Maximum entropy multi-threshold image segmentation based on improved particle swarm optimization

Qiyong Gong1,a, Xin Zhao2, Congyong Bi2, Lei Chen2, Xin Nie1, Pengzhi Wang1, Jun Zhan1, Qian Li1 and Wei Gao3*

1Qingdao Institute of Marine Geology, Qingdao, 266071, China
2Pilot National Laboratory for Marine Science and Technology (Qingdao), 266235, China
3Naval University of Engineering, Wuhan, 430033, China
aqygong@qqnlm.ac
*Corresponding author’s e-mail: depkin@163.com

Abstract. To solve the problem of low speed and low precision of traditional maximum entropy image segmentation algorithm, a multi-threshold image segmentation algorithm based on improved particle swarm optimization algorithm is proposed. Taking the optimal threshold optimization problem in multi-threshold image segmentation as the research object, the optimal objective function is obtained by using the maximum entropy multi-threshold segmentation method, and then the maximum entropy method and particle swarm optimization algorithm are fused. In order to solve the problem that particle swarm optimization (PSO) is prone to fall into local optimization in the later iteration process, the PSO is improved and the expansion model is added. Finally, the maximum entropy multi-threshold image segmentation method based on the standard particle swarm optimization algorithm and the maximum entropy multi-threshold image segmentation method based on the improved particle swarm optimization algorithm segment the h-component image (hue, saturation, value) of HSV. Images are converted from images. The segmentation results of the two algorithms are evaluated by running time, and the structural similarity of the algorithms is evaluated. Evaluation result. Experimental results show that the improved maximum entropy multi-threshold image segmentation algorithm based on particle swarm optimization can better achieve complex image segmentation, and the algorithm has stronger real-time performance.

1. Introduction
Image segmentation is an important technology in the process of image processing and a key step to achieve target detection and recognition. Its purpose is to segment the target area of interest in the image from the whole background, thus providing a good foundation for subsequent research and data analysis [1]. There are many methods for image segmentation. Common image segmentation methods include regional image segmentation [2], texture image segmentation [3], edge detection image segmentation [4] and threshold image segmentation [5]. Threshold image segmentation is widely used in agriculture, medicine, geological survey and industrial production with its high precision and high efficiency. For example, in the medical field, the processing of chest image, brain image and cell image is inseparable from the previous processing of images [6]. In agriculture, remote sensing images can be processed to
effectively segment the data in the required images in advance, to realize the whole-process monitoring of agricultural production [7].

Threshold image segmentation method can be divided into single threshold image segmentation method and multiple threshold image segmentation method according to the number of selected threshold values. The single threshold image segmentation method is often used to solve most simple image problems, while the multi-threshold image segmentation method is mostly used to deal with complex image problems. However, with the increase of the number of thresholds, the technical difficulty of the implementation is also increasing.

It is a technical difficulty of multi-threshold image segmentation to find the optimal threshold vector composed of two or more threshold values to realize image separation and processing. The commonly used methods for threshold calculation include Otsu method, maximum inter-class variance method, minimum cross entropy method and maximum entropy method, etc. [8] [9]. By Kapur, among them the maximum entropy method is put forward through the study of the image segmentation based on histogram of the image, the histogram statistics image of each gray level in probability, and each of the grayscale entropy is calculated value, this method is simple and efficient, high segmentation accuracy and easy to implement, can expand to multiple threshold image segmentation, it has been widely used. However, in the multi-threshold image segmentation method, with the increase of threshold level, the calculation amount of the algorithm increases exponentially, which leads to a significant increase in the calculation time of image segmentation, a continuous increase in the occupancy of system memory, and a significant decrease in practicability.

In view of the maximum entropy method in the threshold image segmentation in the computation time is too long and the real-time performance of this problem, this paper introduce Particle Swarm Optimization to calculate (Particle Swarm Optimization, PSO), is applied to the entropy threshold image segmentation, the maximum entropy algorithm and the improved Particle Swarm algorithm combining to many, the threshold value is obtained by maximum entropy algorithm is needed to optimize the objective function, using the improved Particle Swarm algorithm optimize the objective function, thus obtains more threshold of image segmentation.

2. Multi-threshold segmentation based on maximum entropy algorithm

Entropy is an important concept in information theory, and it is the representation of average information quantity, which is used to determine the amount of information contained in random data sources [10]. The entropy of image is used to measure the instability of image gray spatial distribution. The greater the entropy value is, the more uniform the distribution is. In the field of image segmentation, the entropy value of image gray histogram is measured. If a pixel makes the information of the target area and background area in the image maximum, then the pixel is the threshold image segmentation point [11].

Suppose the size of an image is M*N, and the gray level is L. The single threshold method uses a threshold to divide the image into the foreground and the background and obtain the entropy values of the foreground and background, respectively. When the total entropy value is the maximum, the pixel value that distinguishes the foreground and the experience is the best segmentation value. Set the threshold t to divide the image in the gray range of the image \([0, L-1]\) into two types: target \(w\) and background \(B\), then the expressions of the two regions are:

\[
\begin{align*}
D_w &= \{(x, y) | 0 \leq g(x, y) \leq t-1\} \\
D_B &= \{(x, y) | T \leq g(x, y) \leq L-1\}
\end{align*}
\]

\(g(x, y)\) is the gray value of each pixel in the segmented image. The pixel distribution of \([[0, t]]\) and the pixel of \([t + 1, L-1]\) are
\begin{align}
B & = \left\{ \frac{p_1}{P_1}, \frac{p_2}{P_2}, \ldots, \frac{p_n}{P_n} \right\} \\
W & = \left\{ \frac{1 - p_1}{1 - P_1}, \frac{1 - p_2}{1 - P_2}, \ldots, \frac{1 - p_n}{1 - P_n} \right\}
\end{align}

(2)

\( P_i \) is the frequency of each gray level, \( P_j \) is:

\[ P_i = \sum_{i=0}^{n} p_i \]  

(3)

Let the entropy corresponding to the two parts be \( H_w(t) \) and \( H_b(t) \),

\[
\begin{align}
H_w(t) &= -\sum_{i=0}^{n} \frac{p_i}{P_i} \ln \frac{p_i}{P_i} \\
H_b(t) &= -\sum_{i=n+1}^{n} \frac{1 - p_i}{1 - P_i} \ln \frac{1 - p_i}{1 - P_i}
\end{align}
\]

(4)

Multi-threshold image segmentation processing for complex images, use thresholds \( T = [t_1, t_2, t_3, \ldots, t_k] \), the image is divided into regions; the expression of each piece is:

\[
\begin{align}
D_1 &= \{(x, y) | 0 \leq g(x, y) \leq t_1 - 1 \} \\
D_2 &= \{(x, y) | t_1 \leq g(x, y) \leq t_2 - 1 \} \\
& \vdots \\
D_{k+1} &= \{(x, y) | t_k \leq g(x, y) \leq L - 1 \}
\end{align}
\]

(5)

The entropy of each part is

\[
\begin{align}
H_1(t) &= -\sum_{i=0}^{t_1} \frac{p_i}{P_i} \ln \frac{p_i}{P_i} = \sum_{i=0}^{t_1} p_i \\
H_2(t) &= -\sum_{i=t_1+1}^{t_2} \frac{p_i}{P_i} \ln \frac{p_i}{P_i} = \sum_{i=t_1+1}^{t_2} p_i \\
& \vdots \\
H_j(t) &= -\sum_{i=t_{j-1}+1}^{t_j} \frac{p_i}{P_i} \ln \frac{p_i}{P_i} = \sum_{i=t_{j-1}+1}^{t_j} p_i \\
H_{k+1}(t) &= -\sum_{i=t_k+1}^{L} \frac{p_i}{P_i} \ln \frac{p_i}{P_i} = \sum_{i=t_k+1}^{L} p_i
\end{align}
\]

(6)

\( H_j \) represents the entropy value of the first region. The threshold value sought is the threshold value that maximizes the total entropy among all entropy summations, namely:

\[ T^* = \arg \max \left\{ \sum_{i=1}^{k+1} H_i \right\} \]  

(7)

However, the method used by the simple maximum entropy algorithm to obtain the maximum entropy threshold value of the objective function is the exhaustive method, which takes a long time to calculate. Moreover, the model of the objective function containing logarithmic operation is highly complex, so it is not suitable for image segmentation in practical application and cannot meet the requirements of practical application. Therefore, particle swarm optimization (PSO) is used to optimize the optimal threshold vector in multi-threshold image segmentation to simplify the complexity of the algorithm, shorten the segmentation time and improve the segmentation efficiency.

2.1. Basic idea and parameter setting of the particle swarm algorithm

Particle swarm optimization (PSO) is a stochastic computing technology developed by Kennedy and Eberhart. It studies the migration and flocking behaviours of birds in the process of predation. It is a
stochastic and powerful iterative optimization algorithm based on population [12] [13]. In solving the optimization problem, each particle in the algorithm is a potential solution, corresponding to a fitness value. There are two extremum in particle swarm optimization algorithm, one is individual extremum, that is, the best position each particle experiences in the process of searching, that is, local optimum; the second extreme value is global extreme value, that is, the best position experienced by the whole population particles, that is, global optimum. When a particle is given a flight speed, the particle approaches the two optimal extremum in each iteration, and updates the two extremum by tracking the two extremum, and then a new generation of population is generated. Finally, the combination of the optimal solutions is obtained to realize the optimization.

Suppose in a dimensional space, the total number of particles is, and each particle has an initial position and initial velocity \( x_i = (x_{i1}, x_{i2}, \cdots, x_{iC}) \) and \( v_i = (v_{i1}, v_{i2}, \cdots, v_{iC}) \) represent the initial position vector and initial motion velocity vector of the first particle respectively [14]. The particle continuously adjusts its speed and position through continuous iteration, and finds the current optimal position \( p_{ik} \), And the best position of the entire particle swarm obtained during the optimization process of all particles is \( p_{gk}^* \), \( p_{ik} \) and \( p_{gk}^* \):

\[
\begin{align*}
  p_i' &= (p_{i1}', p_{i2}', \cdots, p_{iC}') \\
  p_{gk}' &= (p_{g1}', p_{g2}', \cdots, p_{gC}')
\end{align*}
\]

(8)

In the t iteration, the expression of particle velocity and position is:

\[
\begin{align*}
  v_{ik}^{t+1} &= \omega v_{ik}^t + c_1 r_1 (p_{ik}^* - x_{ik}^t) + c_2 r_2 (p_{gk} - x_{ik}^t) \\
  x_{ik}^{t+1} &= x_{ik}^t + v_{ik}^{t+1} \quad k = 1, 2, \cdots C ; \quad i = 1, 2, \cdots n ; \quad r_1 \text{ and } r_2 \text{ are Random number in interval [0,1], } c_1 \text{ and } c_2 \text{ are acceleration constant, } c_1 \text{ represents the cognitive ability of the particle itself, } c_2 \text{ represents the cognitive ability to express granular social experience, } c_2 \text{ can adjust the step length of the particles, control and adjust the flying direction of the particles so that the particles are adjusted to the direction of the optimal global position. Therefore, adjusting } c_1 \text{ and } c_2 \text{ the particles can slowly approach the optimal position experienced by themselves and the optimal position experienced by the group. In this paper } c_1 = c_2 = 1.2956 .
\end{align*}
\]

\( \omega \) is inertial factor, adjusting the size of \( \omega \), you can control the extent of particle movement along the original trajectory and the impact of historical particle velocity on current velocity [15]. It is generally believed that a higher value \( \omega \) is beneficial to the particles to explore new areas, but a lower value \( \omega \) is more beneficial to the collection of particles. Therefore, a linearly decreasing dynamic adjustable inertia weight is used, and the expression is:

\[
\omega = \omega_{ini} - \frac{\omega_{ini} - \omega_{min}}{iter_{max} - iter} \times iter 
\]

(10)

\( iter \) is the current iteration number, \( \omega_{ini} \) is the maximum number of iterations set: \( \omega_{ini} \) and \( \omega_{min} \) are the set maximum inertia factor and minimum inertia factor, \( \omega \) varies in the interval of
This ensures that each particle can be detected in the global scope with a larger step length in the early stage of the search, and in the later stage of the iteration, \( \omega \) becomes smaller. The search is more refined, ensuring that the particles are optimized around the extreme value. In this paper \( \omega_{max} = 0.9 \), \( \omega_{min} = 0.1 \).

2.2. Particle swarm algorithm with the expanded model

In the iterative process of particles, the particles move towards the optimal value direction according to the update of velocity and position. However, when the particles move to the local extreme value, the velocity of the particles will decrease, leading to the failure of the particles to fly out of the local extreme value and keep falling into the local extreme value, thus failing to obtain the optimal solution. In view of the shortcoming that particle swarm optimization is easy to fall into local optimization in the later iteration process, the particle swarm optimization algorithm is improved by adding an expanded model to avoid the occurrence of local optimization and further accelerate the speed of search.

The characteristic of the expansion model is to keep the moving direction of the particles unchanged while moving the particles forward. Initially, in the first iteration, the particle position was 
\[
\mathbf{x}_k = \mathbf{x}_i + \mathbf{v}_k
\]
Expansion factor \( \alpha \), the part of the particles 
\[
\mathbf{x}_k^{t+1} = \mathbf{x}_k + \alpha \times \mathbf{v}_k
\]
In this way, the particles that were trapped in the local optimum jump out of the effective mechanism into a mutation effect centred on the optimum.

2.3 Multi-threshold image segmentation based on improved particle swarm algorithm

In this paper, the improved particle swarm optimization (PSO) algorithm is added to the maximum entropy threshold segmentation. Firstly, the optimal objective function is obtained by using the maximum entropy multi-threshold value, and then the improved PSO algorithm is used for optimization. Its specific steps are as follows:

1. By learning a relative basis for all particles, the optimal particles were selected as the initial population, and then the initial velocity, initial position, local optimal value, and global optimal value of the particles were randomly set.

2. The fitness of each particle is evaluated, the objective function of the particle is calculated according to the multi-threshold segmentation method of maximum entropy, and the local optimal value and global optimal value are updated.

3. According to the formula of velocity and position, the particle's motion velocity and position are constantly changed, and the particle's motion velocity and position are adjusted according to the set range. When the optimal solution is unchanged, the particle's position is expanded by using the improved expansion model proposed in this paper.

4. If the termination condition is met, the iteration is terminated when the maximum number of iterations is reached; If the requirements are not met, the calculation is recalculated.

The flowchart of multi-threshold image segmentation based on an improved particle swarm algorithm is shown in Figure 1.
Obtain the objective function through maximum entropy multi-threshold segmentation

The particle swarm algorithm performs relatively basic learning, Screen the particles

Set the initial velocity, initial position, local optimal solution and global optimal solution of the particle

Evaluate the fitness of each particle, Update local optimal value and global optimal value

Adjust the speed and position of the particles

Whether the optimal solution changes

No

Join the expansion

Yes

Whether the termination conditions are met

No

Output global optimal solution

Yes

Figure 1 Flow chart of multi-threshold image segmentation based on improved particle swarm algorithm

3. Human body infrared image segmentation experiment and result analysis

In order to verify the segmentation effect of particle swarm optimization algorithm in image multi-threshold segmentation, this paper USES simulation software to conduct segmentation experiment, check the segmentation effect, and test the segmentation efficiency and feasibility of the algorithm. A 1023*779 infrared image of the human body, as shown in figure 2, was selected to conduct simulation experiments under the environment of windows7 system, 64-bit operating system and Matlab.

Figure 2 Selected infrared image of the human body

In order to better test the feasibility and efficiency of the algorithm, the infrared image of human body has a variety of colors and different areas have different colors. The RGB image is converted into HSV image and the color H component is extracted. The values of the color components range from 0 to 359. The H component image is shown in Figure 3.
By selecting different segmentation threshold levels, multi-threshold segmentation based on standard particle swarm optimization (PSO) and multi-threshold segmentation based on improved particle swarm optimization (PSO) are respectively used to conduct segmentation experiments on processed H-component images. The experimental results are shown in Figure 4.

The two segmentation algorithms are evaluated and compared using structural similarity and algorithm running time indicators. The comparison results are shown in Table 1.

Table 1 Algorithm evaluation comparison table

| segmentation grade | algorithm  | Threshold | time (s) | structure Similarity |
|--------------------|-----------|-----------|----------|----------------------|
| K=1                | Improved  | 45        | 0.425    | 0.6324               |
As can be seen from the experimental results and the overall results in Table 1, with the continuous improvement of the segmentation level K, the structural similarity index value of the two algorithms also keeps rising, indicating that the segmented image is closer to the H-component image, but at the same time, the running time of the algorithm is also increasing. Through the comparison of the segmentation image and the maximum entropy segmentation method based on the improved particle swarm optimization algorithm and the total entropy segmentation method based on the standard particle swarm optimization algorithm, the image segmentation method based on the improved particle swarm optimization algorithm is feasible. Particle swarm optimization (PSO) has better image segmentation and shorter running time. Taking the segmentation level K=3 as an example, the segmentation result graph (B3) of the improved algorithm shows the highlighted yellow and red regions in the original image better than the segmentation result of the standard algorithm (A3). The maximum entropy image segmentation based on improved particle swarm optimization (PSO) is proved to be feasible and effective.

4. Conclusion
Image segmentation is an essential step in image processing. In order to solve the problem of slow segmentation speed of maximum entropy threshold image, particle swarm optimization (PSO) algorithm is combined with maximum entropy algorithm. In view of the shortcoming of particle swarm optimization (PSO) that it is easy to fall into local optimization in the late iteration process, the PSO is improved. Based on the extended model, a maximum entropy multi-threshold image segmentation method based on improved particle swarm optimization (PSO) is proposed. The experimental results show that the improved particle swarm optimization (PSO) based total entropy image segmentation is not easy to fall into local optimum, has high efficiency and strong reliability, and can fully meet the requirements of multi-threshold image segmentation.

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|     | Standard |   |   |   |
|-----|----------|---|---|---|
| K=2 | Improved | 90,251 | 0.751 | 0.7855 |
|     | Standard | 82,261 | 0.865 | 0.7343 |
| K=3 | Improved | 53,159,255 | 1.152 | 0.8461 |
|     | Standard | 98,177,251 | 2.697 | 0.8102 |
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