A Medical Image Threshold Segmentation Method Using Improved Swarm Optimization

Yannning Zhang, Chao Tang*
Department of Computer Science and Technology, Hefei University, Hefei, China
Corresponding Author’s Email: cuonzym@163.com

Abstract: In order to improve the accuracy of medical image segmentation, a new medical image threshold segmentation method is proposed, using improved swarm optimization algorithm. Firstly, the thresholds are regarded as the honey source, using inter-class variance principle and entropy function as the fitness function; Secondly, a current local optimum solution is obtained by each round of cyclic search; Thirdly, the previous solution is introduced to participate in the honey position update during next round of search; Finally, the global optimal solution is achieved. Experiments show that the proposed method can improve the detection and recognition ability of target objects, and obtain better segmentation results than comparison methods.

Keywords: Medical Image Segmentation; Swarm Optimization; Local Optimum

Un Método de Segmentación de Umbral de Imagen Médica Mediante la Optimización Mejorada de Enjambres

Resumen
Propósito para observar el uso de CAPELINE bolsa de ostomía en niños con bajo peso corporal y fistula intestinal, y para resumir los métodos de gestión para reducir la incidencia de fugas y la excreción de la piel en niños con dermatitis alrededor de los estomas de baja masa corporal. Método aplicar CAPELINE bolsa de ostomía en niños con bajo peso corporal debido a una enfermedad congénita o adquirida de fistula intestinal para observar la incidencia de fugas de fecal y piel dermatitis alrededor de la fistula. Para observar la curación de la incisión abdominal y la incidencia de complicaciones después de enterostomía en niños con enfermedades congénitas o adquiridas. Resultado del uso de CAPELINE bolsa de ostomía en niños con bajo peso corporal y fistula intestinal puede prevenir con eficacia el enrojecimiento de la piel y dermatitis y reducir efectivamente la fuga de excremento. Después de la enterostomía, no hubo efecto significativo sobre la incisión la curación. Después de una intervención activa, la incidencia de complicaciones después de enterostomía fue de 21% en nuestro hospital. Conclusión el uso de CAPELINE bolsa de ostomía en niños con bajo peso corporal y fistula intestinal puede prevenir con eficacia el enrojecimiento de la piel y dermatitis y reducir efectivamente la fuga de excremento. La gestión de casos en cada caso, la gestión de manejo perioratorio, y la pronta aplicación de la estoma bolsa no sólo es beneficioso para la curación de la incisión quirúrgica y la reducción de la incidencia total de complicaciones, sino también la comodidad de los niños y la carga psicológica de las familias.

Palabras clave: Segmentación de Imagen Médica; Optimización de Enjambre; Óptimo Local.

1. Introduction
Medical images include X-ray, CT, MRI and ultrasound imaging and so on[1][2]. With the development of modern information science, medical image technology is also constantly developing[3]. At the same time, medical image processing is becoming more and more important in order to obtain accurate lesion information and realize the requirement of computer intelligent analysis[4]. At present, medical image processing mainly includes image pre-processing, image segmentation, image feature recognition and image three-dimensional reconstruction. Among them, image segmentation is a very important part, which plays a significant role in the field of many medical image applications[5].

The main goal of image segmentation is to decompose an image into a collection of several non-overlapping regions[6]. The regions obtained by image segmentation needs to meet two requirements of uniformity and connectivity at the same time [7]. The quality of image segmentation has a direct impact on the
final results of image analysis and clinical diagnosis. Therefore, the research of medical image segmentation has always been one of the hotspots of medical image processing.

The widely used medical image segmentation techniques are mainly divided into edge detection method[8][9][12], region segmentation method[10][13] and threshold segmentation method[11]. Image edge is of great significance to human vision, and is the boundary that distinguishes two adjacent regions. The edge detection method first detects the edge points in the image, then connects the closed curve to form the segmentation region in accordance with certain strategies and algorithms. The gray level, colour and texture of an image usually changes significantly at the edge, and the differential operator is usually used to represent this change in edge detection method. The region segmentation method divides the image according to the characteristics of the image space, and divides the pixels with similar or identical properties into the same region. Threshold segmentation divides pixels into several categories in accordance with gray level through threshold setting. The threshold based image segmentation algorithm has gradually become a widely used segmentation technology because of its simple and stable performance characteristics. The classical threshold segmentation method includes the maximum inter-class variance method (or Otsu) [14], the minimum error method [15], the maximum entropy method [16], and so on, how to select the optimal threshold quickly and effectively is the key to the threshold image segmentation method.

In recent years, various optimization methods for simulating the foraging and evolutionary processes of biological groups have been adopted to solve the problem in medical image segmentation technology. At present, commonly used optimization algorithms are: ACO (Ant Colony Optimization) [17], PSO (Particle Swarm Optimization) [18], and ABC (Artificial Bee Colony) [19] and so on. The performance of these optimization algorithms is compared in the literature [20], and the results show that the artificial swarm algorithm has better optimization ability. Artificial swarm algorithm is an optimization algorithm for simulating the intelligent search behaviour of bee swarm proposed by the Turkish scholar Karaboga [21]. The outstanding advantage of this algorithm is that it has the characteristics of rapidity and easy realization, so it has become a research hotspot in the field of intelligent optimization.

In this study, the swarm algorithm is proposed to search for image threshold, starting from the local optimum points obtained by a previous loop search with different neighbour parameter, a new loop search is used to search furthermore, so that a better set of image thresholds can be obtained. The proposed method has the simple operation, few and precise control parameters, high searching precision, and strong robustness in comparison with the classical optimization method [22].

The rest is organized as follows: The methodology is introduced in Section II. Section III details the evaluation results. The conclusions are achieved in Section IV.

2. Methodology

2.1 Question Definition of Optimization

Optimization refers to finding a set of parameter values under certain constraints, so that some performance indexes of the system are optimized. Optimization technology has produced remarkable economic and social benefits. Many studies and practices show that under the same external conditions, the optimization technology has remarkable effect on the improvement of system efficiency, reduction of energy consumption, rational utilization of resources and improvement of economic benefits. The optimization problem is tantamount to study the characteristics and calculation methods of the global most advantages of the objective function in a region. Optimization issues can generally be expressed as follows:

$$\min f(x) \quad s.t. x \in S$$

where $S$ is a viable domain, also known as a solution space, it is a non-empty collection, $f(t_1, t_2, ..., t_n)$ as the objective function, which is defined as a real value function on $S$. $\min f(x)$ represents the minimum value of the target function. Optimization problems can also be expressed as finding the maximum value of the objective function $\max f(x)$. However, the maximum value can be converted equally to the minimum $\min(-f(x))$. The mathematical model of an optimization problem mainly includes three parts: the constraint condition of the objective function, the feasible domain (searching space) and the optimized parameters need to meet. When a problem is not constrained, the optimization problem is called the unconstrained optimization problem, otherwise it is called the constraint optimization problem.

In this study, the typical steps in solving the optimization problem based on the bionic optimization algorithm are as follows: (1) A set of initial solutions is randomly set; (2) In accordance with a certain method, the solution with the excellent performance is selected as the current solution; (3) The iteration comparison of current solution is performed to obtain a new solution. Bionic algorithms have flexibility and high efficiency in
complex optimization problems, and a useful solution (approximate, suboptimal, and within the scope of precision permission) can be obtained in most cases.

2.2 Fitness Function

In the optimization algorithm, the fitness function is the primary indicator for describing the performance of an individual or solutions, and in this study, inter-class variance function and entropy function are used as fitness functions.

Given that an image with a total pixel of \( N \) has a grayscale range of \([0, L]\), \( n_i \) represents the number of pixels with a grayscale of \( i \), the probability of grayscale can be defined as following formula:

\[
p_i = \frac{n_i}{N}
\]  

(2)

If \( t_1, t_2, \ldots, t_n \) are the threshold of the image, the definition of inter-class variance function is as follows:

\[
f(t_1, t_2, \ldots, t_n) = w_0(\mu_0 - \mu_T)^2 + \cdots + w_k(\mu_k - \mu_T)^2 \cdots + w_n(\mu_n - \mu_T)^2
\]

(3)

\[
w_0 = \sum_{i=0}^{t_1} p_i
\]

(4)

\[
w_k = \sum_{i=t_k+1}^{t_{k+1}} p_i
\]

(5)

\[
\mu_0 = \sum_{i=0}^{t_1} i \times p_i
\]

(6)

\[
\mu_k = \sum_{i=t_k+1}^{t_{k+1}} i \times p_i
\]

(7)

where \( w_k (1 \leq k \leq n - 1) \) represents the total occurrence probability of the \( k \) level grayscale pixels and \( \mu_k (1 \leq k \leq n - 1) \) represents the average grayscale of the \( k \) level pixels. \( \mu_T \) is the average grayscale value of the entire image, and its calculation formula is as follows:

\[
\mu_T = \sum_{i=0}^{t_{n-1}} i \times p_i
\]

(8)

when \( f(t_1, t_2, \ldots, t_n) \) reaches the maximum, the best threshold \( t_1^*, t_2^*, \ldots, t_n^* \) is as follows:

\[
t_1^*, t_2^*, \ldots, t_n^* = \text{argmax} \{f(t_1, t_2, \ldots, t_n)\}
\]

(9)

The definition of entropy is as follow:

\[
H(t_1, t_2, \ldots, t_n) = H_0 + H_1 + \cdots + H_k + \cdots + H_n
\]

(10)

where

\[
H_0 = -\sum_{i=0}^{t_1} \frac{p_i}{w_0} \ln \frac{p_i}{w_0}, \quad w_0 = \sum_{i=0}^{t_1} p_i
\]

(11)

\[
H_k = -\sum_{i=t_k+1}^{t_{k+1}} \frac{p_i}{w_k} \ln \frac{p_i}{w_k}, \quad w_k = \sum_{i=t_k+1}^{t_{k+1}} p_i
\]

(12)

\[
H_n = -\sum_{i=t_n+1}^{t_{n-1}} \frac{p_i}{w_n} \ln \frac{p_i}{w_n}, \quad w_n = \sum_{i=t_n+1}^{t_{n-1}} p_i
\]

(13)

where \( H_k (1 \leq k \leq n - 1) \) represents the sum of entropy of the \( k \) level grayscale pixels. when \( H(t_1, t_2, \ldots, t_n) \) reaches the maximum, the best threshold \( t_1^*, t_2^*, \ldots, t_n^* \) is as follows:

\[
t_1^*, t_2^*, \ldots, t_n^* = \text{argmax} \{E(t_1, t_2, \ldots, t_n)\}
\]

(14)
2.3 Swarm Algorithm

In swarm algorithm, the number of honey and leading or following bees (i.e., equal to half the size of the population) is set to \( S_N \). The algorithm randomly generates \( S_N \) honey in accordance with the search space of the problem, which is generated by the following formula:

\[
x_{i,j} = x_U^{i} + \text{rand}(0,1) \cdot (x_L^{i} - x_U^{i})
\]

where \( i = (1,2,\ldots, S_N) \), \( S_N \), \( x_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \) denotes one solution, \( j = \{1, 2, \ldots, D\} \) represents the \( j \) dimension of the feasible solution, \( D \) represents the dimension of the feasible solution, and \( x_U^i \) and \( x_L^i \) respectively represent the upper and lower bounds of a feasible solution to the \( j \) dimension. After the initial population generated above is evaluated according to fitness values, the algorithm begins to iterate, which including following main stages.

Stage 1: The leading bee randomly selects an individual in the population to cross to produce a new individual in accordance with the following formula:

\[
v_{i,j} = x_{i,j} + r_1(x_{i,j} - x_{k,j}) + r_2(x_{i,j} - x_{pbest,j})
\]

where \( r_1 \) and \( r_2 \) are random numbers between [-1,1], \( j \) is a randomly selected integer in \( [1, D] \), and \( k \) is a honey randomly selected different from \( i \).

Stage 2: The following bee selectively chooses the food source information provided by the leading bee in accordance with the following probability:

\[
p_i = \frac{\text{fit}(x_i)}{\sum_{m=1}^{S_N} \text{fit}(x_m)}
\]

Thereafter, the following bee uses roulette method to choose the leading bee, that is, an evenly distributed random number \( r \) is generated between [0,1], and if the \( r \) is less than \( p_i \), then a new honey is generated around honey \( i \).

Stage 3: If a honey which reaches present circle number limit has not been improved after trial iteration, the solution is considered to be partially optimal, and the honey will be discarded, while the corresponding leading bee is transformed into a reconnaissance bee. The reconnaissance bee will randomly produce a new solution using (11) to replace the old solution. Those procedures from State 1 to 3 are repeated until the pre-set termination conditions are met.

2.4 Proposed Method

In this study, the swarm algorithm is executed in the form of inner and outer double loops. Inner loop performs honey search, outer loop control neighbour search scope. A set of current optimal solutions is generated in the previous inner loop, and is recorded in the foreign memory file at the same time. During the leading and following bee stage of following loop, the current optimal solution is introduced to participate in the update of the honey location. At this stage, the new honey is generated according to the following formula:

\[
v_{i,j} = x_{i,j} + r_1(x_{i,j} - x_{k,j}) + r_2(x_{i,j} - x_{pbest,j})
\]

where \( x_{pbest} \) is the previous best one selected from the updated external file. The randomly selected solution using (13) and the solution using (15) are involved in the update of honey position at the same time, if the new solution is preferable to the old one, the old one will be replaced by the new one, otherwise it will be discarded, so the local optimization ability is improved. Furthermore, in each inner loop, the search range of neighbour is gradually narrowed to improve the search efficiency.

After the algorithm completes, in order to select an optimal solution, the weighted ratio \( F \) of the difference between the classes and the difference within the class under each solution is calculated, and the individual that makes the \( F \) take the maximum value is finally achieved as the optimal solution. Weighted ratio \( F \) is defined as follows:

\[
F = \frac{S_d / s}{S_e / (N - s - 1)}
\]

\[
S_d = \sum_{j=1}^{l} N_j y_j - N_y^2
\]
where \( s \) represents the number of individual thresholds, \( N \) is the total number of image pixels, \( S_s \) and \( S_E \) respectively represent differences between classes and intra-class differences, \( N_j \) is the total number of pixels in class \( j \), \( y \) represents the average grayscale value of all pixels, \( y_j \) indicates the average grayscale level of class \( j \), \( x_{i,j} \) represents the grayscale value of class \( j \) at \( i \). Figure 1 shows the algorithm block diagram.

**Figure 1.** Flow chart of the algorithm

1) Input and initialization.
   a) Randomly generate \( S_N \) honey source using (12).
   b) Calculate the fitness function and evaluate it by (9) and (11).
   c) Set the maximum cycle of inner-loop (LimitCI) and outer-loop (LimitCO)
d) Set the initial value of NP (neighbour parameter).
2) Do for \( o = 1,2...\text{LimitCO} \)
   Do for \( i = 1,2...\text{LimitCI} \)
   i) Leading bee stage. Search honey within the NP scope in accordance with individual crossing strategy using (13) and the current optimal set (initially empty) using (15).
   ii) Following bee stage. Chooses the food source using (14), search around within the NP scope and produce new honey.
   iii) Scout bee stage. If it exists, create a new location.
   iv) If NP <4, Break; record the local current optimum generated into the external memory file.
End Do
NP = NP/2
End Do
3) Output the best global solution.

3. Experimental Results

In this section, the maximum inter-class variance method, the maximum entropy method, the threshold image segmentation method based on single target swarm ABC and the DE (differential evolution) algorithm are used as the comparison algorithm. The segmentation experiment of multiple MR (magnetic resonance) images is carried out here, the proposed method and comparison algorithm are compared quantitatively using the signal-to-noise ratio. The signal-to-noise ratio criterion is defined as follows:

\[
PSMN.R = 20 \log_{10} \left( \frac{255}{RMSE} \right)
\]  

(19)

where \( RMSE \) represents the mean square error before and after image segmentation. The definition of it is as follows:

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

(20)

where \( I(i,j) \) and \( \hat{I}(i,j) \) respectively represent the grayscale value of original image and after the image segment at \((i, j)\), \(M \times N\) represents the image size.

In this experiment, MR image1, 2, and 3 are used to test the effects of the proposed method and comparison algorithm. Figures 2-4 shows the segmentation results of all algorithms on the three MR images. The segmentation results of the three images show that the segmentation effect of the maximum entropy method and DE method is not ideal, a certain degree of dislocation is observed, and the granularity of the maximum entropy method is serious. The segmentation results of the maximum inter-class variance method are good, but some error segmentation points remain to exist. The ABC algorithm performs well in most cases. The visual segmentation results obtained by this algorithm is the most ideal among all the algorithms, which not only has fewer errors, but also can better retain the details of the image.

![Figure 2. Results of image MR1](image-url)
The Figure 5 displays the PSNR distribution obtained by each algorithm. It can be found that the proposed method is obtained on three MR images. The PSNR values are higher than the other algorithms, which illustrates the advantages of the proposed method.

Figure 5. PSNR of the three MR images
4. Conclusions

A new medical threshold image segmentation method based on swarm optimization is proposed. The single-cycle model of traditional swarm algorithm has been transformed into a double-cycle model, a current local optimum solution is introduced to the leading bee and following bee stage during next inner-loop, so that the algorithm can approximate the optimal threshold more effectively to get a better image segmentation effect. The experimental results on multiple MR images show that the proposed method has better segmentation effect than the maximum entropy method, maximum inter-class variance method, DE method and ABC algorithm. The threshold number is set well in advance when image segmentation is carried out, how to determine the number of thresholds adaptively, and then realize automatic multi-threshold segmentation is worth studying.

References

