A New Hybrid Image Segmentation Method Based on Fuzzy C-Mean and Modified Bat Algorithm

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Received 16 No .2019, Revised 10 Jun. 2020, Accepted 24 Jun. 2020, Published 1 Jul. 2020

Abstract: Magnetic resonance imaging (MRI) plays an important role in clinical diagnosis, because of that it has attracted increasing attention in recent years. The symptom of many diseases corresponds to the brain’s structural variants. The detection of various diseases has become very useful through the segmentation methods. Fuzzy c-means (FCM) considers among the popular clustering algorithms for medical image segmentation. However, FCM is sensitive to the noise and falls into local optimal solution easily because of the random initialization of the cluster centers. In this research, we propose a hybrid method based on modified fuzzy bat algorithm (MFBA) and the FCM clustering algorithm named MFBAFCM. This developed approach uses the MFBA to get better initial cluster centers for the FCM algorithm by using a new fitness function, which combines intra cluster distance with fuzzy cluster validity indices. Experimental results on several MRI brain images corrupted by different levels of intensity non-uniformity and noise, show that the proposed method produced better results than the standard FCM and some other recent published works.

Keywords: MRI, Segmentation, Fuzzy c-means (FCM), Bat algorithm, Hybrid method.

1. INTRODUCTION

Image segmentation is one of the most important task in the image processing. This task refers to dividing an image into various regions with different characteristics and proposing objects of interest [1]. It takes an essential part in medical imaging. This process has been useful in several medical areas, such as brain tumor detection [2], cancer diagnosis [3], blood vessels analysis [4] and diabetic retinopathy [5]. It can assist doctors and radiologists to diagnose illnesses, therapy evaluation, tissue volume measurements, aid in computer guided surgery, planning for treatments, anatomical structure study and surgery simulator [6].

Fuzzy c-means (FCM) is a well-known algorithm and it is considered as one of the most effective and extensively used algorithm in the area of image segmentation [7, 8]. It is a major technique and the mainstream in fuzzy clustering method. It has some strength points for instance, simple implementation, no threshold set, unsupervised and practicality. Meanwhile, there are a few shortcomings as sensitivity to the cluster center initializations, getting stuck in the local minima and low convergence rate [9, 10, 11]. To treat these drawbacks, many works were proposed by using bio-inspired techniques.

In this paper the segmentation is done by using and modifying the standard bat algorithm that is developed by Xin-She Yang in 2010 [12, 13], the echolocation behavior of microbats plays the basic role in the BA characteristics. First we defined the fuzzy Bat algorithm FBA to get the initial cluster centers of the FCM algorithm. Then, we proposed a modified fuzzy Bat algorithm MFBA to enhance the convergence speed and quality of the solution. Generally, the fitness function of the hybrid methods is the objective function of FCM given in (1). However, in our method we present a new fitness function which combines intra cluster distance with fuzzy cluster validity indices.

The rest of the paper is organized as follows: section 2 describes the comprehensive literature review, in section 3, we briefly introduce the standard FCM algorithm with the cluster validity indices and the performance measures that have used to evaluate the quality of the segmentations. The basic bat algorithm, the fuzzy bat algorithm (FBA) and a modified bat algorithm (MFBA) are presented in section 4. Our proposed algorithm MFBAFCM is explained in section 5. Experimental results are summarized in section 6. In section 7, we conclude our work and we address some future issues.

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2. RELATED WORK

During the recent years, many works have focused on improving medical image segmentation by using different techniques.

Mekhmoukh and Mokrani [14] proposed a segmentation technique named IKPCM. It is based on using PSO algorithm for choosing optimal cluster centers and modified KPCM membership function by considering outlier rejection, ending by using level set for finalized the segmentation. Their work has succeeded to improve KPCM algorithm but it consumed more time.

HAFSA is a hybrid segmentation method presented by Li Ma et al. [15]. The authors have focused on combining traditional FCM with artificial fish swarm algorithm (AFSA). As they were improving the convergence rate by involving noise reduction technique and metropolis criterion to AFSA. Their proposed method had good segmentation results on MRI and reduced the noise but it was slower than the standard FCM.

Dubey al. [16] suggested a segmentation algorithm for brain MR images called a rough set based intuitionistic fuzzy c-means RIFCM. They worked on using intuitionistic fuzzy roughness measure in order to get an optimal initial values of centroids. Furthermore, they proposed a new intuitionistic fuzzy complement function. The results show that RIFCM reduce the noise and get good segmentation results.

Yang et al. [17] introduced new image segmentation approach for MRI brain images. They improved HS algorithm by using rough set theory to initialize the fuzzy clustering algorithm. The results showed that their method achieved better convergence and more accurate results than the original HS algorithm and standard FCM, but the method was not tested in different levels of noise and intensity non-uniformity.

Ramudu and Tummala [18] proposed a segmentation method called KFPSO for MRI biomedical images. The authors used the PSO algorithm to get the optimal initial cluster centers for Kernel Fuzzy C-Means (KFCM). Then, the method was modified to the level set model for better segmentation results. The experimental results confirmed that their proposed method reduced the noise and had accurate results. Although, KFPSO method have a lot of parameters.

Guerrout et al. [19] presented an approach for brain image segmentation based on Hidden Markov Random Fields (HMRF) and PSO algorithm. The authors used HMRF for modeling the segmentation, this operation leads to a problem of function minimization solved by combining PSO with HMRF. They investigated parameters setting of HMRF and PSO to optimize the segmentation. After all, they had good results but the algorithm has many parameters that need more investigation for better results.

For MRI Image Segmentation, a Hybrid Ant Fuzzy Algorithm (HFA) has been presented by Bozhenyuk et al. [20]. In their method, c-means algorithm has been used to recalculate the center of each segment and apply a superposition of several optimality criteria for the resulting solutions, considering different characteristics of the image. The HAFA algorithm get the optimal solution in any case. However, the convergence time is not defined since the algorithm depends on the initial parameters.

El-Khatib et al. [21] combined Ant Colony Optimization (ACO) with k-means algorithm and suggested a hybrid clustering algorithm for MRI images segmentation. The main role has been taken apart by the ACO algorithm, it defined the relationship of each pixel with clusters of the image. To evaluate and estimate the time complexity, they used drift analysis method. The proposed method can solve segmentation task in polynomial time.

3. FCM ALGORITHM

A. Fuzzy c-Means Algorithm

FCM is a clustering algorithm, it was proposed by Dunn [10] and improved by Bezdek [11]. This method is an unsupervised learning approach that is capable of partitioning identical data elements based on level of similarity, which decreases the similarity among elements between various groups and increases the similarity of elements within a group [22, 23]. The basic FCM algorithm minimizes the cost function by dividing the image data into several partition c (2 ≤ c ≤ N).

The FCM algorithm uses fuzzy memberships to assign pixels \( x = \{x_1, x_2, x_3, ..., x_N\} \) for each category. The algorithm is an iterative optimization that minimizes the cost function defined as follows [22]:

\[
J = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{i,j}^m \left\| x_i - z_j \right\|^2
\]

(1)

With the following constraints:

\[
\forall i \in \{1..N\}, \forall j \in \{1..c\} \sum_{j=1}^{c} u_{i,j} = 1;
\]

(2)

\[
0 \leq u_{i,j} \leq 1; \sum_{i=1}^{N} u_{i,j} > 0
\]

Where \( u_{i,j} \) is the membership of pixel \( x_i \) in the \( j \)-th cluster, \( z_j \) is the \( j \)-th cluster center, \( l \) is a norm metric and \( m \) (\( m>1 \)) is a constant controls the fuzziness of the resulting partition. The membership functions and cluster centers are updated by (3) and (4) respectively.
Algorithm 1: The standard FCM

Input: $c$, $m$, $itermax$, and $\epsilon$

Output: $U$ and $Z$

1: Randomly initialize cluster centers $z_j$
2: for $t = 1$ to $itermax$ do
3: Update $u_{ji}$ by (3)
4: Calculate $z_j$ by (4)
5: Calculate the objective function by (1)
6: if $|J^t - J^{t-1}| < \epsilon$ then
7: Break
8: end if
9: end for

B. Cluster Validity Indices

The cluster validity indices are necessary to evaluate the quality of the clustering process. The main point is to determine whether the partitions resulted by the clustering algorithm have presented the data correctly or not. We describe four indices, which are presented as follows:

1) Partition Coefficient (PC): A useful index can measure the amount of "overlapping" between clusters. PC index value lies between $1/c$ and 1. It is defined by Bezdek [11] as follows:

$$PC = \frac{\sum_{i=1}^{N} \sum_{j=1}^{c} (u_{ji})^2}{N}$$

2) Classification Entropy (CE): CE and PC indices are similar. It can only measure the fuzziness of the cluster partition [26].

$$CE = \frac{-\sum_{i=1}^{N} \sum_{j=1}^{c} u_{ji} \log(u_{ji})}{N}$$

3) Partition Index (SC): it represents a set of individual cluster validity measures normalized through division by the fuzzy cardinality of each cluster [27].

$$SC = \frac{\sum_{i=1}^{N} \sum_{j=1}^{c} (u_{ji})^m \|x_i - z_j\|^2}{N \min_{j,k} \|z_k - z_j\|^2}$$

4) Separation Index (S): for partition validity, the separation index S uses a minimum-distance separation [27].

$$S = \frac{\sum_{i=1}^{N} \sum_{j=1}^{c} (u_{ji})^m \|x - z_j\|^2}{N \sum_{k=1}^{N} \|z_k - z_j\|^2}$$

To end up with a better partition, the three indices CE, SC and S should be minimized. Meanwhile, the PC value should be maximized.

C. Performance Measures

There are many performance measures to evaluate the quality of the image segmentations. We used in this study jaccard and dice coefficients.

1) Jaccard Similarity Coefficient (JS): in the segmentation process, jaccard similarity measures the dissimilarity between observed and expected images [28], a comparison is made between pixels of the ground truth ($R_g$) and resulting image ($R_i$), it is defined as:

$$Jaccard = \frac{|R_i \cap R_g|}{|R_i \cup R_g|}$$

2) Dice Similarity Coefficient (DS): is a powerful performance measure that can be used in the segmentation process to measure the extent of spatial overlap between observed and expected images [28], it is defined as:

$$Dice = \frac{2 \times |R_i \cap R_g|}{|R_i| + |R_g|}$$

The both dice and jaccard coefficients values are bounded by 0 and 1, a better performance is achieved when the results are higher.

4. BAT ALGORITHM

A. Standard Bat Algorithm

A metaheuristic algorithm named Bat Algorithm proposed by Yang in 2010. Its main characteristics are...
rely on the echolocation capability of micro bats guiding them on their foraging behavior, the rules in BA are [12]:

- The echolocation technique is used by all bats to sense distance and perceive their surroundings, the location of a bat $x_i$ is encoded as a solution to an optimization problem.
- Bats fly randomly with velocity $v_i$ at position $x_i$ with a varying wavelength $\lambda$ and loudness $A$ or a varying frequency ($f_{\text{max}}, f_{\text{max}}$) to search for prey.
- Loudness decreases from high value $A_0$ to a positive low constant value $A_{\text{min}}$.

During the iterations, the position $x_i$ and the velocity $v_i$ of each bat should be defined and subsequently updated according to these rules [13]:

\begin{align}
    f_i &= f_{\text{min}} + \beta (f_{\text{max}} - f_{\text{min}}) \tag{11} \\
    v_i^t &= v_{i-1}^t + (x_i^t - x_*)f_i \tag{12} \\
    x_i^t &= x_i^{t-1} + v_i^t \tag{13}
\end{align}

Where $\beta$ indicates a random value, $x_*$ is the current global best location. For each bat, a new solution is generated locally using random walk given by (14).

\[x_{\text{new}} = x_{\text{old}} + \varepsilon A^t \tag{14}\]

Where $\varepsilon$ is a random value lies between -1 and 1, $A^t$ represents the average of all the bats' loudness at this time step. During the iterations, the loudness and pulse emission rates can be decreased and increased as follows.

\begin{align}
    A_i^{t+1} &= \alpha A_i^t \tag{15} \\
    r_i^{t+1} &= r_i^0 (1 - e^{-\gamma t}) \tag{16}
\end{align}

Where $\alpha$ and $\gamma$ are constants. As $t \rightarrow \infty$ we have $A_i^t \rightarrow 0$ and $r_i^t \rightarrow r_i^0$. Rank the bats and find the current best $x_*$.

B. Fuzzy Bat Algorithm

The standard BA needs some adjustments to be able to solve fuzzy clustering problem. In this sub-section, we present the FBA (fuzzy bat algorithm):

- The position of bat $X$, represented by matrix $c$ rows and $N$ columns and it is similar to the membership matrix $U$.

\[X = \begin{bmatrix} U_{11} & \cdots & U_{1c} \\ \vdots & \ddots & \vdots \\ U_{c1} & \cdots & U_{cn} \end{bmatrix} \tag{17}\]

- The velocity $V$ also represented by matrix $c$ rows and $N$ columns.

Where the symbol $\oplus$ is used to indicate the addition between matrices, the symbol $\ominus$ indicates the subtraction. Meanwhile, the symbol $\otimes$ refers to multiplication between the matrix and real number.

C. Modified Fuzzy Bat Algorithm

In this paper, we proposed a modified Fuzzy bat algorithm MFBA to improve the quality of the FBA results and to avoid falling into local solution. We did that by replacing all bats, its fitness value does not change four times sequentially by new solution, this solution generated by calculating the average of the best five solutions achieved. In MFBA each bat have:

- $X_i (c \times N$ matrix) represent the position of a bat.
- $V_i (c \times N$ matrix) represent the velocity of a bat.
- $f_i, A_i, r_i$ represent the frequency, loudness and emission rate respectively.
- rep, parameter to count how many times the same fitness value is repeated. The steps of the MFBA are as follows:

**Algorithm 2: MFBA**

**Input:** Np, itermax, $f_{\text{max}}, f_{\text{min}}$

**Output:** best solution $x^*$

1: Define the objective function $F(x)$
2: Initialize bat population $X_i$ and velocity $V_i$
3: Initialize pulse rates $r_i$ and loudness $A_i$
4: **Repeat**
5: for $i \leftarrow 1$ to Np do
6: Adjust frequency by (11)
7: Update velocity by (18)
8: Update location by (19)
9: if (rand $> r_i$) then
10: Select a solution among the best

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solutions, generate a local solution around the selected best solution by (20)
11: end if
12: Generate a new solution randomly
13: if (rand < A_i and F(x_i) < F(x*)) then
14: Accept the new solution
15: Decrease A_i and increase r_i by (15,16)
16: end if
17: if (x_i^t - x_i^{t-1}) = 0 then
18: rep_i ← rep_i + 1
19: Else
20: rep_i ← 0
21: end if
22: if rep_i = 4 then
23: Replacing X_i by average of the best five solutions achieved
24: end if
25: end for
26: Rank the bats and find the current best x*
27: Until t > itermax

5. PROPOSED METHOD

A. Fitness Function
Fitness function evaluates how close is a given solution to reach the aimed result. We propose a new fitness function defined as follows:

\[
\text{Fitness} = \frac{\text{intra} \_ \text{cluster} + \text{SC}}{\text{PC}}
\]  

(21)

Where SC is the partition index given in (7), PC is the partition coefficient given in (5) and the intra cluster [29] is calculated using the equation given below:

\[
\text{Intra} \_ \text{cluster} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{c} ||x_i - z_j||^2
\]  

(22)

B. Modified Bat Algorithm for Fuzzy c-Means Clustering
The purpose of the study is to propose and develop a new hybrid method, in order to improve the MRI image segmentation process and overcome the shortcomings of the standard FCM. In the first step, the MFBA algorithm is used to get the best solution x* by minimizing the new fitness function given in (21). The second step starts by extracting the optimal cluster centers from the best solution x* by (4), then use them as the initial seed of the standard FCM. Bearing in mind that the fitness is minimized when the value of PC is high and the value of (intra_cluster + SC) is low. The flow chart and the steps of the MFBAFCM algorithm are as follows:

- **Step 1**: input the original image, set the initial values of the parameters c, m, itermax, ε, Np, f_max, f_min.
• **Step 2:** initialize bat population $X_r$, velocity $V_r$, pulse rates $r_l$ and loudness $A_l$, then start MFBA.

• **Step 3:** for each bat, adjust frequency, update velocity and locations by (11, 12, 13) respectively.

• **Step 4:** depending on a random number and a pulse rate $r_l$, a local search is done by generating a local solution around one of the best by (20).

• **Step 5:** generate a new solution randomly.

• **Step 6:** depending on loudness $A_l$, a random number, the fitness of the new solution and the best solution, the new solution is accepted while $A_l$ is decreased and $r_l$ is increased, by (15, 16).

• **Step 7:** replace all bats, its fitness value does not change four times sequentially by the average of the best five solutions achieved.

• **Step 8:** rank the bats and find the current best solution $x_r$.

• **Step 9:** repeat steps 3 to 8 until reaching the maximum number of MFBA iterations.

• **Step 10:** end of MFBA, extract the initial cluster centers $Z$ from $x_r$, by (4), note that the best solution $x_r$ is similar to the membership matrix $U$.

• **Step 11:** start the FCM algorithm.

• **Step 12:** use the membership matrix $U$ that is resulted by FCM to reshape the segmented image.

• **Step 13:** output the segmented image.

6. **Experimental Results**

The experiments has been carried out using a computer with Intel Core i3, 4GB RAM, and were performed in MATLAB 2018b compiler. We have compared MFBAFCM with both traditional FCM and FBAFCM on 60 simulated MRI brain images from 60th to 120th, downloaded from Brainweb [30]. The testing images are from T1 modality, corrupted by different levels of intensity non-uniformity (INU) (0%, 20%, 40%) and noise (0%, 3%, 5%). The study was performed using the following parameters: $N_p=20$, $\text{itermax} = 100$, good results obtained with $m = 2$ [31], $\varepsilon = 0.001$ since well performance achieved with $\varepsilon \in [0.01, 0.001] [32]$, $f_{\text{min}} = 1$, $f_{\text{max}} = 2$, $A_0 = 0.9$, $r_0 = 0.1$, $\alpha = \gamma = 0.9$ as in [12] and the number of cluster $c = 4$ (white matter, head gray matter, cerebrospinal fluid and background).

The results of FCM, FBAFCM and MFBAFCM on T1 are given in terms of four indices values PC, CE, SC and S respectively given in (5), (6), (7) and (8).

After 20 independent runs of simulation, the results are listed in Table I, Table II and Table III. The best values are shown in bold, these tables show that the PC values of MFBAFCM are larger than both FBAFCM and the traditional FCM in different levels of INU (0%, 20%, 40%) and noise (0%, 3%, 5%). Meanwhile, the CE, SC and S values of MFBAFCM are smaller than both FBAFCM and the traditional FCM. We can see that the proposed method MFBAFCM provides a better separated clusters than other tested methods.

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After 20 independent runs of simulation, the results of the comparison between FCM, FBAFCM and MFBAFCM in terms of Jaccard and Dice values respectively given in (9) and (10) are listed in Table IV,
Table V and Table VI, these tables show that the Jaccard and the Dice values of MFBAFCM are larger than FBAFCM and FCM in different noise levels (0% 3%, 5% and 20% of INU indicating that the proposed algorithm MFBAFCM is more efficient and provides better segmentation results than both FBAFCM and the traditional FCM.

**TABLE IV. RESULTS OF FCM, FBAFCM AND MFBAFCM USING JACCARD AND DICE COEFFICIENTS ON 0% NOISE AND 20% INU.**

<table>
<thead>
<tr>
<th>Index</th>
<th>Tissue</th>
<th>FCM</th>
<th>FBAFCM</th>
<th>MFBAFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CSF</td>
<td>0.840318</td>
<td>0.908305</td>
<td>0.948170</td>
</tr>
<tr>
<td>Jaccard</td>
<td>GM</td>
<td>0.893875</td>
<td>0.944270</td>
<td>0.976024</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.922613</td>
<td>0.950005</td>
<td>0.981431</td>
</tr>
<tr>
<td></td>
<td>CSF</td>
<td>0.900398</td>
<td>0.957973</td>
<td>0.972554</td>
</tr>
<tr>
<td>Dice</td>
<td>GM</td>
<td>0.931089</td>
<td>0.960064</td>
<td>0.988017</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.953094</td>
<td>0.978008</td>
<td>0.991303</td>
</tr>
</tbody>
</table>

**TABLE V. RESULTS OF FCM, FBAFCM AND MFBAFCM USING JACCARD AND DICE COEFFICIENTS ON 3% NOISE AND 20% INU.**

<table>
<thead>
<tr>
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<th>MFBAFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CSF</td>
<td>0.826630</td>
<td>0.898338</td>
<td>0.929060</td>
</tr>
<tr>
<td>Jaccard</td>
<td>GM</td>
<td>0.857753</td>
<td>0.915903</td>
<td>0.950927</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.890521</td>
<td>0.938850</td>
<td>0.967106</td>
</tr>
<tr>
<td></td>
<td>CSF</td>
<td>0.880594</td>
<td>0.932664</td>
<td>0.954427</td>
</tr>
<tr>
<td>Dice</td>
<td>GM</td>
<td>0.909950</td>
<td>0.961040</td>
<td>0.976061</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.928906</td>
<td>0.976007</td>
<td>0.978043</td>
</tr>
</tbody>
</table>

**TABLE VI. RESULTS OF FCM, FBAFCM AND MFBAFCM USING JACCARD AND DICE COEFFICIENTS ON 5% NOISE AND 20% INU.**

<table>
<thead>
<tr>
<th>Index</th>
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<th>FBAFCM</th>
<th>MFBAFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CSF</td>
<td>0.789044</td>
<td>0.888101</td>
<td>0.903032</td>
</tr>
<tr>
<td>Jaccard</td>
<td>GM</td>
<td>0.830738</td>
<td>0.900043</td>
<td>0.930116</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.873259</td>
<td>0.921004</td>
<td>0.950829</td>
</tr>
<tr>
<td></td>
<td>CSF</td>
<td>0.865590</td>
<td>0.900694</td>
<td>0.929611</td>
</tr>
<tr>
<td>Dice</td>
<td>GM</td>
<td>0.886003</td>
<td>0.920447</td>
<td>0.950934</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.903376</td>
<td>0.946933</td>
<td>0.960032</td>
</tr>
</tbody>
</table>

Fig. 2, Fig. 3 and Fig. 4 present a comparison of segmentation results on simulated MRI brain images with different noise levels (0%, 3%, 5%) respectively as shown in Figs. 2(a)(b), Figs. 3(a)(b) and Figs. 4(a)(b). The segmentation results obtained by FCM are shown in Figs.2(c)(d)(e), Figs.3(c)(d)(e) and Figs.4(c)(d)(e). Figs. 2(f)(g)(h), Figs. 3(f)(g)(h) and Figs. 4(f)(g)(h) show the segmented images provided by FBAFCM. Figs. 2(i)(j)(k), Figs. 3(i)(j)(k) and Figs. 4(i)(j)(k) show the segmented images provided by MFBAFCM. Figs. 2(l)(m)(n), Figs. 3(l)(m)(n) and Figs. 4(l)(m)(n) show the ground truth images of CSF, GM and WM. The MFBAFCM algorithm provides more detail and achieves a good segmentation effect than its counterparts FBAFCM and FCM.
Figure 3. The Segmentation results of the CSF, GM and WM (from left to right) by the different algorithms on a T1-weighted MRI brain image with 3% noise and 20% INU (a),(b) MRI brain image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth.

Figure 4. The Segmentation results of the CSF, GM and WM (from left to right) by the different algorithms on a T1-weighted MRI brain image with 5% noise and 40% INU (a),(b) MRI brain image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth.
We have compared between MFBAFCM and FBAFCM on 10 simulated MRI brain images, by evaluating the fitness values in term of iterations' number. Fig.5 shows that MFBAFCM gets better fitness values than FBAFCM in less number of iterations, this proving that MFBAFCM is faster and better than FBAFCM in the segmentation process.

![Figure 5](image1)

(a) Fitness value of MFBAFCM algorithm in term of iterations' number.

(b) Fitness value of FBAFCM algorithm in term of iterations' number.

### A. Comparative Study

To evaluate the quality and the performance of our MFBAFCM method, we made a comparative study with both LGMM [33] and HMRF-PSO [19] on the basis of Dice Similarity coefficient. We have used the slices (85, 88, 90, 95, 97, 100, 104, 106, 110) from Brainweb database corrupted by different noise levels N (1%, 5%) and 0% intensity non-uniformity INU. Table VII shows that the Dice values of MFBAFCM are larger than HMRF-PSO and LGMM in different noise levels (0%, 3%, 5%) as for different INU levels (0%, 20%) indicating that the proposed algorithm MFBAFCM can produce more accurate segmented MRI brain images than other tested techniques.

### TABLE VII. RESULTS OF LGMM, HMRF-PSO AND MFBAFCM USING DICE SIMILARITY.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(0%,0%)</td>
<td>GM</td>
<td>0.69</td>
<td>0.95</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.66</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>CSF</td>
<td>0.75</td>
<td>0.95</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>0.70</td>
<td>0.96</td>
<td>0.973</td>
</tr>
<tr>
<td>(3%,20%)</td>
<td>GM</td>
<td>0.90</td>
<td>0.94</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.94</td>
<td>0.96</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>CSF</td>
<td>0.891</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>0.91</td>
<td>0.95</td>
<td>0.953</td>
</tr>
<tr>
<td>(5%,20%)</td>
<td>GM</td>
<td>0.91</td>
<td>0.91</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td><strong>0.95</strong></td>
<td><strong>0.95</strong></td>
<td><strong>0.95</strong></td>
</tr>
<tr>
<td></td>
<td>CSF</td>
<td>0.88</td>
<td>0.92</td>
<td>0.93</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>0.91</td>
<td>0.93</td>
<td><strong>0.936</strong></td>
</tr>
</tbody>
</table>

Another comparative study was made between our method MFBAFCM with both MFCM [34] and RIFCM [16] in terms of Dice similarity (DS) and Jaccard Similarity (JS) values. We have used the slice (No. 91) from Brainweb database corrupted by different noise levels N (1%, 5%) and 0% intensity non-uniformity. Table VIII and Table IX show that the Jaccard and the Dice values of MFBAFCM are larger than RIFCM and MFCM in different noise levels (1%, 5%), indicating that the proposed algorithm MFBAFCM can provide better and more accurate segmentation results than other tested methods.

### TABLE VIII. RESULTS OF MFCM, RIFCM AND MFBAFCM USING JACCARD SIMILARITY.

<table>
<thead>
<tr>
<th>N</th>
<th>Tissue</th>
<th>MFCM [34]</th>
<th>RIFCM [16]</th>
<th>MFBAFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>CSF</td>
<td>0.8853</td>
<td>0.8992</td>
<td>0.9306</td>
</tr>
<tr>
<td></td>
<td>GM</td>
<td>0.9218</td>
<td>0.9703</td>
<td><strong>0.9788</strong></td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.9676</td>
<td>0.9564</td>
<td><strong>0.9691</strong></td>
</tr>
<tr>
<td>5%</td>
<td>CSF</td>
<td>0.8583</td>
<td>0.9116</td>
<td><strong>0.9202</strong></td>
</tr>
<tr>
<td></td>
<td>GM</td>
<td>0.8885</td>
<td>0.9565</td>
<td><strong>0.9615</strong></td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.9467</td>
<td>0.9456</td>
<td><strong>0.9573</strong></td>
</tr>
</tbody>
</table>

### TABLE IX. RESULTS OF MFCM, RIFCM AND MFBAFCM USING DICE SIMILARITY.

<table>
<thead>
<tr>
<th>N</th>
<th>Tissue</th>
<th>MFCM [34]</th>
<th>RIFCM [16]</th>
<th>MFBAFCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>CSF</td>
<td>0.9391</td>
<td>0.9469</td>
<td><strong>0.9580</strong></td>
</tr>
<tr>
<td></td>
<td>GM</td>
<td>0.9593</td>
<td>0.9849</td>
<td><strong>0.9886</strong></td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td><strong>0.9835</strong></td>
<td>0.9777</td>
<td>0.9833</td>
</tr>
<tr>
<td>5%</td>
<td>CSF</td>
<td>0.9236</td>
<td>0.9537</td>
<td><strong>0.9684</strong></td>
</tr>
<tr>
<td></td>
<td>GM</td>
<td>0.941</td>
<td>0.9777</td>
<td><strong>0.9816</strong></td>
</tr>
<tr>
<td></td>
<td>WM</td>
<td>0.9726</td>
<td>0.9720</td>
<td><strong>0.9860</strong></td>
</tr>
</tbody>
</table>

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7. Conclusion

In this paper we have proposed a modified fuzzy bat algorithm MFBA and its obtained results are taken to improve the initialization step of the FCM algorithm. This operation is done by using new fitness function which combined intra cluster distance with fuzzy cluster validity indices. The results show that the proposed algorithm MFBAFCM can segment MR images more accurately than RIFCM, MFCM, HMRF-PSO, LGMM, FBAFCM and traditional FCM algorithm in different levels of intensity non-uniformity and noise.

Our future work will focus on finding a better fitness function to make MFBAFCM more efficient against noise. In addition to, we will compare our method with other recent literature works by using other real and synthetic MRI images in order to validate its effectiveness.

References


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