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

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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 became 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 have 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 (HAFA) 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 ($2 \leq c \leq N$).

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]:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ji}^{m} \left\| x_i - z_j \right\|^2 \tag{1}$$

With the following constraints:

$$\forall i \in \{1..N\}, \forall j \in \{1..c\} \sum_{j=1}^{c} u_{ji} = 1;$$
$$0 \leq u_{ji} \leq 1; \sum_{i=1}^{N} u_{ji} > 0 \tag{2}$$

Where u_{ji} is the membership of pixel x_i in the *j-th* cluster, z_j is the j-th cluster center, ‖.‖ 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.

$$u_{ji} = \left(\sum_{k=1}^{c} \left(\frac{\left\| x_i - z_j \right\|}{\left\| x_i - z_k \right\|} \right)^{2/(m-1)} \right)^{-1} \quad (3)$$

$$z_j = \sum_{i=1}^{N} u_{ji}^{m} x_i \cdot \left(\sum_{i=1}^{N} u_{ji}^{m} \right)^{-1} \quad (4)$$

The FCM starting with a random cluster centers, then converges to a solution for z_j representing a saddle point or the local minimum of the cost function. By comparing the changes in the cluster center or the membership function at two successive iteration steps, the convergence can be detected [25]. The FCM algorithm steps are presented as follows:

Algorithm 1: The standard FCM

Input: *c*, *m*, *itermax* and ε
Output: U and Z

Randomly initialize cluster centers z_j
for $t \leftarrow 1$ to *itermax* **do**
  Update u_{ij} by (3)
  Calculate z_j by (4)
  Calculate the objective function by (1)
    if $| J^{(t)} - J^{(t-1)} | < \varepsilon$ **then**
      Break
    end if
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 has 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:

$$PC = \frac{\sum_{i=1}^{N} \sum_{j=1}^{c} \left(u_{ji} \right)^2}{N} \quad (5)$$

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

$$CE = \frac{-\sum_{i=1}^{N} \sum_{j=1}^{c} u_{ji} \log\left(u_{ji} \right)}{N} \quad (6)$$

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

$$SC = \sum_{j=1}^{c} \frac{\sum_{i=1}^{N} \left(u_{ji} \right)^m \left\| x_i - z_j \right\|^2}{N \sum_{k=1}^{c} \left\| z_k - z_j \right\|^2} \quad (7)$$

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

$$S = \frac{\sum_{j=1}^{c} \sum_{i=1}^{N} \left(u_{ji} \right)^m \left\| x_i - z_j \right\|^2}{N \min j,k \left\| z_k - z_j \right\|^2} \quad (8)$$

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_t), it is defined as:

$$Jaccard = \frac{R_t \cap R_g}{R_t \cup R_g} \quad (9)$$

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

$$Dice = \frac{2 \times \left| R_t \cap R_g \right|}{\left| R_t \right| + \left| R_g \right|} \quad (10)$$

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 λ and loudness A or a varying frequency (f_{min}, f_{max}) to search for prey.
- Loudness decreases from high value A_0 to a positive low constant value A_{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]:

$$f_i = f_{min} + \beta\,(f_{max} - f_{min}) \tag{11}$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x_*\right) f_i \tag{12}$$

$$x_i^t = x_i^{t-1} + v_i^t \tag{13}$$

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

$$x_{new} = x_{old} + \varepsilon \overline{A}^t \tag{14}$$

Where ε is a random value lies between -1 and 1, $\overline{A}^t$ 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.

$$A_i^{t+1} = \alpha A_i^t \tag{15}$$

$$r_i^{t+1} = r_i^0\left(1 - e^{\gamma t}\right) \tag{16}$$

Where α and γ are constants. As $t \longrightarrow \infty$ we have $A_i^t \longrightarrow 0$ and $r_i^t \longrightarrow r_i^0$ .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.

$$X = \begin{bmatrix} U_{11} & \cdots & U_{1N} \\ \vdots & \ddots & \vdots \\ U_{c1} & \ldots & U_{cN} \end{bmatrix} \tag{17}$$

- The velocity V also represented by matrix c rows and N columns.
- f_i, f_{min}, f_{max}, A and r represented by real numbers.

Because of these adjustments, the rules of updating the position, velocity and generating a local solution will be:

$$v_i^t = v_i^{t-1} \oplus (x_i^t \ominus x_*) \otimes f_i \tag{18}$$

$$x_i^t = x_i^{t-1} \oplus v_i^t \tag{19}$$

$$x_{new} = x_{old} \oplus \varepsilon \overline{A}^t \tag{20}$$

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_i 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_{max}, f_{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←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

solutions, generate a local solution around the selected best solution by (20)
end if
Generate a new solution randomly
if (rand < A_i **and** F(x_i) < F(x_*)) **then**
Accept the new solution
Decrease A_i and increase r_i by (15,16)
end if
if $(x_i^t - x_i^{t-1}) = 0$ **then**
$rep_i \leftarrow rep_i + 1$
Else
$rep_i \leftarrow 0$
end if
if $rep_i = 4$ **then**
Replacing X_i by average of the best five solutions achieved
end if
end for
Rank the bats and find the current best x_*
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:

$$Fitness = \frac{intra\_cluster + SC}{PC} \qquad (21)$$

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:

$$Intra\_\text{cluster} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c}\left\| x_i - z_j \right\|^2 \qquad (22)$$

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:

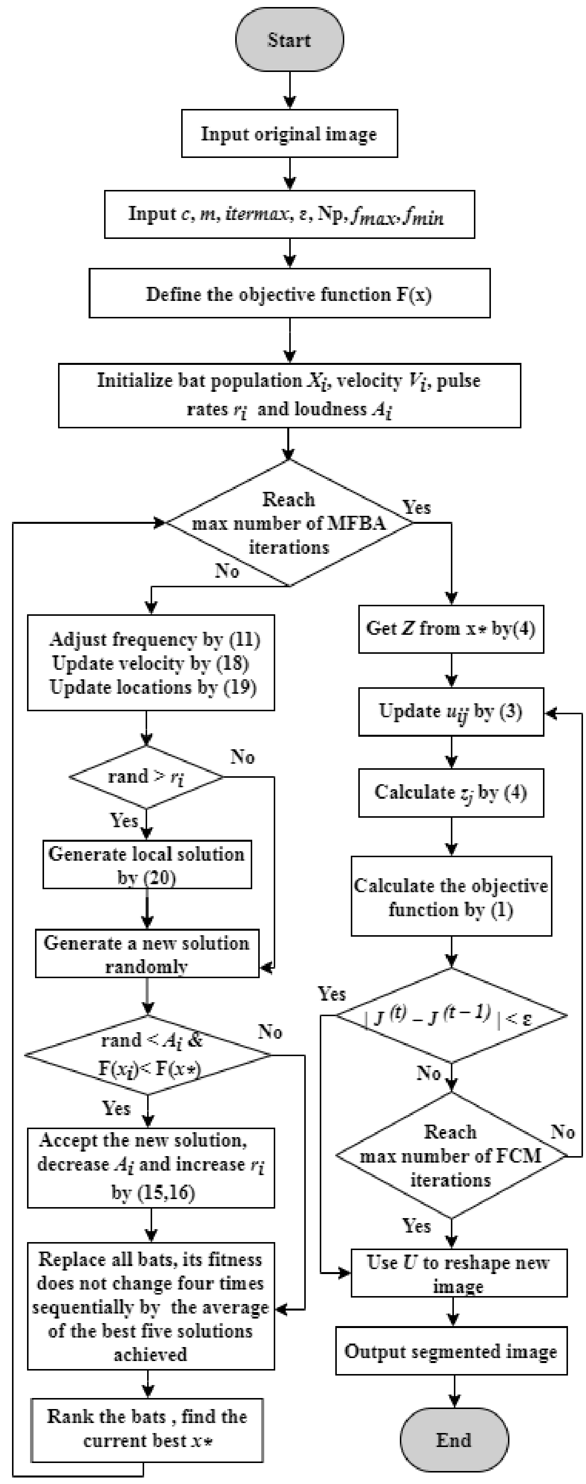


Figure 1. MFBAFCM flow chart

- **Step 1**: input the original image, set the initial values of the parameters *c, m, itermax, ε, Np*, f_{max} and f_{min}.

- **Step 2:** initialize bat population X_i, velocity V_i, pulse rates r_i and loudness A_i, 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 rates r_i, 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_i, a random number, the fitness of the new solution and the best solution, the new solution is accepted while A_i is decreased and r_i 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_*.
- **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_* by (4), note that the best solution x_* 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 between 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: Np=20, *itermax* = 100, good results obtained with m = 2 [31], ε = 0.001 since well performance achieved with $\varepsilon \in [0.01, 0.0001]$ [32], $f_{min} = 1$, $f_{max} = 2$, $A_0 = 0.9$, $r_0 = 0.1$, $\alpha = \gamma = 0.9$ as in [12] and the number of cluster c = 4 (white matter, 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 smallest than both FBAFCM and the traditional FCM. We can see that the proposed method MFBAFCM provides a better separated clusters than other tested methods.

TABLE I. RESULTS OF FCM, FBAFCM AND MFBAFCM ON 0% NOISE

INU	index	FCM	FBAFCM	MFBAFCM
0%	PC	0.912343	0.967852	**0.988372**
	CE	0.147221	0.074628	**0.043296**
	SC	0.445407	0.419945	**0.393241**
	S	0.000015	0.000012	**0.000010**
20%	PC	0.918001	0.960743	**0.984904**
	CE	0.150748	0.080064	**0.044033**
	SC	0.451434	0.428548	**0.393963**
	S	0.000016	0.000012	**0.000010**
40%	PC	0.910250	0.955732	**0.979852**
	CE	0.154873	0.088806	**0.044004**
	SC	0.459633	0.430074	**0.394731**
	S	0.000017	0.000014	**0.000011**

TABLE II. RESULTS OF FCM, FBAFCM AND MFBAFCM ON 3% NOISE

INU	Index	FCM	FBAFCM	MFBAFCM
0%	PC	0.908348	0.960462	**0.982664**
	CE	0.157061	0.094628	**0.044643**
	SC	0.450398	0.419405	**0.398036**
	S	0.000016	0.000013	**0.000010**
20%	PC	0.903541	0.959931	**0.980088**
	CE	0.159400	0.086064	**0.049298**
	SC	0.451434	0.428548	**0.393963**
	S	0.000017	0.000012	**0.000011**
40%	PC	0.900930	0.955822	**0.972051**
	CE	0.158853	0.085993	**0.050027**
	SC	0.461931	0.437723	**0.408470**
	S	0.000018	0.000014	**0.000012**

TABLE III. RESULTS OF FCM, FBAFCM MFBAFCM ON 5% NOISE

INU	index	FCM	FBAFCM	MFBAFCM
0%	PC	0.905422	0.953244	**0.976691**
	CE	0.160064	0.085970	**0.049956**
	SC	0.465790	0.438058	**0.409218**
	S	0.000019	0.000014	**0.000012**
20%	PC	0.898001	0.950483	**0.973380**
	CE	0.162727	0.088068	**0.051183**
	SC	0.476996	0.446328	**0.411367**
	S	0.000019	0.000015	**0.000014**
40%	PC	0.875004	0.947862	**0.971402**
	CE	0.183440	0.079825	**0.054004**
	SC	0.477033	0.449011	**0.413810**
	S	0.000020	0.000016	**0.000014**

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.

Index	Tissue	FCM	FBAFCM	MFBAFCM
Jaccard	CSF	0.840318	0.908305	**0.948170**
	GM	0.893875	0.944270	**0.976024**
	WM	0.922613	0.950005	**0.981431**
Dice	CSF	0.900398	0.957973	**0.972554**
	GM	0.931089	0.960064	**0.988017**
	WM	0.953094	0.978008	**0.991303**

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

Index	Tissue	FCM	FBAFCM	MFBAFCM
Jaccard	CSF	0.826630	0.898338	**0.929060**
	GM	0.857753	0.915903	**0.950927**
	WM	0.890521	0.938850	**0.967106**
Dice	CSF	0.880594	0.922664	**0.947442**
	GM	0.909950	0.951040	**0.969061**
	WM	0.928906	0.966007	**0.978043**

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

Index	Tissue	FCM	FBAFCM	MFBAFCM
Jaccard	CSF	0.789044	0.888101	**0.903302**
	GM	0.830738	0.900043	**0.930116**
	WM	0.871259	0.921004	**0.950029**
Dice	CSF	0.865590	0.900694	**0.929011**
	GM	0.886003	0.920447	**0.949034**
	WM	0.903376	0.946933	**0.960032**

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.

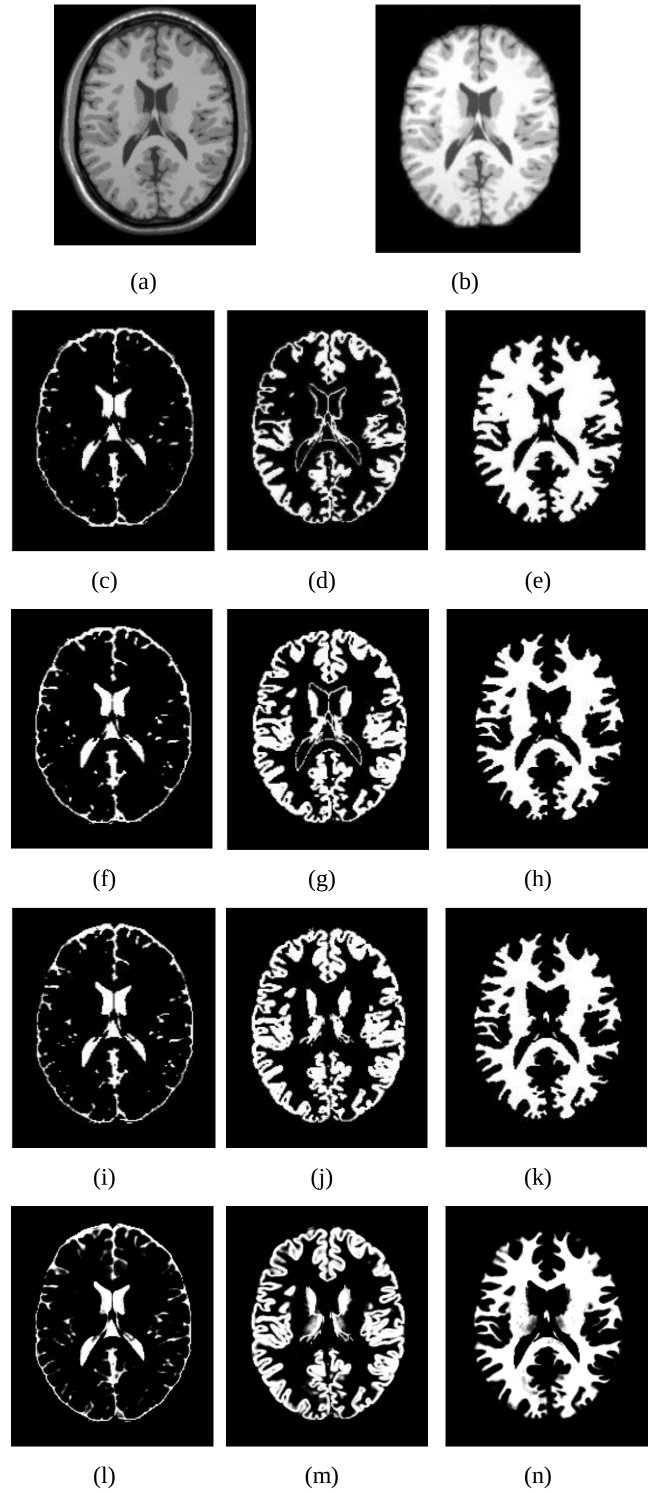


Figure 2. The Segmentation results of the CSF, GM and WM (from left to right) by the different algorithms on a T1-weighted MRI brain image with 0% noise and 0% INU (a),(b) MRI brain image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth .

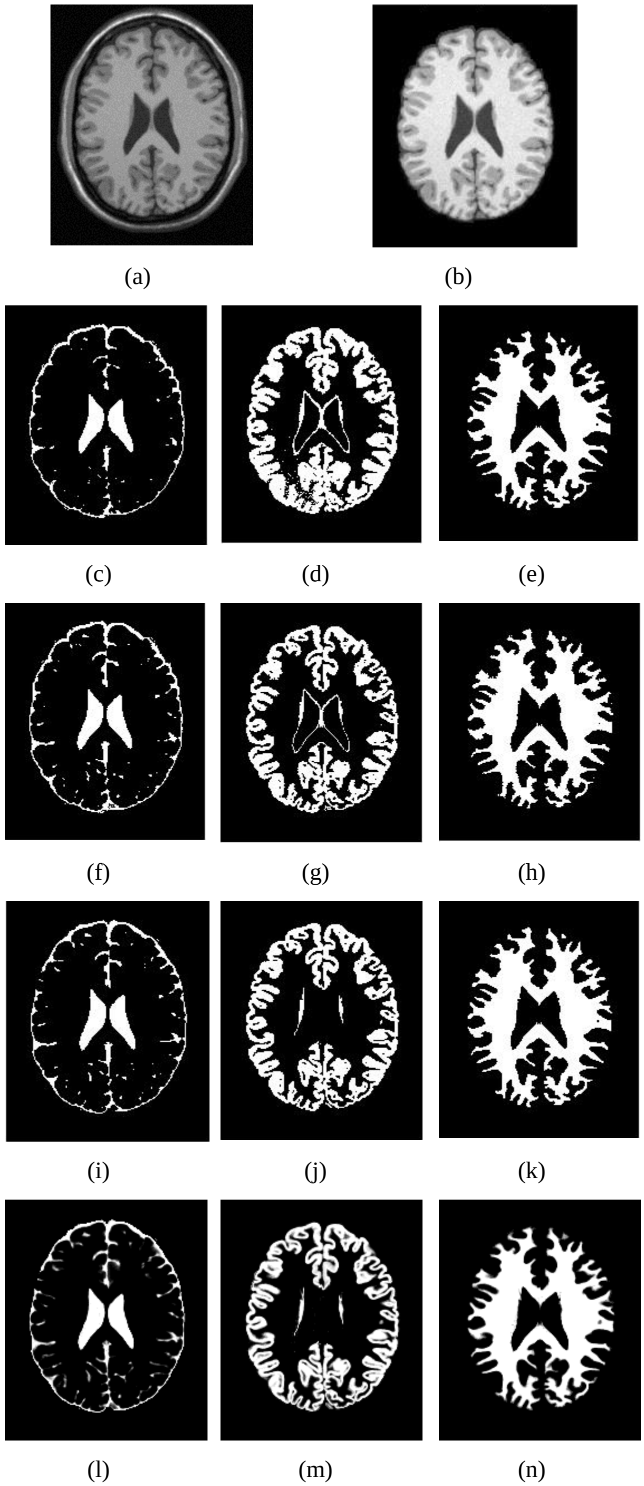


Figure 3. The Segmentation results of the CSF, GM and WM (from left to right) by the different algorithms on a T1-weighted MRI brain image with 3% noise and 20% INU (a),(b) MRI brain image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth .

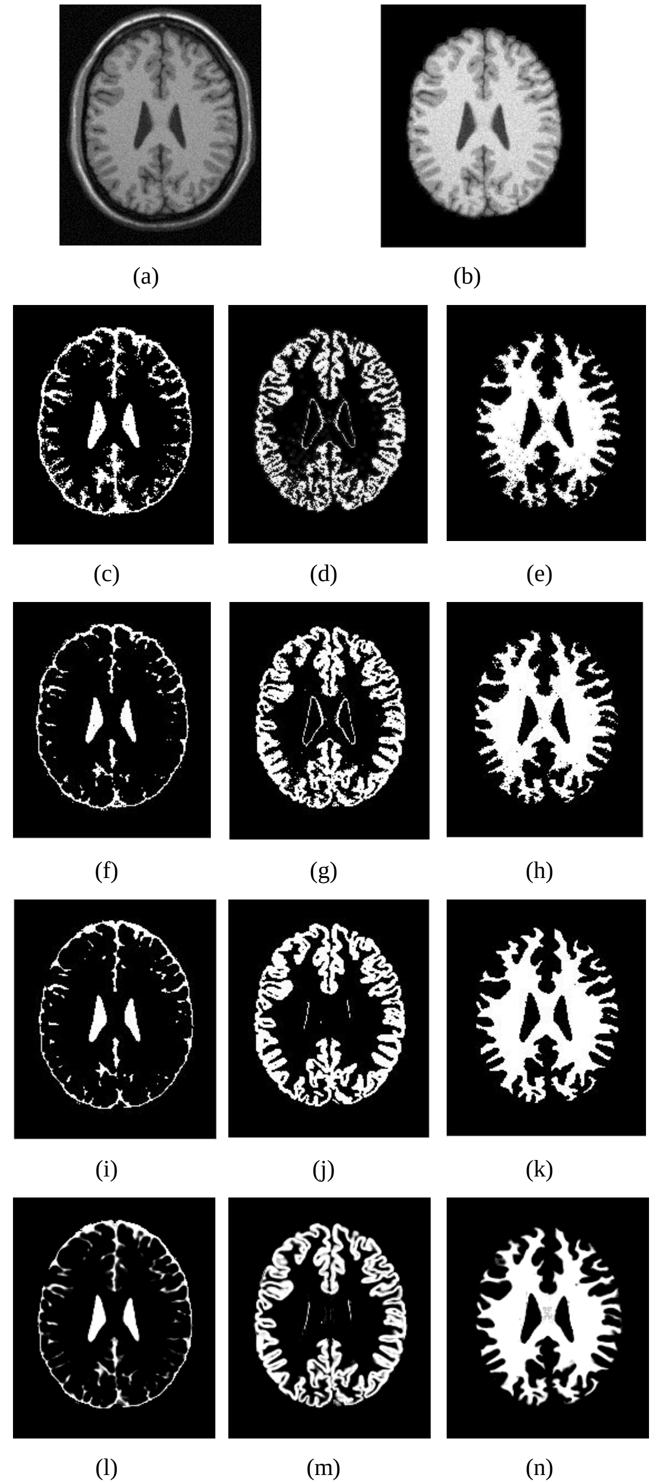
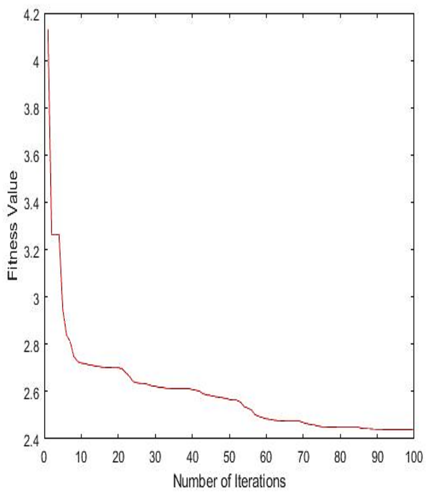
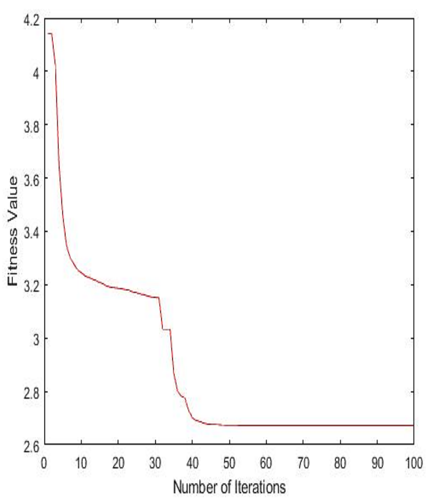


Figure 4. The Segmentation results of the CSF, GM and WM (from left to right) by the different algorithms on a T1-weighted MRI brain image with 5% noise and 40% INU (a),(b) MRI brain image without skull. (c)–(e): FCM algorithm; (f)–(h): FBAFCM algorithm; (i)–(k): MFBAFCM algorithm; (l)–(n): ground truth .

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.



(a)



(b)

Figure 5. Comparison between MFBAFCM and FBAFCM. (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 and 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.

(N,INU)	Tissue	LGMM [33]	HMRF-PSO [19]	MFBAFCM
(0%,0%)	GM	0.69	0.95	**0.97**
	WM	0.66	0.98	**0.99**
	CSF	0.75	0.95	**0.96**
	Mean	0.70	0.96	**0.973**
(3%,20%)	GM	0.90	0.94	**0.95**
	WM	0.94	0.96	**0.97**
	CSF	0.891	**0.94**	**0.94**
	Mean	0.91	0.95	**0.953**
(5%,20%)	GM	0.91	0.91	**0.93**
	WM	**0.95**	**0.95**	**0.95**
	CSF	0.88	0.92	**0.93**
	Mean	0.91	0.93	**0.936**

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.

N	Tissue	MFCM[34]	RIFCM[16]	MFBAFCM
1%	CSF	0.8853	0.8992	**0.9306**
	GM	0.9218	0.9703	**0.9788**
	WM	0.9676	0.9564	**0.9691**
5%	CSF	0.8583	0.9116	**0.9202**
	GM	0.8885	0.9565	**0.9615**
	WM	0.9467	0.9456	**0.9573**

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

N	Tissue	MFCM [34]	RIFCM [16]	MFBAFCM
1%	CSF	0.9391	0.9469	**0.9580**
	GM	0.9593	0.9849	**0.9886**
	WM	**0.9835**	0.9777	0.9833
5%	CSF	0.9236	0.9537	**0.9684**
	GM	0.941	0.9777	**0.9816**
	WM	0.9726	0.9720	**0.9860**

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

[1] Y. Zhang, S. Ye and W. Ding,"Based on rough set and fuzzy clustering of MRI brain segmentation," International Journal of Biomathematics, vol.10, no. 2, 2017.

[2] Y. A. Hamad, K. V. Simonov and M. B. Naeem,"Detection of Brain Tumor in MRI Images, Using a Combination of Fuzzy C-Means and Thresholding," International Journal of Advanced Pervasive and Ubiquitous Computing, vol.11, no.1, pp. 45-60, January 2019.

[3] I. Y. Maolood, Y. E. A. Al-Salhi and S. Lu,"Thresholding for Medical Image Segmentation for Cancer using Fuzzy Entropy with Level Set Algorithm," Open Medicine,vol. 13,no. 1, pp. 374-383, September 2018.

[4] K. Ahmadi, A. Karimi and B. F. Nia,"New Technique for Automatic Segmentation of Blood Vessels in CT Scan Images of Liver Based on Optimized Fuzzy C-Means Method," Computational and Mathematical Methods in Medicine, December 2016.

[5] P. T. Vishnu, V, G. Stephanie; K. S. Pradeep,"Segmentation of Diabetic Retinopathy Images Using Fuzzy C-Means Clustering," Journal of Computational and Theoretical Nanoscience,, vol. 15, no. 11-12,pp. 3542-3545, Novembre 2018.

[6] M. A. Balafar, A. R. Ramli, M. I. Saripan and S. Mashohor, "Review of brain MRI image segmentation methods," Artificial Intelligence Review, vol. 33, pp. 261-274, March 2010.

[7] G. B. Coleman and H. C. Andrews, "Image segmentation by clustering," Proceedings of the IEEE, vol. 67, no. 5, pp. 773–785, May 1979.

[8] P. Takur and N. Madaan, "A survey of image segmentation techniques," International Journal of Research in Computer Applications and Robotics, vol. 2, no. 4, pp. 158–165, April 2014

[9] M. S. M. Rahim, A. Norouzi, I. B. M. Amin, and A. E. Rad, "Current methods in medical image segmentation and its application on knee bone," Archives des Sciences Journal, vol. 65,no. 9, 2012.

[10] J. C. Dunn, "A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters," Cybernetics and Systems, vol. 3, no. 3, pp. 32–57, 1973.

[11] J. C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms,"Plenum Press, New York, NY, USA, 1981.

[12] X.-S. Yang, "A new metaheuristic bat-inspired algorithm,"In Nature inspired cooperative strategies for optimization,vol. 284, pp. 65–74, Springer,April 2010.

[13] B. Xing and W.-J. Gao, "Bat inspired algorithms," In Innovative Computational Intelligence: A Rough Guide to 134 Clever Algorithms,pp. 39–44. Springer, 2014.

[14] A. Mekhmoukh andK. Mokrani, "Improved Fuzzy C-Means based Particle Swarm Optimization (PSO) initialization and outlier rejection with level set methods for MR brain image segmentation," Computer Methods and Programs in Biomedicine, vol. 122, no. 2,pp. 266–281, August 2015.

[15] L.Ma Y. Li, S. Fan and R. Fan, "A Hybrid Method for Image Segmentation Based on Artificial Fish Swarm Algorithm and Fuzzyc-Means Clustering," Computational and Mathematical Methods in Medicine, pp. 1–10, November 2015.

[16] Y. K. Dubey, M. M.Mushrif and K. Mitra, "Segmentation of brain MR images using rough set based intuitionistic fuzzy clustering," Biocybernetics and Biomedical Engineering, vol. 36, no. 2, pp. 413–426, January 2016.

[17] Z. Yang, Y. Shufan, G. Li andD. Weifeng, "Segmentation of MRI Brain Images with an Improved Harmony Searching Algorithm," BioMed Research International, pp. 1–9, 2016.

[18] K. Ramudu andR. B.Tummala, "Segmentation of Tissues from MRI Biomedical Images Using Kernel Fuzzy PSO Clustering Based Level Set Approach," Current Medical Imaging,vol. 14,no. 3,pp. 389-400, May 2018.

[19] E.Guerrout, R. Mahiou and S. Ait-Aoudia, "Hidden Markov Random Fields and Particle Swarm Combination for Brain Image Segmentation," The International Arab Journal of Information Technology, vol.15, no.3, pp. 462-468, 2018

[20] A. Bozhenyuk,S. El-Khatib, J. Kacprzyk, M. Knyazeva and S. Rodzin, "Hybrid Ant Fuzzy Algorithm for MRI Images Segmentation," Lecture Notes in Computer Science, vol. 11509pp. 127–137, May 2019.

[21] S. A. El-Khatib, Y. A Skobtsov andS. I Rodzin, "Theoretical and Experimental Evaluation of Hybrid ACO-k-means Image Segmentation Algorithm for MRI Images Using Drift-analysis," Procedia Computer Science, 150, pp. 324–332, 2019.

[22] J. Nayak, B. Naik, and H. Behera, "Fuzzy C-means (FCM) clustering algorithm: a decade review from 2000 to 2014," in Computational Intelligence in Data Mining-vol. 2, ed: Springer, 2015, pp. 133-149 January 2015.

[23] J. C. Bezdek, C. Coray, R. Gunderson, and J. Watson, "Detection and characterization of cluster substructure i. linear structure: Fuzzy c-lines," SIAM Journal on Applied Mathematics, vol. 40, pp. 339-357, 1981.

[24] J. Kang, L. Min, Q. Luan, X. LI, and J. Liu, "Novel modified fuzzy c-meansalgorithm with applications," Digital Signal Processing, vol. 19 no. 2 pp. pp. 309 – 319, 2009.

[25] k. Chuang, H. Tzeng, S. Chen, J. Wu and T. Chen, "Fuzzy c-means clustering with spatial information for image segmentation," Computerized Medical Imaging and Graphics vol. 30, no. 1, pp. 9-15, February 2006.

[26] J. C. Bezdek, "Cluster validity with fuzzy sets," Journal of Cybernetics, vol. 3,no. 3,pp. 58–73, 1973.

[27] A.M. Bensaid, L.O. Hall, J.C. Bezdek, L.P. Clarke, M.L. Silbiger, J.A. Arrington, and R.F. Murtagh, "Validity-guided (Re) Clustering with applications to imige segmentation," IEEE Transactions on Fuzzy Systems, vol. 4, no. 2,pp. 112-123, May 1996.

[28] R. Agrawal and M. Sharma, "Review of Segmentation Methods for Brain Tissuewith Magnetic Resonance Images"," I.J. Computer Network and Information Security, vol. 6, no. 4, pp. 55-62, March 2014.

[29] J. Chen, Z. Zhao, J. Ye, and H. Liu, "Nonlinear adaptive distance metric learning for clustering," In Proceedings of International Conference on Knowledge Discovery and Data Mining, pp. 123–132, August 2007.

[30] BrainWeb: Simulated Brain Database. Available at:http://www.bic.mni.mcgill.ca/brainweb/,[Last visited onNovember 10th, 2019].

[31] J. C. Bezdek, J. Keller, R. Krisnapuram and N. Pal, "Fuzzy models and algorithms for pattern recognition and image processing," Springer Science & Business Media, vol. 4, 1999.

[32] D. -Q. Zhang, S.-C. Chen , "A novel kernelized fuzzy c-means algorithm with application in medical image segmentation," Artificial Intelligence in Medicine, vol. 32, no. 1, pp. 37-50, October 2004.

[33] J. Liu and H. Zhang, "Image Segmentation Using A Local GMM in Avariational Framework," Journal of Mathematical Imaging and Vision, vol. 46, no. 2, pp. 161-176, June 2013.

[34] Z. Ji, Q-S. Sun andD-S.Xia, "A framework with modified fast FCM for brain MR images segmentation," Pattern Recognitvol. 44, no. 5, pp. 999–1013 May 2011.

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