Adaptive Artificial Bee Colony for Segmentation of CT lung Images

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ABSTRACT
Image segmentation of pulmonary parenchyma can be detected from multisliced CT images using image segmentation. It can be modeled as a nonlinear multimodal global optimization problem. The traditional 2D Otsu algorithm, though effective, is quite time consuming for determining the optimum threshold values. In this paper we propose a combination of 2D Otsu method with modified ABC algorithm (called Adaptive ABC or AABC) to reduce the response and computational time. The proposed method has been implemented and tested on three images. Experimental results show the competence of the proposed method for selecting the optimum threshold.

General Terms
Image Segmentation, Algorithms.

Keywords
2D Otsu, ABC, thresholding, image segmentation.

1. INTRODUCTION
Thresholding, an important part of image processing, is an effective tool to separate objects from the background [12]. Image segmentation can be used for various purposes such as object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up and in medical image processing [13-14].

In medical image processing segmentation has been used for various purposes like: surgical planning, heart image extraction from cardiac cine angiograms, detection of tumors, measuring tumor volume, detection of micro classification on mammograms, detection of the coronary border in angiograms, its response to therapy, automated classification of blood cells, etc. [15-18]. In some applications, it may be applied to classify image pixels into anatomical regions [19]. Since there is nogeneral solution to the image segmentation problem, these techniques often have to be combined with domain knowledge in order to effectively solve an image segmentation problem for a given problem domain. For grayscale images four popular approaches are: threshold techniques, edge-based methods, region-based techniques, and connectivity-preserving relaxation methods [1-7,13, 14, 20 - 24]. Mathematically speaking, an image segmentation problem can be modelled as a global optimization problem for which a suitable approach is desired.

One of the most commonly used and possibly one of the oldest methods for image segmentation is due to Otsu. This method though popular and reasonably effective has a drawback that it is computationally very costly. This drawback may be reduced to a large extent by merging or hybridizing it with some other technique for global optimization.

In the past few years, researchers have shown considerable interest in nature inspired metaheuristics like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony algorithm (ABC) and Ant Colony Optimization (ACO) etc. for dealing with various aspects of image processing including segmentation [10, 11].

In the present study we have proposed a modified Artificial Bee Colony (ABC) called Adaptive ABC or AABC and have merged it with 2D Otsu method for segmentation of CT lung images.This paper consists of 7 sections. Brief view of ABC is given in section 2. 2D Otsu method is discussed in section 3. Section 4 presents the modified AABC algorithm and in section 5, the proposed methodology is given. Experimental results and analysis are given in section 6, and finally the paper concludes with section 7.

2. ARTIFICIAL BEE COLONY ALGORITHM
ABC classifies the foraging artificial bees into three groups, namely, employed bees, onlooker bees and scout bees. Half of the colony consists of employed bees, and the other half includes onlooker bees. In the foraging process of honeybee colonies, initially, some bees search randomly for food in a given area around the hive. After finding a food source, these bees take some nectar back to the hive, deposit the nectar and share the nectar information of the food sources with other bees waiting at the dance area (where waggle dance is performed) within the hive. The bee colony then enters a new cycle of iterations. At each iteration, following steps take place: (1) after sharing the information, an employed bee will either become an onlooker after abandoning the food source or continue to forage its previously visited site; (2) some onlookers in the hive will simultaneously follow some employed bees based on the received information in order to further forage on some specific memorized food sources; and (3) some scouts will spontaneously start a random search. An important stage of the ABC algorithm, from which in fact the collective intelligence arises, is the sharing of information. This is achieved by influencing the behavior of onlookers which will select their food source according to following probability:

$$P_i = f_i / \sum_{k=1}^{SN} f_k \quad (1)$$

wheref_i , is the fitness value of a i, food source (position in parameter space). In other words onlookers will explore promising locations with higher probability than others.

Candidate food sources are generated from memorized ones according to:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{i,j} - x_{k,j}) \qquad (2)$$

where $i,k = 1,\dots,SN,\ j = 1,\dots,n,$ and v_i is the new food source generated by using both, the current food source x_i and a randomly chosen food source x_k from the population and $-1 \le \phi_{ij} \le 1$ (generated at random every time it is used) determines the step size of the movement. Both, *i* and *j* are generated at random but $k \neq i$. When a source does not improve after a certain number of iterations, it is abandoned and replaced by one found by a scout bee, using Eq. 2: which involves the generation of a new solution at random.

$$x_{i,j} = x_{\min,j} + rand(0,1)(x_{\max,j} - x_{\min,j}) \qquad (3)$$

Where i = 1,2,..,SN. j = 1,2,…,n. $x_{max,j}$ and $x_{min,j}$ are upper and lower bounds of parameter *j*, respectively. These food sources are randomly assigned to *SN* number of employed bees and their fitnesses are evaluated.

Computational steps of basic ABC:

1: Initialize Population.
2: Repeat.
3: Place the employed bees on their food sources.
4: Place the onlooker bees on the food sources depending on their nectar amounts.
5: Send the scouts to the search area for discovering new food sources.
6: Memorize the best food source found so far.
7: until requirements are met.

3. 2D OTSU METHOD FOR SEGMENTATION

Initially, 1D Otsu method was proposed for segmenting the lung CT images. But it was observed that only for high contrast images 1D Otsu method gave good result. Consequently, 2D Otsu method was proposed for dealing with lung CT images even with low contrast. We now explain in brief the 2D Otsu method for segmentation.

An image with size M×N can be represented by a 2D gray level intensity function *f(x, y)*. The value of *f(x, y)* is the gray level, ranging from 0 to *L*-1, where *L* is the number of distinct gray levels. In a 2D thresholding method, the gray level of a pixel and its local average gray level are both used. The local average gray level is also divided into the same *L* values, let *g(x, y)* be the function of the local average gray level [26].

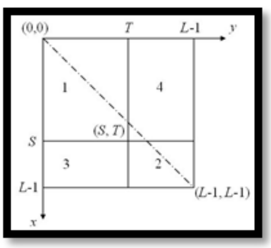

Fig.1: .Two dimensional Histogram

Let be the total number of occurrence (frequency) of the pair *(i,j)* which reprsents pixel *(x, y)*with *f(x, y)=i* and *g(x, y)=j* , *r M N ij* 0 ≤ ≤ × , then the joint probability mass function *pij* is given by:

$$p_{ij} = \frac{r_{ij}}{M} \times N \qquad where\ i,j = 0, 1, 2, \dots L\text{-}1 \quad (4)$$

$$\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{ij} = 1 \qquad (5)$$

The 2D histogram of the image is p_{ij} . Figure 1 shows the top view of 2D histogram. It covers a square region with size $L \times L$. The x-coordinate (i) represents gray level and the coordinate (j) represents the local average gray level. The 2D Histogram is divided into four quadrants at a vector(S, T), where $0 \le (S,T) \le L-1$. The dash dot line is the diagonal of 2D histogram. The pixels interior to the objects or the background should contribute mainly to the near-diagonal elements because of the homogeneity. Because of the pixels interior to the objects and background, the gray level of a pixel and its local average gray level are similar. For pixels in the neighbourhood of an edge between the objects and the background, the gray level of a pixel differs fairly from its local average gray level. Therefore, quadrants 1 and 2 contain the distributions of background and object classes, whereas the off diagonal quadrants 3 and 4 contain the distributions of pixels near edges and noises [26].

Now suppose that the pixels are partitioned into two classes C0 and C1 (background and objects) by a threshold pair(s, t), then the probabilities of class occurrence are given by:

$$p_0(s,t) = \sum_{i=0}^{s} \sum_{j=0}^{t} p_{ij} \qquad (6)$$

$$\boldsymbol{p_1(s,t) = \sum_{i=s+1}^{l-1} \sum_{j=t+1}^{l-1} p_{ij}} \qquad (7)$$

And the corresponding class means levels are

$$\mu_0 = (\mu_{00}, \mu_{01})^T = \left(\frac{\sum_{i=0}^{s} \sum_{j=0}^{t} i.p_{ij}}{p_0}, \frac{\sum_{i=0}^{s} \sum_{j=0}^{t} j.p_{ij}}{p_0} \right)^T \qquad (8)$$

$$\mu_1 = (\mu_{10}, \mu_{11})^T = \left(\frac{\sum_{i=s+1}^{l-1} \sum_{j=t+1}^{l-1} i.p_{ij}}{p_1}, \frac{\sum_{i=s+1}^{l-1} \sum_{j=t+1}^{l-1} j.p_{ij}}{p_1} \right)^T \qquad (9)$$

The total mean level vector of 2D Histogram is:

$$\mu_T = (\mu_{T0}, \mu_{T1})^T = \left(\sum_{i=0}^{l-1} \sum_{j=0}^{l-1} i.p_{ij}, \sum_{i=0}^{l-1} \sum_{j=0}^{l-1} j\,p_{ij} \right)^T (10)$$

Because of assumption that the occurrences of image data in off-diagonal quadrants of 2D histogram can be neglected, it is easy to be verified that

$$p_0 + p_1 \approx 1, \mu_T \approx p_0\mu_0 + p_1\mu_1 \qquad (11)$$

The between class variance matrix is defined as:

$$S_B = \sum_{k=0}^{1} p_k [(\mu_k - \mu_T)(\mu_k - \mu_T)^T] \qquad (12)$$

By using trace of SB as measurement of between class variance, there is

$$t_r S_B = (\mu_i(s,t) - p_0\mu_{T0})^2 + \frac{(\mu_j(s,t) - p_0\mu_{T1})^2}{p_0(1-p_0)} \quad (13)$$

Where

$$\mu_i(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} i.\,p_{ij}$$

$$\mu_i(s,t) = \sum_{i=0}^{s}\sum_{j=0}^{t} j.\,p_{ij}$$

A threshold vector is selected by maximizing $t_r S_B$

$$t_r S_B(s,t) = max_{0<s,t<l-1}\{t_r S_B(s,t)\} \quad (14)$$

The traditional 2-D Otsu needs to iterate every threshold vector, thus the computation complexity is very large, the computation order of complexity is about $O(L^4)$ [26], therefore this paper introduces ABC algorithm to solve this problem.

4. PROPOSED AABC

Like other evolutionary algorithms, ABC also faces up to some inherent problems like slow or premature convergence particularly in case of multimodal problems. The proposed algorithm is a combination of modified ABC algorithm called AABC and 2D Otsu method. In the proposed AABC the initial population of food sources is a union of random numbers and the numbers generated using opposition based learning [25]. Further in the algorithm the employed bee and onlooker bee searches the food sources using the following Equation:

$$v_{ij} = x_{ij} + F(x_{ij} - x_{kj}) \quad (15)$$

Where F is calculated using following equations:

$$F_{G+1} = \begin{cases} F_l + rand_1\sqrt{rand_2^2 + rand_3^2} & if\ P_F < rand_4 \\ F_u & otherwise \end{cases} \quad (16)$$

$rand_1 \ldots rand_4 \in [0,1]$ are random numbers generated uniformly and P_F is the probability to adjust the factor *F*. F_u&F_l are adjusted to 0.1 & 2.0 respectively. To keep F_u&F_l in range following bound is used:

$$F_{G+1} = \begin{cases} 2*F_l - F_{G+1} & if\ F_{G+1} < F_l \\ 2*F_u - F_{G+1} & if\ F_{G+1} > F_u \end{cases} \quad (17)$$

The generation of a new food sources is seen as a black box procedure depending on *F*. This modification makes the algorithm sort of adaptive in nature. Also, it may help in maintaining the diversity and balancing the exploration-exploitation factors. The Pseudocode of the proposed AABC is givenin Fig. 2.

1. Initialize the population of Food Sources SN, **[25]**
2. Evaluate the fitness
3. Repeat (till termination criterion not satisfied)
4. For i = 1 to SN
5. Generate new Food source V_i using

   $$v_{ij} = x_{ij} + F(x_{ij} - x_{kj})$$

   where*F* is amplification factor.
6. if $f(V_i)$< $f(X_i)$ then
7. $X_i = V_i$
8. else
9. Generate new Food source V_i using

   $$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj})$$

10. if $f(V_i)$< $f(X_i)$ then
11. $X_i = V_i$
12. End if
13. End if
14. End for

Fig.2: Pseudocode of the AABC

5. PROPOSED METHODOLGY

The proposed methodology is a simple and efficient blend of 2D Otsu and modified AABC algorithm. The proposed method starts with 2D Otsu method to obtain the fitness function.

$$f_i = (\mu_i(s,t) - p_0\mu_{T0})^2 + \frac{(\mu_j(s,t) - p_0\mu_{T1})^2}{p_0(1-p_0)} \quad (18)$$

Once the objective function is obtained, AABC is applied to find the optimized values of parameters *s* and *t*.

6. EXPERIMENT RESULTS AND ANALYSIS

To evaluate the proposed algorithm, we compared it with classical Otsu algorithm, ABC embedded Otsu method and proposed AABC embedded Otsu Method. Experiment data is shown in 6.1, 6.2 and 6.3.

6.1 Computation Time Comparison Table

Table 1. Comparison of Total Segmentation Time(ST) and Thresolding Selection Time

Input Image	2D Otsu Method		2D Otsu with ABC		2D Otsu with AABC	
	Total st(sec)	*Threshold Selection Time(Sec)*	*Total st(sec)*	*Threshold Selection Time(Sec)*	*Total st(sec)*	*Threshold Selecetion Time(Sec)*
CT-1	150	85	93.1	1.7261	77.28	1.6223
CT-2	135	85	61.6	1.2637	79.91	1.1291
CT-3	114	66	67.9	.8562	65.32	.8626

6.2 Performance Evaluation Table

Table 2. Evaluation Results Using Region Non Uniformity

Input Image	*2D Otsu Method*	*2D Otsu using ABC*	*2D Otsu using AABC*
CT-1	.1406	.1335	**.1401**
CT-2	.1387	.1368	**.1267**
CT-3	.1215	.1186	**.1190**

6.3 Performance Evaluation Table Using Correlation

Table 3. Evaluation Results Using Correlation

Input Image	*Correlation Value*
CT-1	.9965
CT-2	1.015
CT-3	.9967

7. CONCLUSION

In the present study we proposed a simple and effective blend of modified ABC algorithm called AABC and 2D Otsu method. While Otsu is used to generate the function to be optimized, AABC is applied to determine the optimized values of threshold parameters. The proposed method is compared with the basic 2D Otsu method and 2D Otsu combined with PSO. The results indicate the competence of the proposed method. In future we plan to investigate the different aspects of medical imaging which can be formulated as optimization problems and develop effective methods for

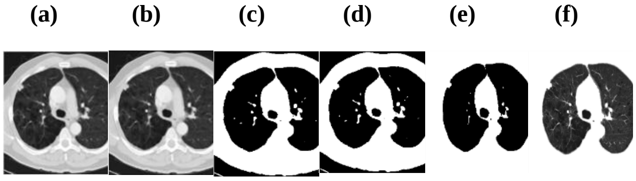

Fig. 3. (a) CT image 1 (CT-1). (b) Filtered image. (c) Lung segmented image using 2D Otsu method. (d) Lung segmented image using 2D Otsu optimized by DE. (e) Erosion applied image. (f) Parenchyma segmented image.

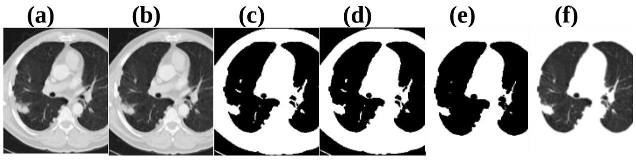

Fig. 4. (a) CT image 2(CT-2). (b) Filtered Image (c)Lung segmented image using 2D Otsu method.(d) Lung segmented image using 2D Otsu optimized by DE.(e) Erosion applied image. (f) Parenchyma segmented image.

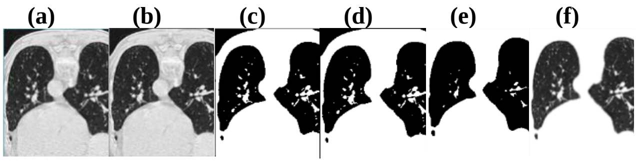

Fig. 5. (a) CT image 3(CT-3). (b) Filtered image (c) Lung segmented image using 2D Otsu method. (d) Lung segmented image using 2D Otsu optimized with DE. (e) Erosion applied image. (f) Parenchyma segmented image.

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