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Artificial Bee Colony Based Fuzzy Clustering Algorithms For Mri Image Segmentation

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Abstract: **Fuzzy clustering algorithms (FCM) have some disadvantage. The main disadvantage is the cluster centroids initialization sensitivity and trapped in local optima. This study proposed a novel clustering method by coupling artificial bee colony with fuzzy c-means (ABC-FCM) algorithm. The technique exploits the superior capabilities of ABC in searching for optimum initial cluster centers and uses these clusters as the input for FCM, thus improving the segmentation of MRI brain images. The performance of the newly developed approach was tested using two sets of MRI images: simulated brain data and real MRI images.**

I.Introduction

Fuzzy clustering technique is a very popular method. This is because of its superior capability in handling unclear segment boundaries present in most MRI images. More specifically, fuzzy c-means (FCM), which is a special type of fuzzy clustering algorithm [1], is most frequently employed in image segmentation processes [2, 3]. Both image segmentation and image clustering share a common goal, i.e. determining the accurate classification of their input images. In the clustering method, the image pixels are represented as patterns, where each image pixel belongs to a specific cluster (image segment) based on similarity and distance [4].

In recent times, many metaheuristic search algorithms have been merged with FCM algorithm in order to identify the optimal cluster centers. Such modified algorithms have the ability to explore the whole search space for the purpose of identifying probable solutions [5]. The present study investigates the effectiveness of the new hybrid algorithm in utilizing the near-optimal initial cluster centres. These cluster centers are generated by the ABC algorithm and then used by the FCM algorithm for the purpose of image segmentation. This hybrid approach exploits the strengths of the two algorithms, thus ensuring superior and consistent results in MRI image segmentation.

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The remainder of this paper is structured as follows: section 2 provides an overview of the ABC search algorithm; section 3 describes the essential features of fuzzy clustering with FCM; section 4 discusses the newly developed hybrid method; section 5 details the results of experiments used to assess the performance of the (ABC-FCM) algorithm; and finally, section 6 presents the conclusion.

II. ARTIFICIAL BEE COLONY ALGORITHM (ABC)

The Artificial Bee Colony (ABC) algorithm has been proposed by Karaboga (2005) [6], based on the smart foraging behaviour of honey bee swarms. The ABC is effective, and basic population based random optimization algorithm; particularly when compared with other Metaheuristic algorithms, such as, Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Differential Evolution (DE)[7]. Fundamentally, the artificial bee colony include three categories of bees, such as, scouts bees, employed and onlookers; where the initial part of the colony is occupied by the employed bees, and the onlookers occupy the subsequent part of the colony. The volume of food sources are equivalent to the number of employed bees; after the food source has been deserted by of the employed bees, then they become a scout. A probable option to the optimization problem has been signified by the location of a food source; furthermore, the amount of nectar in the food source refers the excellence of fitness of the corresponding solution, depicted by the food source. Based on the probability-based selection process the onlookers are positioned on the food sources. The increase in the amount of nectar in the food source triggers the increase in probability value of the food source, desired by the onlookers

III. CLUSTERING WITH FUZZY C-MEANS

Clustering is a type of unsupervised learning technique which is employed in computing in order to classify similar data points (patterns). The data points are grouped based on some similarity among them and in such a way that it maximizes the intra-cluster similarity and minimizes the inter-cluster similarity [8]. Fuzzy partitioning based clustering is used on a group of n objects (pixels), each of which consists of a feature vector. The feature vectors themselves consist of d real-valued measurements which describe the essential characteristics of the object represented by xi. The fuzzy clusters c of the objects thus formed can be easily represented by a fuzzy membership matrix known as the fuzzy partition. In such a partition, the u_{ij} quantity points to the fuzzy membership of the i^{th} object in the j^{th} fuzzy cluster. In this particular arrangement, each individual data object is a member of a particular (possibly null) degree of every fuzzy cluster. FCM utilizes iterative operations and is able to perform local minimization of the following objective function.

where the j terms represent the centroids of the clusters and denotes an inner-product norm (e.g. Euclidean distance) from the data point x_i to the j^{th} cluster center, The parameter m 2 [1;1] represents a weighting exponent which is used for each fuzzy membership and helps determine the degree of fuzziness due to the categorization.

The steps in FCM is as follows: (1) The number of fuzzy clusters is selected, as represented by c, (2) the initial cluster centers are then selected, (3) the elements of the fuzzy partition matrix are then calculated, (4) Finally, the cluster centers are computed. Steps 3 and 4 are repeated until the iteration number' t' exceeds a certain limit or until a criteria for termination is encountered.

IV. Proposed method

This section investigates the performance of the ABC in terms of finding the near-optimal cluster centers' values. These values are required for initializing the FCM algorithm. The proposed hybrid algorithm uses a clustering technique comprising two phases. In phase one, the ABC algorithm is employed to explore the search space in order to find the near-optimal cluster centers. These centers are evaluated using the FCM objective function which has been refined. In phase two, the best cluster centres are used as the initial cluster centres for use in the FCM algorithm. The two phases are discussed in more detail below.

A. Identifying near-optimal cluster centres using ABC search.

The cluster centres related to a specific data set are encoded by each solution generated by the ABC search. The solutions can be represented mathematically by Eq. 10 below:

$$a - \Big(\overset{s_1}{a_1 a_2 \dots . a_d}\,,\ \overset{s_2}{a_1 a_2 \dots . a_d}\,,\ \overset{s_3}{a_1 a_2 \dots . a_d}\Big). \qquad (10)$$

Where a_i is a mathematical quantity which describes a cluster center and $a_i \in A$. A is the collection of all possible array of each and every pixel characteristics. This means that each individual cluster center s_i can be fully described by d numerical features comprising the set$\{a_1, a_2, \dots, a_d\}$. As a consequence, each solution possesses an actual size of$(c \times d)$, where c stands for the number of clusters and d represents the feature number outlining the given data.

To better understand the connection between the clustering and image segmentation, it is convenient to think that every single pixel in an image can be mapped as a data point in the clustering sector. Also, it is possible to represent the different image regions as clusters or classes. Therefore, for a 256 x 256 sized image, there are 65,536 data points or pixels. For example, a grey MRI image of the brain has three separate regions (the white matter (WM), the grey matter (GM), and the cerebrospinal fluid (CSF)). Also, it typically has an 8-bit depth and three other essential features (i.e., intensity value, energy, and entropy). These parameters will be present for each and every pixel. The possible pixel intensity value related to the depth of the image is then in the interval ∊ [0,255]. On the other hand, the deterioration and energy aspects are in the interval $\in [0, 10]$. An ABC solution of such an image could be (5, 2.5, 2.6, 30, 6.2, 2.1, 80, 2.3, 1.3), where the first three digits (5, 2.5, 2.6) represent the values of the cluster centre for the first image region of each image sequence. The second three digits (30, 6.2, 2.1) represent the cluster centre values for the second image region. Finally, the third cluster centre (80, 2.3, 1.3) represents the center values for the third image region. The initialization step of the ABC search algorithm is evaluated. All possible cluster centers for the different solutions can be initialized at random depending upon the spread of data for their image attributes.

Subsequently, the fitness value is evaluated for all possible solutions using the objective function. The output of the evaluation contains all the solutions arranged in descending order of their individual objective function value. After this, ABC determines the minimum values by comparing the values of the probable solutions with the objective function. This comparison enables the accurate identification of the near-optimal cluster centres by ABC and ensures that the fuzzy c-means approach can locate the near-global optima instead of getting stuck in some local optima. Therefore, this process significantly enhances the performance of the FCM, indicating that (ABC-FCM) has the potential to replace the traditional approach of performing multiple random initializations in order to identify the cluster centers of datasets.

The fitness degree for each solution is evaluated from its assessment or fitness value. The present study utilized an improved version of the traditional FCM objective function [9] for fitness calculations. This was done because the cluster centers are used primarily during the evolution phase at the first stage of (ABC-FCM). The modified FCM objective function is dependent upon the calculations pertaining to the cluster centres. Therefore, due to these adjustments, the membership matrix U, which represents the standard objective function, is not used. According to Hathaway and Bezdek (1995) [9], in general both standard and reformulated objective functions are comparable in their effectiveness. However, the latter or reformulated objective function is much simpler. This simplicity of the objective function translates directly into lower computational time. The reformulated and modified version of the FCM's objective function is represented below:

$$R_m = \sum_{i=1}^{n} \left(\sum_{j=1}^{c} D_{ji}^{\frac{1}{1-m}} \right)^{1-m}$$

Where D_{ij} is $\|x_i - v_j\|$ the distance from pixel intensity x_i to the jth cluster Centre. M Indicates the degree of fuzziness of the resulting classification and it is fixed at 2. 'n' Represents the total number of pixels for the given image. The proposed algorithm measures the aggregate of all the distances among the pixels of the given image with respect to each cluster centre generated from the new solution. However, the ABC algorithm tries to minimize this R_m (cluster validity), thereby identifying the likely near-optimal solution. It can also stop when the stopping criterion is met.

The objective function is calculated for the new ABC solutions $f(a')$. This updates the existent solutions with the newly calculated values $a' = (a'_1, a'_2, a'_3, \dots, a'_N)$. If the value of the new solution is better than the worst previous solution, the new one replaces the old solution. Otherwise, the new solution to the objective function is disregarded.

The iterations related to the evolving processes of ABC is terminated when the optimum number of improvisations (max generations) is met. Lastly, the optimum solution is selected for the particular problem concerned. However, this type of clustering technique is very computationally intensive, specifically for problems involving a huge number of objects [10]. Therefore, to address this problem, a simplification phase in included to help the efficiency of ABC search. This is done by minimizing the number of objects to be clustered. This in turn minimizes the total time required in identifying the near-optimal solution.

B. FCM-based clustering

The FCM algorithm begins the clustering process with the cluster centres generated by the ABC algorithm. These cluster centres are used for initialization and everyiteration the fuzzy membership of each individual data point with regards to every cluster is determined as per Eq. 7. Depending upon these membership values, the cluster centres are recalculated as per Eq. 8. The FCM algorithm terminates the iterative process when no further change happens to the cluster centres.

V. experiments and results

In experiment part the data set used consists of two different sets of 3 dimensional MRI images of the brain. first data set contained three MRI simulated brain mages [11]. The second dataset consisted of three images representing 3 dimensional MRI images of real and normal brains[12].

The suitability and quality of a solution generated by an optimization algorithm is usually evaluated with respect to its intent function. In the present study, the tests were designed in order to measure the efficiency of the ABC search algorithm in determining preliminary cluster centers for the FCM algorithm. These generated clusters could then be used in the initialization of FCM instead of using the conventional random initialization technique discussed previously. The result obtained by using FCM with ABC search initialization is called (ABC-FCM), whereas the outcomes for the FCM with random initialization are denoted as FCM. The current study used the intent function value as a standard for measuring the effectiveness of the clustering generated by ABC. The outcomes demonstrate that a major portion of the analyzed images have considerable improvement with regards to minimization of the objective function values when using (ABC-FCM). The bold items in Table 1 highlight equal or better results obtained by (ABC-FCM) in comparison with FCM.

Figure1, 2 and 3 illustrate the original images, ground truth images and segmented images by (ABC-FCM) for all simulated and real MRI brain images. This figures show the robust and stability of segmented images by (ABC-FCM). The segmented images investigate good matching with ground truth images (i.e. the segmented images by radiologist expert.

TABLE I :COMPARATIVE RESULTS (RM) BETWEEN (ABC-FCM) AND FCM.

MRI	(ABC-FCM)		FCM	
	AVG Rm	SD±	AVG Rm	SD±
S01	68549832	889745	74052495	113098812
S02	726388912	434458	85187983	11770134
S03	76321907	2179469	79319368	8836978
R01	72930209	594471	92058746	25458388
R02	80590613	936307	84778061	5342354
R03	86801283	8237290	87843696	3891235

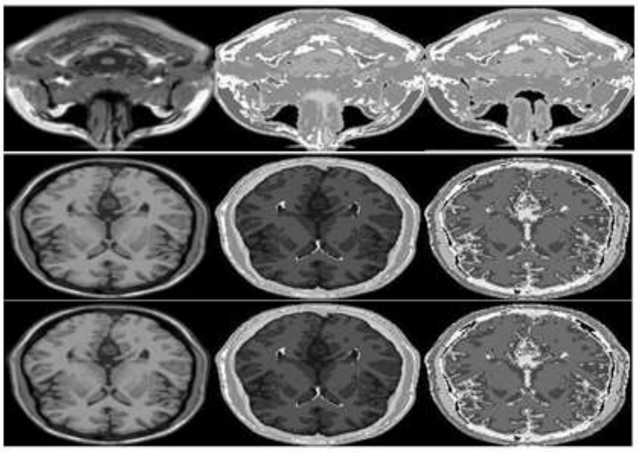

Figure 1. from left to right, original simulated MRI T1 images, ground truth simulated MRI T1 images, and simulated MRI T1 image segmented by (ABC-FCM).

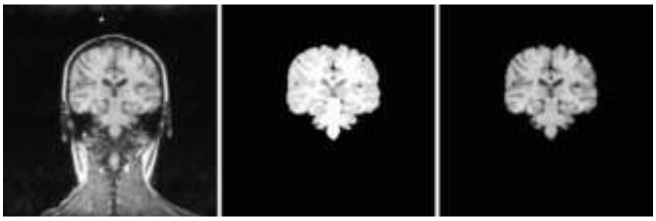

Figure 2.Tissue removal steps for real MRI images from left to right, original volume, ground truth, region of interest.

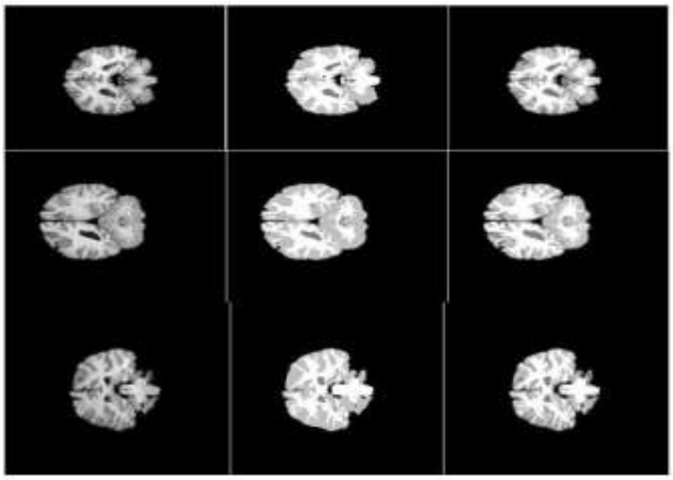

Figure 3. real MRI images, from left to right, original images, ground truth images, and segmented images by (ABC-FCM).

VI. Conclusion

This research paper proposes a novel image data clustering technique developed by coupling ABC algorithm (ABC) with fuzzy c-means algorithm (FCM). It is aptly named (ABC-FCM) and is used to segment MRI brain images obtained from authentic published sources. The technique consists of two stages. The first stage utilizes the versatility of the ABC algorithm in identifying optimal initial cluster centres. The second stage then uses these results to initialize the FCM, which performs the final clustering of the images. The (ABC-FCM) was subsequently used to segment MRI images of simulated and real MRI brain images obtained from authentic sources. Its performance was then compared to the randomly initialized FCM segmentation approach.

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