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An Artificial Bee Colony Optimization for MRI Fuzzy Segmentation of Brain Tissue

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***Abstract*—Image segmentation aims to separate the structure of interest objects from the background and the other objects. Many approaches have been developed to segmentation of brain MR images, which among them the fuzzy c-mean (FCM) algorithm is widely used in MR images segmentation. In this paper we introduce a noise probability for each pixel within the image; then according to their noise probability, the artificial bee colony (ABC) algorithm classified all pixels into two groups: *Normal* and *Noisy*. In proposed algorithm, ABC optimization is used before performing the FCM clustering algorithm. Our algorithm reduced the response time with a higher quality than the previous approaches. Finally, we segment some real MR images with the proposed algorithm and compare it with the other approaches.**

Keywords-segmentation; artificial bee colony optimization; fuzzy c-means (FCM) algorithm; magnetic resonans imaging (MRI);

I. INTRODUCTION

The basic goal in segmentation process is to partition an image into regions that are homogeneous with respect to one or more characteristics [1]. Segmentation is an important tool in medical image processing and it has been useful in many applications, such as: detection of tumors, detection of the coronary border in angiograms, surgical planning, measuring tumor volume and its response to therapy, automated classification of blood cells, detection of micro calcifications on mammograms, heart image extraction from cardiac cine angiograms, etc [2]-[5]. In some applications, it may be useful to classify image pixels into anatomical regions, such as bones, muscles, and blood vessels, while in others into pathological regions, such as cancer, tissue deformities, and multiple sclerosis lesions. In magnetic resonance (MR) images processing, the goal is to divide accurately the entire image into sub regions included gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) spaces of the brain [6]. For example, in a number of neurological disorders such as multiple sclerosis (MS) and Alzheimer's disease, the volume changes in total brain, WM, and GM can provide important information about neuronal and axonal loss [7].

In recent years, many algorithms have been proposed for brain MRI segmentation. The most popular methods are included thresholding [8], region-growing [9], and clustering. The full automated intensity-based algorithms have high sensitivity to various noise artifacts such as intra-tissue noise and inter-tissue intensity contrast reduction. Thresholding is very simplicity and efficiency. If the target is clearly discernible from background, the intensity histogram of the image is bimodal and it can easier get to the optimal threshold by simply choosing the valley bottom as the threshold point. However, in most of real images, there are not clearly discernible marks between the target and the background. Clustering is most popular approach for segmentation of brain MR images and typically performs better than the other methods [10].

Evolutionary algorithms also have been used to image segmentation [11-13]. Lee *et al.* [11] has proposed an ACO-based algorithm for segmentation of brain MR images; they defined the "food" as object segmentation in the image that is memorized by ants during segmentation process. The ants iteratively change their position in the image pixels according to transition rule. Artificial Bee Colony (ABC) is a novel optimization algorithm inspired of the natural behavior of honey bees in their search process for the best food sources [14]. The ABC search process is almost similar to ACO search process, but ABC has some advantage in comparison with ACO. In recent years, ABC algorithm has been successfully applied to hard combinational optimization problems included traveling salesman problem [15], job shop scheduling [16], etc; however, it has not been used to image segmentation as yet.

Fuzzy C-Means (FCM) clustering algorithm has already been used to segmentation of MR images [10],[17-19]. Experiments show that classical FCM algorithm has an excellent performance for normal brains; however accuracy of this algorithm for abnormal brains with edema, tumor, etc, is not efficient [20]. FCM algorithm only takes care to pixels intensity and does not consider their location or neighborhood properties or any other features in the image. As a result, noisy images influence effectiveness of this algorithm. Unfortunately, MR images always contain a significant amount of noise caused by operator, equipment, and the environment, which lead to serious inaccuracies in the segmentation. It is caused any changes in pixels intensity such as noise, significantly affects the clustering results.

Some works have been done to overcome this drawback. Shen *et al.* [10] introduced the new extension of FCM. They introduced two influential parameters in segmentation where address issues of neighborhood attraction. The first parameter is the feature difference between neighboring pixels in the image, and the second one is the relative location of the neighboring pixels. They calculated these two parameters using an artificial neural network through an optimization problem. In [12], a hybrid approach based on genetic algorithm (GA) and Improved-FCM algorithm, has proposed in order to compute optimum values of these two parameters. In [17] a modified objective function is proposed to improve the efficiently of FCM algorithm. A possible partition based approach is also used by [18]. In [19] a smoothing filter is applied before using FCM; this is not preferable since some important details may be last by smoothing filter. So in this paper we introduce a noise probability for each pixel within the image; then according to their noise probability by using a simple *noise threshold* all pixels are classified into two groups: *Normally* and *Noisy*. The value of this threshold is optimized by ABC algorithm. In proposed ABC-based image segmentation algorithm, an ABC optimization is used before performing the FCM clustering algorithm.

II. Artificial Bee Colony Optimization

Artificial Bee Colony (ABC) is a novel optimization algorithm inspired of the natural behavior of honey bees in their search process for the best food sources, which proposed by Karaboga and Basturk in 2006 [14]. In groups of insects which live in colonies like the ants and bees, an individual only can do simple task on its own, while the cooperative work of colony is the main reason determining the intelligent behavior of them. A colony of artificial bees in ABC algorithm contains three groups of bees: *employed*, *onlooker* and *scout* bees [21]. Employed bees carry with them information about their food sources, its distance and direction from the nest, and the nectar amount of the source; scout bees are searching the environment surrounding the nest for finding new food sources; and onlooker bees waiting in the hive and finding a food source through the information shared by employed bees. In ABC, two key behaviors are defined: recruitment to a nectar source, and abandonment of a source [22].

In ABC algorithm, a stochastic selection scheme based on the nectar (fitness) values, which carried out by onlooker bees, is similar to the "roulette wheel selection" in GA. Also the production mechanism of neighbor source (solution) that used in ABC algorithm is similar to the mutation process in GA. Unlike GA, there is no precise crossover in ABC algorithm. However, the sharing of information between the bees is carried out by the mutation process in ABC [21]. In ABC, a food source represents a possible solution to the optimization problem. Therefore, at the initialization step, a set of food source positions are randomly considered. The nectar amount of a food source corresponds to the quality of the solution represented by that source searched by the bee. So the nectar amounts of the food source existing at the initial positions are determined. On the other hand, the quality values of the initial solutions are calculated.

Each employed bee is moved onto her food source area for determining a new food source within the neighborhood of the present one, and then its nectar amount is evaluated. If the nectar amount of the new one is higher, then the bee forgets the previous one and memorizes the new one. After the employed bees complete their search, they come back into the hive and share their information about the nectar amounts of their food sources with the onlookers waiting in the hive [21]. If the nectar amount of a food source is much higher in comparison with other food sources, it means that this source will be chosen with more probability by the onlooker. This process is similar to the natural selection process in evolutionary algorithms. Each onlooker determines a neighbor food source within the neighborhood of the one to which she has been assigned and then its nectar amount is evaluated. The search process to discover the best solutions by the artificial bees can be summarized as follow:

1. Employed bees move randomly to find solutions in the search space.
2. Review the information obtained by the employed and scout bees with onlooker bees in colony space (note that at the first yet there is no scout bee).
3. Check the stopping criterion: stop, if satisfied condition, otherwise continue.
4. Selecting scout bees and perform the recruitment process for them.
5. Vocalize of new population of bees.
6. Search neighborhood using scout bees guide, and also search randomly with some employed bees.

III. Fuzzy C-Means (FCM) Clustering Algorithm

The FCM algorithm introduced by Bezdek [23], and is an improvement of earlier clustering methods. The objective function of FCM algorithm is defined as the sum of distances between the patterns and the cluster centers:

$$J = \sum_{i=1}^{M} \sum_{j=1}^{C} U_{ij}^{q} d(x_i, v_j) \quad (1)$$

Where, C is the number of clusters that in this problem is equal to number of needed segmentation regions. The v_j represents the center of cluster j; M is the number of brain MR image pixels; the parameter q is larger than 1, and adjusts the fuzzifier intensity; U_{ij} is the membership function of attribute x_i to cluster j, which should satisfy these conditions:

$$U_{ij} \in [0,1]; \quad \sum_{j=1}^{C} U_{ij} = 1; \quad 0 < \sum_{i=1}^{M} U_{ij} < M \quad (2)$$

In Eq. 1, the $d(x_i, v_j)$ measures the dissimilarity between x_i and v_j. The popular selection for $d(x_i, v_j)$ is:

$$d(x_i, v_j) = \|x_i - v_j\|^2 = \|x_i - v_j\|^T * W_f * \|x_i - v_j\| \quad (3)$$

Here, W_f is a positive symmetric definite matrix. In order to optimize Eq. 1, the gradient descent can be used.

$$U_{ij} = 1 / \sum_{k=1}^{C} \left(\frac{d(x_i, v_j)}{d(x_i, v_k)} \right)^{(2/q-1)} \quad (4)$$

And the cluster center v_j is defined as:

$$v_j = \frac{\sum_{i=1}^{M} U_{ij}^{q} x_i}{\sum_{i=1}^{M} U_{ij}^{q}} \quad (5)$$

Note that brain MR images are gray scale images, so the dimension of feature vectors is equal to one. The FCM algorithm can optimize the objective function J using Eq. 4,5 in an interactive way. To terminate this process, an ending criterion such as $U(t) - U(t-1) < \varepsilon$ can be used.

IV. METHODOLOGY

In clustering problems, often the number of clusters is pre-known information. In brain MR images, typically clusters are four as: background, GM, WM and CSF. However, since the intensity values of background and CSF are nearly same, they are usually considered a region; so the number of clusters is reduced to three. A noise probability is introduced for each pixel within the image; the pixels according to their noise probability by using a simple *noise threshold* are classified into two groups: *Normal* and *Noisy*. The noise probability of study pixel g is defined as:

$$P_g = \frac{D_g}{255}, \quad D_g = \left| I_g - \frac{3M(I_{n1})+2M(I_{n2})+M(I_{n3})}{6} \right| \tag{9}$$

Where I_g is the intensity of study pixel g, $M(I_{n1})$ is the mean of the intensities of the pixels that are in first level of neighborhood of study pixel; $M(I_{n2})$ and $M(I_{n3})$ are mean of the intensities of second and third level respectively (Fig. 1).

$$Neighbor_{gk} = (a_g, a_k)^2 + (b_g, b_k)^2 \tag{8}$$

Note that $(a_g\ ,\ b_g)$ and $(a_k\ ,\ b_k)$ respectively the coordinates of the study pixel and the neighbor pixel k. Note that for first level pixels, $Neighbor_{gk}$=1, for second level $Neighbor_{gk}$=2, and for third level $Neighbor_{gk}$=4. The neighbors of the study pixel with coordinate (i,j) is shown in Fig. 1.

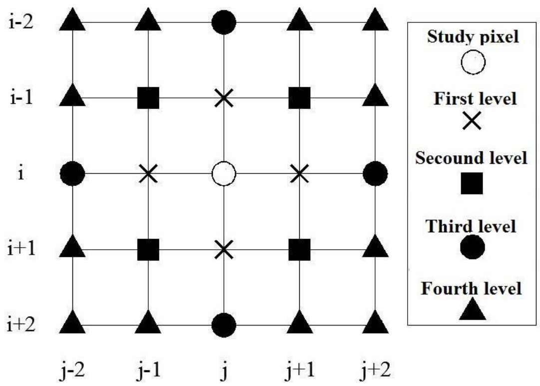

Figure 1. The neighborhood structure of study pixel within (i,j)

We introduce also a noise threshold (called λ) valued between 0~1. All pixels are compared with this threshold, if $P_g > \lambda$, it means that the study pixel g is a noisy pixel; and otherwise, the pixel g is a normal pixel. The optimal value for λ is calculated by bees. Finally we introduce a modified intensity (ModiI) matrix for the image, which is used for clustering by FCM algorithm.

If g is a noisy pixel: $\quad ModiI_g = I_g$

If g is a normal pixel: $\quad ModiI_g = \dfrac{2M(I_{n1})+M(I_{n2})}{3}$ (5)

As noted above, the interval change of the λ is between 0~1; the obtained accuracy of algorithm is based on the number of decimal digits of this parameter. In the each iteration, two intervals are defined as neighborhood for the employed bees to increase the search accuracy. In this manner, the neighborhood area for the λ for each bee is in far vicinity up to two decimal places and for close vicinity up to four decimal places. So the output response accuracy is controllable based on the number of decimal digits or modifying neighborhood area for the employed bees. In fact, with development of neighborhood area, we tried to achieve higher accuracy and higher response rate.

The basic process begins with generating a number of k artificial employed bees, which are then searching randomly in the search space; these bees perform a number of iterations. During every iteration t, each bee selects the λ according to its nectar amount. The nectar amount of a food source corresponds to the quality of the solution represented by that source searched by the bee. At the first, the early population of bees that consists of employed bees will constitute. The initial population searches randomly the search space. In the beginning total search space has the same value for all bees, and recruitment operations won't be made in this stage. After finishing the initial search, the information obtained from search space is considered as food source, and the operation of sharing information is begun in the hive space. The chance for selecting a bee as a scout bee by onlookers is computed by:

$$Chance_k = \frac{nectar_k^{\ \alpha}}{\sum_{i=1}^{N} nectar_i^{\ \alpha}} \tag{7}$$

Where $nectar_k$ is the nectar amount within the food source k, and $\sum_{i=1}^{N} nectar_i$ is the total amount of nectar available around the hive. In addition to the points above mentioned in ABC algorithm another parameter is used to avoid being trapped in local minima area, which increases the speed of this algorithm. Regarding to this parameter, the growth rate of a food source is surveyed. This growth rate reviews the changes; if the current changes in respect to previous changes are in the lack of any positive changes in several iterations, reduces the number of recruitments to search for this specific food source and avoid to search ineffective in a local minima point. The way that is used in our algorithm for recruitment, is such that selecting the number of soldiers is based on amount of optimized of the solutions in the each iterations. For the solution which has a better cost, the less number of soldiers is used. The number of soldiers for each scout bee is determined as:

$$Soldiers_i = \beta \times (P_i^{\mu} / H^{\mu}) + \gamma \tag{10}$$

Where $Soldiers_i$ is the percentage of soldiers that are selected for the i-th scout bee, P_i is the preference of the i-th scout bee, and H is the number of all scout bees. The μ is a parameter that has a constant value, or changes iteratively; this approach leads to avoid being trapped in local minima. The overall search process to discover the best value for λ and achieve to efficient brain MR image segmentation can be seen in the flow chart of Fig. 2.

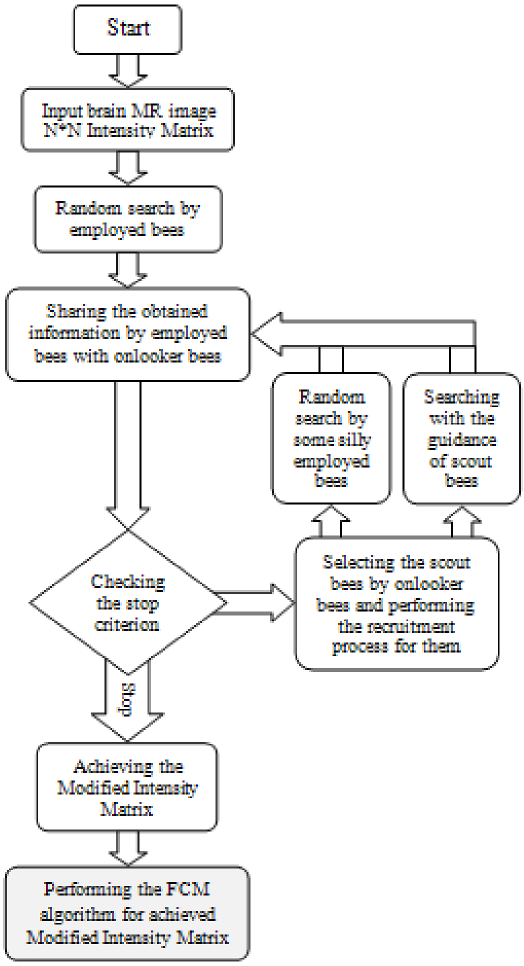

Figure 2. Fig. 2: The overall flow chart for proposed ABC-based algorithm

V. Experimental Results

All of the experiments were processed on an Intel PC with 2.53GHz processor and 4GB memory, running MATLAB R2008a on windows vista. In order to tune the ABC parameters, different values were tested, and the best ones considered. We set α=1, q=2. The number of employed bees and scout bees were set to 50 and 5 respectively, and max-iterations determined in range of 50~200. To assess the performance of the proposed ABC-based segmentation algorithm, we used real brain MR images provided by [], which are 256*256 pixels, 8bit grayscale with intensity values scaled in the interval of 0 to 255.

We applied the proposed algorithm with 50 iterations in a brain MR image with 10% noise; finally λ was achieved 0.1348. In Fig. 3,4 we can see the results of classic FCM algorithm with 100 iterations, and the results of our algorithm. We also performed the proposed approach with GA and ACO algorithms; Fig. 5 illustrates a comparison among GA, ACO and ABC. We repeated our experiments with the images consist of 5%, 15% and 20% noise. To evaluate the efficiently of proposed algorithm, we compared the results with the segmentation results by a Radiologist. For this aim, we removed background from the image, the remained were 29261 pixels. We introduced the *Accuracy* of segmentation as divided error pixels to all goal pixels (29261 pixels). Obtained results summarized in Table 1.

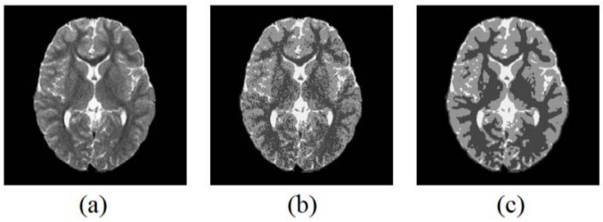

Figure 3. (a) the original image, (b) result of segmentation by classic FCM algorithm, (c) results of segmentation by our algorithm

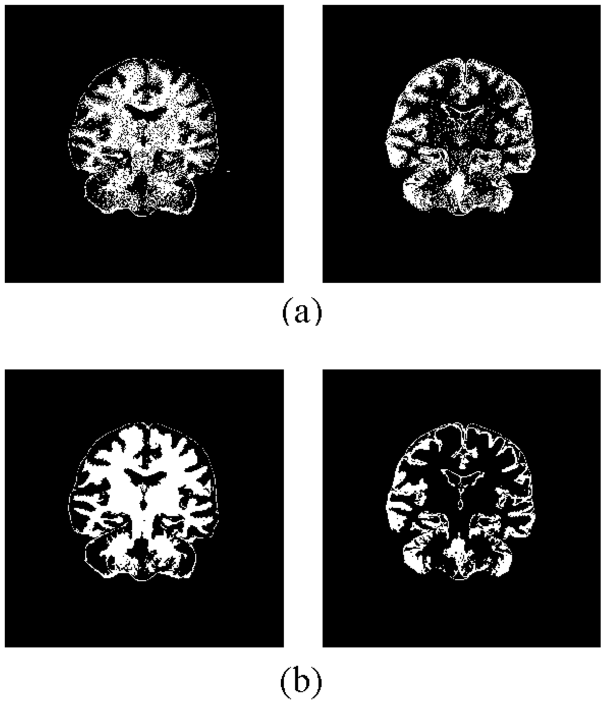

Figure 4. Results of brain MR image segmentation, divided to GM, WM and CSF respectively from left to right. (a) via classic FCM algorithm,(b) via proposed algorithm.

TABLE I. Comparison the obtained results with our algorithm

Noise	Classic FCM		Our algorithm	
	No.error pixels	Accuracy	No.error pixels	Accuracy
≈0	535	98.17%	472	98.38%
5%	1374	95.30%	554	98.10%
10%	2471	91.55%	717	97.54%
15%	4486	84.66%	892	96.95%
20%	5712	80.47%	1086	96.28%

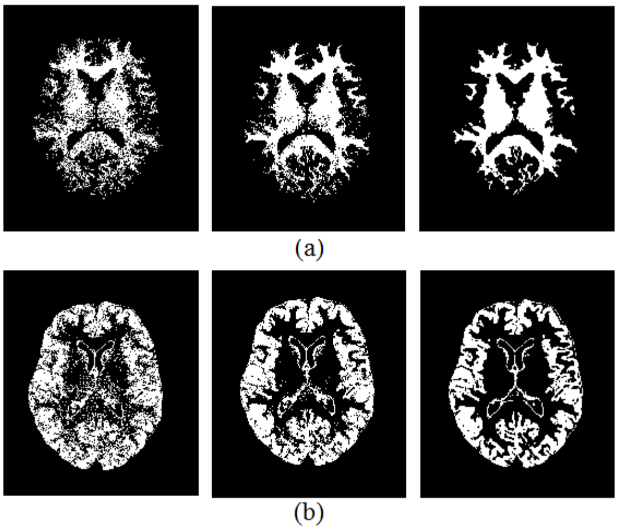

Figure 5. Respectively from left to right consist of segmentation via GA, ACO and proposed ABC-based algorithms, divided to (a) GM, (b) WM.

VI. CONCLUSION

This paper discussed the shortcoming of Traditional FCM clustering algorithm for MR images segmentation, which may performs very fast and simple, but this algorithm do not guarantee high accuracy especially for noisy or abnormal images. Unfortunately, MR images always contain a significant amount of noise caused by operator, equipment, and the environment, which lead to serious inaccuracies in the segmentation. We introduced a Modified Intensity matrix using ABC before performing FCM clustering algorithm, in order to avoid sensitivity to noise. The proposed algorithm is efficient in terms of performance, speed and avoidance trapping in local minima points. From the obtained results, ABC it achieved better performances compared with GA and ACO algorithms. Also, the ABC algorithm is quicker than in finding optimal solution.

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