{k} + \text{rand} \times (g_{i}^{k} - p_{i}^{k}) \times \alpha_{f}, & \frac{1}{3} \leq q < \frac{2}{3} \\
    p_{i}^{k} + \text{rand} \times (p_{m}^{k} - p_{i}^{k}) \times \alpha_{f}, & q \geq \frac{2}{3}
\end{cases}
\]

where \( p_{c}^{k} \) is the history optimal position of an arbitrary adult lion other than itself in \( k^{th} \) generation, \( p_{m}^{k} \) represents the history optimal position of lioness in \( k^{th} \) generation. \( \alpha_{f} \) is perturbation factor, so the lioness execute large-scale search in the early stage and small-scale search in the late stage to accelerate the convergence of the algorithm. \( \text{rand} \) is a random number generated by Uniform distribution \( U(0,1) \).

In the original algorithm, the cub have three main behaviors. When hungry, they approach the king, learn to hunt with the lioness, and when they grow up, they keep away from the group. The third kind of behavior applies the elite opposition, when the global optimal value is close to zero or the feasible region is symmetric about zero, the elite opposition will make the lion move quickly to the vicinity of the zero region. Therefore, the LSO algorithm converges very fast for optimization problems with optimal values near the zero domain. On the contrary, for the situation that the global optimal value is non-zero or the feasible region is not symmetrical about the zero point, LSO algorithm has no advantage in the optimization speed. We use the cub to enhance the communication between different kinds of lions in the group. The position updating function of cub is

\[
x_{i}^{k+1} = \begin{cases} 
    p_{i}^{k} + \text{rand} \times (p_{\text{King}}^{k} - p_{i}^{k}) \times \alpha_{c}, & q < \frac{1}{3} \\
    p_{i}^{k} + \text{rand} \times (p_{m}^{k} - p_{i}^{k}) \times \alpha_{c}, & \frac{1}{3} \leq q < \frac{2}{3} \\
    p_{i}^{k} + \text{rand} \times (p_{k}^{k} - p_{i}^{k}) \times \alpha_{c}, & q \geq \frac{2}{3}
\end{cases}
\]

where \( p_{i}^{k} \) is the history optimal position of an arbitrary cub other than itself in \( k^{th} \) generation is. \( \alpha_{c} \) is a perturbation factor to accelerate the convergence of the algorithm as well.

Each lion has a sign \( \text{trial} \), when the fitness value of a lion does not change for two consecutive times \( \text{trial} \) plus one. When a lion falls into local optimal position for \( lt \) times, the lion execute random search. \( lt \) is

\[
lt = (lt_{\text{max}} - lt_{\text{min}}) \left(1 - e^{-\frac{20}{T}}\right) + lt_{\text{min}}
\]

where \( lt_{\text{max}} \) and \( lt_{\text{min}} \) represents the maximum value and minimum value of the limited number of search respectively. By this, the lion can execute more global search in the early stage and reduce random search in the later stage.
After a certain number of iterations, the group will be sorted and the excellent positions will be allocated to the adult lions, this can ensure the effectiveness of local search.

4. Multi-threshold Image Segmentation by ILSO

When proceeding Multi-threshold image segmentation by ILSO, we hope to get a set of thresholds in the range of $0 \sim L-1$. Firstly, initialize the lion group through integer coding:

$$x_{i,j} = rand_{L-1}, i = 1,2,...,N \quad j = 1,2,...,M$$

where $rand_{L-1}$ is a random integer in the range of $0 \sim L-1$. $M$ represents the number of segmentation thresholds.

In order to promote the performance of local search, we raise the scale factor $\beta$ in equation (1) from $0 \sim 0.5$ to $0.5 \sim 0.7$. In addition, we set $step = 0.2 \times (L-1)$, $l_{\text{min}} = 5$, $l_{\text{max}} = 15$ to improve the global search ability.

After initializing the group and parameters, the maximum inter-class variance criterion is selected as fitness function, calculate the fitness value of each individual, and save the global optimal position and history optimal position of every lion. Then classify the lion group and start iteration.

5. Experimental Results and Analysis

The experimental hardware platform is: Intel i5-4210M, 8G ram, 64-bit system. In order to verify the superiority of ILSO algorithm, PSO, ABC and LSO algorithms are selected as the comparison algorithms.

We choose image #12003 from Berkeley, set threshold numbers $M = 2$ and $M = 5$, fitness value evolution curve of 4 algorithms as follows in figure 1.

![Figure 1. Fitness value evolution curve of 4 algorithms.](image)

(a) $M=2$  (b) $M=5$

It can be seen form figure 1 that the ILSO algorithm proposed in this paper can get the global optimal value quickly and efficiently compared with other three algorithms under the maximum inter-class variance criterion. When $M$ is larger, the performance of ILSO algorithm improves significantly compared with other algorithm.

We choose image #12003, and, #3063 from Berkeley database, the results of image segmentation by ILSO algorithm is as follows in figures 2-3.

Figures 2 and 3 show the segmentation results of two images with different threshold numbers, and from the subjective point, the ILSO algorithm proposed in this paper can obtain ideal image segmentation effect.
Figure 2. Image segmentation results of #12003 by ILSO.

(a) Original  (b) M=2  (c) M=3  (d) M=4  (e) M=5

It is obvious from the following table 1 that the ILSO can obtain ideal image segmentation effect, and with the increase of $M$ the advantage of ILSO algorithm is more obvious.

Figure 4 shows that the calculation speed of the ILSO algorithm is faster than the original LSO algorithm. But there is no advantage in computing speed compared with the other two algorithms.

Table 1. The PSNR of images obtained by four algorithms.

| Image  | M | PSNR   |   |       |   |       |   |       |
|--------|---|--------|---|--------|---|--------|---|--------|
|        |   | PSO    |   | ABC    |   | LSO    |   | ILSO   |
| #12003 | 2 | 28.6494|   | 28.6494|   | 28.6494|   | 28.6494|
|        | 3 | 29.3886|   | 29.4339|   | 29.4381|   | 29.4842|
|        | 4 | 30.1977|   | 30.1843|   | 29.9956|   | 30.3197|
|        | 5 | 30.8198|   | 30.8176|   | 30.8165|   | 31.0168|
| #35049 | 2 | 29.2784|   | 29.2784|   | 29.2784|   | 29.2784|
|        | 3 | 29.7607|   | 29.6128|   | 29.7698|   | 29.8431|
|        | 4 | 29.4504|   | 34.1117|   | 31.6931|   | 34.9126|
|        | 5 | 35.532 |   | 34.5140|   | 32.8724|   | 36.1657|
| #3063  | 2 | 29.3318|   | 29.3318|   | 29.3318|   | 29.3318|
|        | 3 | 29.4903|   | 29.3844|   | 29.4506|   | 29.8193|
|        | 4 | 30.1308|   | 29.9831|   | 29.1488|   | 30.8636|
|        | 5 | 32.0084|   | 29.838 |   | 30.2396|   | 32.0541|

Figure 4. The time of image #3063 segmentation by four algorithms.
6. Conclusion
An improved Lion Swarm Optimization algorithm is proposed in this paper, combine with the global search method of ABC, and revise the position updating function. The ILSO algorithm has better performance of global and local search than the original LSO algorithm. Compared with PSO, ABC and LSO algorithm, ILSO has obvious improvement in convergence speed and optimization accuracy, especially in high-dimension optimization problems. Although the calculation speed is improved compared with the original LSO algorithm, there is still a certain gap with PSO and ABC algorithm. The improved lion group algorithm proposed in this paper can quickly and effectively realize image segmentation and obtain ideal segmentation effect for multi-threshold image segmentation.

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