Bio-Medical Materials and Engineering 26 (2015) S1345–S1351
DOI 10.3233/BME-151432
IOS Press

A hybrid flower pollination algorithm based modified randomized location for multi-threshold medical image segmentation

Rui Wang[a,b], Yongquan Zhou[a,b,*], Chengyan Zhao[a,b] and Haizhou Wu[a,b]

[a]*College of Information Science and Engineering, Guangxi University for Nationalities, Nanning, China*

[b]*Guangxi High School Key Laboratory of Complex System and Computational Intelligence, Guangxi University for Nationalities, Nanning, China*

Abstract. Multi-threshold image segmentation is a powerful image processing technique that is used for the preprocessing of pattern recognition and computer vision. However, traditional multilevel thresholding methods are computationally expensive because they involve exhaustively searching the optimal thresholds to optimize the objective functions. To overcome this drawback, this paper proposes a flower pollination algorithm with a randomized location modification. The proposed algorithm is used to find optimal threshold values for maximizing Otsu's objective functions with regard to eight medical grayscale images. When benchmarked against other state-of-the-art evolutionary algorithms, the new algorithm proves itself to be robust and effective through numerical experimental results including Otsu's objective values and standard deviations.

Keywords: Flower pollination algorithm, randomized location, Otsu method, multi-threshold image segmentation, medical image segmentation

1. Introduction

Image segmentation is a fundamental technique in the widely applied field of image processing and computer vision. In most cases, it can be described as the preprocessing stage of pattern recognition. Image segmentation is the process of dividing an image into different disjoint pixel classes, which have similar characteristics like gray level, color, or texture. Segmentation is a critical and challenging task that involves a multi-level thresholding technique, a powerful tool that is used extensively in the field of image processing.

Computer scientists and scholars have studied image segmentation for years, devising numerous innovations that have been explored and anticipated in the literature. In 1979 N. Otsu proposed a nonparametric, unsupervised method of automatic threshold selection for picture segmentation, which

[*] Address for Corresponding: Yongquan Zhou, Guangxi University for Nationalities, College of Information Science and Engineering, 188 University East Road, Nanning, China. Tel.: 13607882594; Fax: 0771-3260264; E-mail: yongquanzhou@126.com.

was subsequently named Otsu's method after its inventor [1]. In 1999 Yin PY applied a variant of a genetic algorithm and embedded a learning strategy to enhance its searching ability for multilevel thresholding [2]; In 2007 Cheng proposed a cell-based two-region competition algorithm to define boundaries in two-dimensional ultrasound images [3]. In 2008 Maitra inserted a cooperative learning operator and comprehensive learning operator into a particle swarm algorithm [4], strengthening its segmentation ability significantly; Cheng used cell competition algorithms for breast lesion demarcation in 2010 [5]. In 2014 Feng Zhao proposed a multi-objective spatial fuzzy clustering algorithm [6] for segmentation, and simulation results show a high level of effectiveness [7]. Researchers have even applied this popular technique to artificial bee colony (ABC) optimization [8].

This paper explores the use of a modified randomized-location flower pollination algorithm (FPA) for medical image segmentation. Proposed by Yang in 2012, FPA [9] is a population-based intelligent optimization algorithm that simulates flower pollination behavior in nature; although relatively new, it has been extensively researched over the past two years. Yang and Xingshi He used FPA to solve a multi-objective optimization problem in 2013 [10], and Osama Abdel-Raouf used an improved FPA to solve sudoku puzzles in 2014 [11]. Already in 2015 Prathiba has used FPA to solve different economic load dispatch problems [12].

The remainder of this paper is organized as follows: section 2 introduces the problem formulation of Otsu's method; section 3 specifies the implementation procedure of our proposed modified randomized-location FPA (MRLFPA); section 4 describes simulation experiments; and section 5discusses our conclusions; acknowledgments are described in section 6.

2. Problem formulation of Otsu's method

Otsu's method is the most basic image segmentation method [1]. Widely used by scholars, it is based on the maximization of between-class variance. The particular procedure can be described as follows.

Assume that a grayscale image has L gray levels, n is the number of pixels in the image, n_i is the number of pixels whose gray level is i , and p_i denotes the probability of pixels at level i . Given these parameters, we can derive the equation $p_i = n_i / n$. The gray levels of the pixels in the test image can then be divided into two classes (C_0, C_1) by threshold t , where $C_0 = \{0,1,2,...,t\}$, and $C_1 = \{t+1, t+2,..., L-1\}$. We can calculate the probability of C_0 and C_1 through the equations below

$$w_0 = \sum_{i=0}^{t} p_i = w(t); \tag{1}$$

$$w_1 = \sum_{i=t+1}^{L-1} p_i = 1 - w(t); \tag{2}$$

The average value of C_0 and C_1 can be obtained by the following equations:

$$u_0 = \sum_{i=0}^{t} i \frac{p_i}{w_0} = \frac{u(t)}{w(t)}, \tag{3}$$

$$u_1 = \sum_{i=t+1}^{L-1} i\frac{p_i}{w_1} = \frac{u_T - u(t)}{1 - w(t)}, \tag{4}$$

where $u(t) = \sum_{i=0}^{t} ip_i$ and $u_T = \sum_{0}^{L-1} ip_i$. Therefore, the variance of these two classes can be calculated by the following equation:

$$\delta^2 = w_0\left(u_0 - u_T\right)^2 + w_1\left(u_1 - u_T\right)^2 \tag{5}$$

The optimal partition or the optimal threshold selection can be obtained by maximizing Eq. (5). Otsu's method can easily be generalized to higher dimensions for multilevel image thresholding. Namely, for $k+1$ classes $C_i, (i = 0,1,...,k)$ the optimization objective is the maximize the objective function stated below

$$\delta^2 = w_0\left(u_0 - u_T\right)^2 + w_1\left(u_1 - u_T\right)^2 + ... + w_k\left(u_k - u_T\right)^2 \tag{6}$$

The calculation of $u_i\ (i = 1,2,...,k)$ should refer to Eqs. (1) and (2).

3. Flower pollination algorithm with modified randomized location

The standard FPA proposed by Xin-she Yang in 2012 has proven to be an efficient tool for unimodal optimization problems. When faced with multi-modal optimization cases that have a large number of local minima, FPA's limitations can be discovered readily: It is relatively easy to fall into a local optimum, and hard to escape from the local region.

Analysis shows that population diversity is the fatal factor behind this weakness. To overcome this limitation of the standard FPA, we appended two optimization strategies to enhance the diversity of population. We will present these two enhanced operators, randomized location strategy (RLS) and crossover strategy (CS), in detail in the remainder of this section.

3.1. Randomized location strategy

The local search process of the standard flower pollination algorithm has demonstrated familiarity with the mutation operator of differential evolution (DE) [13]. In the standard FPA, there is no rule for the selection of random vectors x_j^t and x_k^t in the population except that these vectors should differ from the target vector x_i^t. However, the position of x_j^t, x_k^t ,and x_i^t are unknown to us. They may be located in a small cluster, which fails to ensure the searching diversity of the population.

In this subsection, we suggest a modified mutation mechanism such that instead of a random selection, each solution vector represents a distinct region of the search space. The proposed strategy can be explained as follows. All solution vectors in the population should first be sorted according to their fitness values, and these vectors should be divided into three sub-regions, S_1, S_2, S_3 . S_1 represents the set of solutions with the best fitness, S_2 represents the set of next-best solution vectors, and

S_3 represents the remaining vectors. Suppose that x_b^t is a solution vector selected from S_1 , and x_j^t and x_k^t are solution vectors randomly selected from S_2 and S_3 , respectively. The mutation vector v_i^t can be obtained from the equation below

$$v_i^t = x_b^t + F\left(x_j^t - x_k^t\right) \tag{7}$$

where F is the mutagenic factor, which should be set to 0.3 here. Subsequently, v_i^t should be used in the crossover strategy. Randomized location, which ensures that the candidate vectors are selected strategically so as to cover most of the search space, will enhance the diversity of the population. Selecting a solution vector x_b^t from the best fitness set as the base vector of mutation operation will speed up the convergence speed. Thus, this mechanism will improve both the global search ability and the local search ability. In this paper, the sub-population sizes of $S_1, S_2\ and\ S_3$ are set to be equal for simplicity.

3.2. Crossover strategy

Subsection 3.1 applies RLS in the local search process, increasing its exploitation ability and also speeding up the convergence speed. The mutation vector v_i^t obtained by RLS be used to enhance the diversity of the population and choose the crossover operator. The crossover operator can be expressed using the following equation:

$$x_{i,k}^{t+1} = \begin{cases} v_{i,k}, & rand_{i,k}[0,1] < \mathrm{C}_r \\ x_{i,k}^t, & else \end{cases} \qquad k = 1,2,3...d; j = 1,2,...n. \tag{8}$$

where $x_{i,k}$ is the kth variable of ith solution vector and is the crossover rate, which is set to 0.7 in this paper. The crossover operator helps to increase the population diversity in the local search process and to avoid becoming trapped in the local optimum. Specific implementation steps of the MRLFPA for segmentation can be summarized in the pseudo code shown in Algorithm 1.

Algorithm 1. Modified randomized location flower pollination algorithm for segmentation

```
Initialize a population X of n flowers or pollen gametes with random solutions.
Each flower represents a threshold sequence for multi-threshold segmentation.
Find the best solution B in the initial population.
Define a switch probability p ∈ (0,1)
while (t < MaxGeneration)
  for i=1:n(all the flowers in the population)
    if (rand < p)
       (Global search process)
       Draw a step vector L obeys a Lévy distribution.
       Use global pollination to get the new solution x_i^{t+1}.
```

else
(Local search process)
Carry out RLS and find the mutation vector v_i^t.
Carry out CS and find x_i^{t+1}.
end if
Evaluate the new threshold sequence x_i^{t+1} using Eq. (6).
if$\left(fitness\left(x_i^{t+1}\right) > fitness\left(x_i^t\right)\right)$
Update flower x_i ;
end if
end for
Find the current best threshold sequence B.
end while
Output the best threshold sequence.

4. Simulation experiments

4.1. Experimental setup

All algorithms were programmed in MATLAB R2012a, and a numerical experiment was set up on an AMD Athlon^{TM} II*4600 processor with 2 GB memory.

4.2. Comparison of each algorithm performance

The proposed Modified Randomized Location Flower Pollination Algorithm is compared with mainstream meta-heuristic algorithms genetic algorithm (GA) [14], particle swarm optimization (PSO) [8], differential evolution (DE) [13], flower pollination algorithm (FPA) [9]. And the control parameters of mentioned segmentation algorithms are listed in Table 1. Table 2 shows the comparison of mentioned segmentation methods for 8 thresholds cases. And the segmentation results of proposed MRLFPA is described in Figure 1.

This subsection described ample simulation experiments that used nine test images to evaluate the performance of the proposed MRLFPA. The test library used for this paper is related to medical science, and most test samples were obtained from CT or MRI machines.

Table 1

Parameter settings of segmentation methods

Algorithms	Parameter 1	Parameter 2	Parameter 3	Parameter 4
GA	$n=30$	$p_m=0.001$	$p_c=0.6$	
PSO	$n=30$	$w=0.7298$	$c_1=1.4962$	$c_2=1.4962$
DE	$n=30$	$F=0.5$	$CR=0.9$	
FPA	$n=30$	$p=0.8$		
MRLFPA	$n=30$	$p=0.8$		

Table 2

Comparison of various methods for 8 thresholds segmentation

Test image		GA	PSO	DE	FPA	MRLFPA
HAND	Value	339.4316	342.7717	345.6877	346.1089	**346.1346**
(256×256)	Time	9.9013	16.3832	9.67991	10.5014	**9.8153**
FOOT	Value	1473.7288	1501.1893	1524.7482	1527.4137	**1527.3999**
(256×256)	Time	9.8197	16.2280	9.616768	10.4779	**10.3456**
LUNG	Value	3348.6108	3418.9595	3420.8154	3421.6535	**3421.5418**
(512×512)	Time	9.9892	16.2812	9.788917	10.6379	**9.9928**
KNEE	Value	15795.216	16041.2162	16241.294	16324.867	**16367.295**
(512×512)	Time	9.9535	15.8310	9.510368	10.4544	**9.7286**
SPINE	Value	1788.6561	1808.6541	1850.9436	1860.2390	**1862.2791**
(512×512)	Time	10.1360	16.1760	10.089473	10.7952	**9.6569**
CANCER	Value	820.4710	831.7973	838.90364	839.4196	**839.54768**
(512×512)	Time	10.1535	16.7168	10.106214	10.7903	**9.6835**
LIVER	Value	2695.7343	2750.4876	2772.9475	2781.9909	**2782.5755**
(256×256)	Time	9.8746	16.1503	9.497611	10.4323	**9.7130**
HEAD CT	Value	5570.4188	5664.9448	5709.5253	5728.5423	**5728.7978**
(512×512)	Time	9.9911	16.0165	9.675155	10.5801	**10.1208**

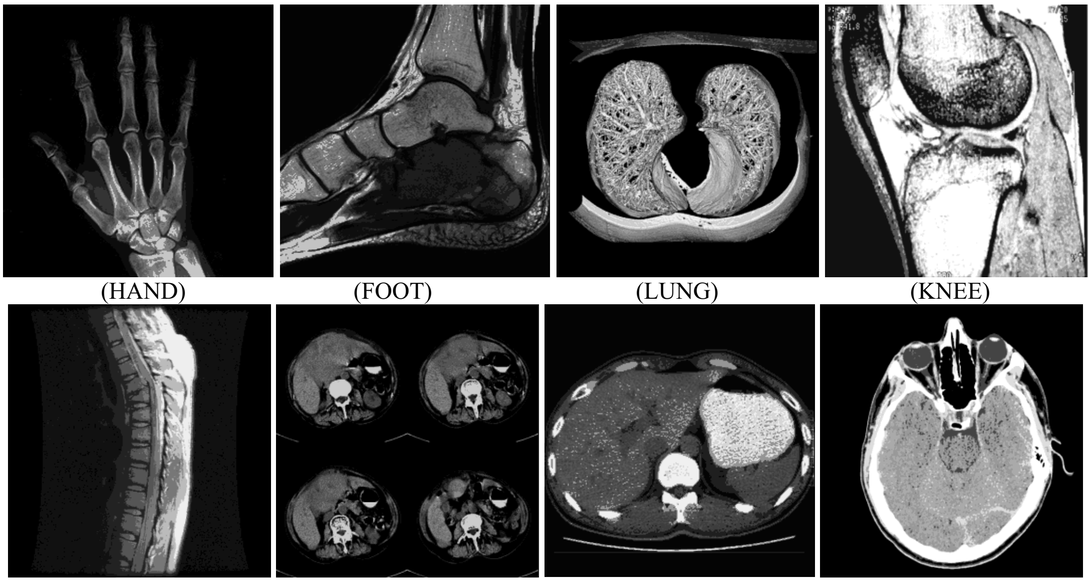
(HAND) (FOOT) (LUNG) (KNEE)
(SPINE) (CANCER) (LIVER) (HEAD CT)

Fig. 1. Eight thresholds segmentation results of MRLFPA.

Table 1 lists the objective values and CPU running time of MRLFPA for each case. Figure 1 show the segmentation results for 8 thresholds segmentation, describing MRLFPA's effectiveness at segmentation in an intuitive way. The better objective values represent MRLFPA's strength in solving segmentation problems, while the smaller CPU running time suggest that the proposed segmentation algorithm is much more efficient than GA, PSO, DE, and FPA. Furthermore, the segmentation results shown in Figure 1 are clearly separated by gray levels into different regions. This remarkable achievement indicates that MRLFPA holds outstanding promise for gray scale segmentation.

5. Conclusion

This paper pursued the challenging issue of multi-thresholding image segmentation, an exponential problem that is appropriate for meta-heuristic algorithms. FPA is a new population-based algorithm, with a strong ability for exploitation. We modified FPA and proposed MRLFPA for multi-threshold segmentation. In order to verify its efficiency and effectiveness, we considered Otsu's objective function and used eight medical images to test the proposed algorithm. The results obtained through MRLFPA agreed with those produced by GA [14], PSO [13], DE [8], and FPA [9]. Based on data in Table 2, we can conclude that MRLFPA can obtain objective values for Otsu's functions, with more impressive deviation results than in the other methods. The experimental results show that our proposed method outperforms other methods in terms of solution quality, stability, and computation efficiency.

Acknowledgments

This work is supported by National Science Foundation of China under Grant No. 61165015 and No. 61463007.

References

[1] N. Otsu, A threshold selection method from gray-level histograms, Automatica **11** (1975), 23–27.
[2] P.-Y. Yin, A fast scheme for optimal thresholding using genetic algorithms, Signal processing **72** (1999), 85–95.
[3] J.Z. Cheng, Cell-based two-region competition algorithm with a map framework for boundary delineation of a series of 2D ultrasound images, Ultrasound in medicine & biology **33** (2007), 1640–1650.
[4] M Maitra and A Chatterjee, A hybrid cooperative–comprehensive learning based PSO algorithm for image segmentation using multilevel thresholding, Expert Systems with Applications **34** (2008), 1341–1350.
[5] J.Z. Cheng, ACCOMP: Augmented cell competition algorithm for breast lesion demarcation in sonography, Medical physics **37** (2010), 6240–6252.
[6] A.W.C. Liew, W.C. Alan and H. Yan, An adaptive spatial fuzzy clustering algorithm for 3-D MR image segmentation, IEEE Transactions on Medical Imaging **22** (2003), 1063–1075.
[7] F. Zhao, H. Liu and J. Fan, A multiobjective spatial fuzzy clustering algorithm for image segmentation, Applied Soft Computing **30** (2015), 48–57.
[8] E. Cuevas, F. Sención and D. Zaldivar, A multi-threshold segmentation approach based on artificial bee colony optimization, Applied Intelligence **37** (2012), 321–336.
[9] X.S. Yang, Flower Pollination Algorithm for Global Optimization, Unconventional Computation and Natural Computation, Springer Berlin Heidelberg, Germany, 2012, pp. 240–249.
[10] X.S. Yang, K. Mehmet and X.S. He, Multi-objective flower algorithm for optimization, Procedia Computer Science **18** (2013), 861–868.
[11] M. Sharawi, E. Emary and I.A. Saroit, Flower pollination optimization algorithm for wireless sensor network lifetime global optimization, International Journal of Soft Computing and Engineering **4** (2014), 54–59.
[12] R. Prathiba, M.B. Moses and M. Sakthivel, Flower pollination algorithm applied for different economic load dispatch problems, International Journal of Engineering and Technology **6** (2014), 1009–1016.
[13] R. Storn and K. Price, Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces, Journal of Global Optimization **11** (1997), 341–359.
[14] U. Maulik and S. Bandyopadhyay, Genetic algorithm-based clustering technique, Pattern recognition **33** (2000), 1455–1465.