EVALUATING THE PERFORMANCE OF VARIOUS HYBRID FUZZY CLUSTERING ALGORITHMS ON BRAIN MAGNETIC RESONANCE IMAGES

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ABSTRACT

Image segmentation is an indispensable process in the visualization of human tissues, particularly during clinical analysis of MR Images. The Objective of this paper is to talk about the usage of Fuzzy Logic in MRI Brain image segmentation. There are different fuzzy approaches to segment the MRI Brain image. In this paper, different fuzzy clustering algorithms are used for the segmentation of brain MR Images. One of the major issues of the fuzzy clustering algorithm based brain MR image segmentation is how to select the initial prototypes of different classes or categories. In this paper, the quantitative indices are described to extract local features of brain MR Images, when applied on a set of synthetic and real brain MR Images, for segmentation.

Keywords: Brain Image, Hard C Means, Fuzzy C means, Gaussian Kernel FCM, Spatial Constrained Fast Kernel FCM, Multiple Kernel FCM.

1. INTRODUCTION

Segmentation is a process of partitioning an image space into some nonoverlapping meaningful homogeneous regions. The success of an image analysis system depends on the quality of segmentation [1]. A segmentation method is supposed to find those sets that correspond to distinct anatomical structures or regions of interest in the image. In the analysis of medical images for computer aided diagnosis and therapy, segmentation is often required as a preliminary stage. However, medical image segmentation is a complex and challenging task owing to the intrinsic nature of the images. The brain has a particularly complicated structure and its precise segmentation is very important for detecting tumors, edema and necrotic tissues, in order to prescribe appropriate therapy [2].

In medical imaging technology, a number of complementary diagnostic tools, such as X-ray computer tomography, magnetic resonance imaging (MRI) and position emission tomography are available. The MRI is an important diagnostic imaging technique for the early detection of abnormal changes in tissues and organs. Its unique advantage over other modalities is that it can provide multispectral images of tissues with a Varity of contrasts on the basis of the three MR parameters ρ, T1 and T2.Therefore, the majority of research in medical image segmentation concerns MR images [2].

Conventionally, brain MR images are interpreted visually and qualitatively by radiologists. Advanced research requires quantitative information such as the size of the brain ventricles after a traumatic brain injury or the relative volume of ventricles to brain. Fully automatic methods sometimes fail, producing incorrect results and requiring the intervention of a human operator. This is often true owing to the restrictions imposed by image acquisition, pathology and biological variation. So, it is important to have a faithful method to measure various structures in the brain. One such method is the segmentation of images to isolate objects and regions of interest.

Segmentation of major brain tissues, including Gray Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CF), from magnetic resonance images plays an important role in both clinical practice and neuroscience research. Many image processing techniques have been proposed for MR Image segmentation [3, 4], most thresholding [5, 7], region growing [8], edge detection [9], pixel classification [10, 11] and clustering [12-14]. Some algorithms using the neural network approach have also been investigated in MR image segmentation problems [15, 16]. In this paper, the three different hybrid fuzzy algorithms namely, Gaussian Kernel Fuzzy C Means [GKFCM][17],Spatially Constrained Kernel Fuzzy C Means [SFKFCM][18], and Multiple Kernel Fuzzy C Means [MKFCM] [19] are presented for segmentation of Brain MR Images. Details of these algorithm has presented in Section 3.

2. CLASSICAL CLUSTERING ANALYSIS

2.1 Hard C -Means Clustering (HCM)

Hard C-Means clustering is a non hierarchical technique that follows a simple and easy way to classify a given image through a certain number of clusters. It is a non fuzzy clustering method whereby each pattern can only belong to one cluster at any one time [1].The aim of the Hard C means is the minimization an objective function

$$J_{HFCM} = \sum_{i=1}^{n}\sum_{j=1}^{c}\left\|x_i - a_j\right\|^2 \quad (1)$$

ALGORITHM

Step-1: Assume

a) $X = \{x_1, x_2 \ldots, x_n\}$, $x_i \varepsilon R(s)$, the data set

b) $a = \{a_1, a_2 \ldots, a_c\}$, the set of centers

c) c_i is the number of data points in the i^{th} cluster

d) $2 \le c \le n$, c as the number of clusters

e) Randomly select 'c' cluster centers initially

f) Initialize the cluster centres randomly

Step-2: Calculate the distance between each data point and cluster centers.

Step-3: Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.

Step-4: Recalculate the new cluster center using (2)

$$a_i = \left(1/c_i\right)\sum_{j=1}^{c_i} x_i \quad (2)$$

Step-5: Recalculate the distance between each data point and new obtained cluster centers.

Step-6: If no data point was reassigned then stop, otherwise repeat from step-2.

2.2 Fuzzy C - Means Clustering (FCM)

FCM clustering is an unsupervised technique that has been successfully applied to feature analysis, clustering, and classifier designs in fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method (developed by Dunn in 1973 and improved by Bezdek in 1981) is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J_{FCM} = \sum_{i=1}^{n}\sum_{j=1}^{c}\left(\mu_{ij}\right)^m \left\|x_i - a_j\right\|^2 \quad (3)$$

where m is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i^{th} of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centers c_j.

ALGORITHM

Step-1: Assume

a) $X = \{x_1, x_2, \ldots, x_n\}$, xi ε R(s), the data set
b) $a = \{a_1, a_2 \ldots, a_c\}$, the set of centers
c) m - is the fuzziness index m € [1, ∞]
d) $2 \le c \le n$, c as the number of clusters
e) μ_{ij} - membership of i^{th} data to j^{th} cluster
f) d_{ij} - Euclidean distance between i^{th} data and j^{th} cluster center.
g) ∈- termination criterion between 0 and 1
h) Randomly select 'c' cluster centers initially

Step-2: Compute membership function, $\mu_{(s)}$ with cluster centre, $a_{(s-1)}$ using (5)

$$\mu_{ij} = 1 \Big/ \sum_{k=1}^{c}\left(d_{ij}/d_{ik}\right)^{\left(2/m-1\right)} \quad (4)$$

Step-3: Update the cluster centers, $a_{(s)}$ with membership function, $\mu_{(s)}$ using (4)

$$a_j = \frac{\left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^m x_i\right)}{\left(\sum_{i=1}^{n}\left(\mu_{ij}\right)^m\right)},\ \ j = 1,2,\ldots\ldots,c \quad (5)$$

Step-4: Update If $\left\|a_{(s)} - a_{(s-1)}\right\| < \in$, Stop and output. Else s=s+1 and return to step -2.

2. HYBRID FUZZY CLUSTERING

2.1 Gaussian Kernel fuzzy c –means [17]

The Gaussian kernel based FCM technique is used to increase the accuracy of the intuitionist fuzzy c-means by exploiting a kernel function in calculating the distance of data point from the cluster centres. i.e. mapping the data points from the input space to a high dimensional space in which the distance is measured using a Radial basis kernel function. The kernel function can be applied to any technique that solely depends on the dot product between two vectors. Wherever a dot product is used, it is replaced by a kernel function. The basic ideas of KFCM is to first map the input data into a feature space with higher dimension via a nonlinear transform and then

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perform FCM in that feature space. Thus the original complex and nonlinearly separable data structure in input space may become simple and linearly separable in the feature space after the nonlinear transform. GKFCM can automatically learn the parameters by prototype driven learning scheme, and presents more efficiency and robustness. GKFCM is very time consuming especially for large data sets or a large image and is sensitive to the weighting exponent m.

The objective function of Gaussian Kernel-based FCM is

$$J_{GKFCM} = 2\sum_{i=1}^{n}\sum_{j=1}^{c}\mu_{ij}^{m}(1-K(x_i,a_j)) \qquad (6)$$

ALGORITHM

Step-1: Assume

a) $X = \{x_1, x_2 . . ., x_n\}$, x_i ε R(s), the data set

b) $2 \le c \le n$, c as the number of clusters

c) ε > 0, the stopping criterion of algorithm

d) $a_0(0), a_1(0).....a_c(0)$the initials of cluster centers

e) Initialize the membership function μ_0

f) Let s=1

Step-2: Compute membership function,$\mu_{(s)}$ with cluster centre, $a_{(s-1)}$ using (8)

$$\mu_s(i,j) = \frac{\left(1-K(x_j,a_i)\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c}\left(1-K(x_j,a_k)\right)^{\frac{-1}{m-1}}}, i = 1,\dots,c, j = 1,\dots,n \quad (7)$$

Step-3: Update the cluster centers, $a_{(s)}$ with membership function, $\mu_{(s)}$ using (7)

$$a_s(i) = \frac{\sum_{j=1}^{n}\mu_{ij}^{m}\left(K(x_j,a_i)\right)x_j}{\sum_{j=1}^{n}\mu_{ij}^{m}\left(K(x_j,a_i)\right)}, i = 1,2,\dots,c \quad (8)$$

Step-4: Update If$\left\|a_{(s)} - a_{(s-1)}\right\| <$∈,Stop and output. Else s=s+1 and return to step2.

Where, Kernel function K is chosen to be the Gaussian function with

$$K(x_i,a_j) = exp\left(-\left\|x_i - a_j\right\|^2/\sigma^2\right) \qquad (9)$$

Where

$\sigma$is the standard deviation

2.2 SPATIAL CONSTRAINED FAST KERNEL FCM [18]

Spatial Constrained Fast Kernel FCM is an effective technique. It is extended from the Fuzzy C means technique. Different kernels will induce different measures for the original space, which leads to a new family of clustering techniques. This method can also be used to improve the performance of other FCM-like techniques based on adding some type of penalty terms to the original FCM objective function.

The objective function of the SFKFCM is

$$J_{SFKFCM} = \sum_{i=1}^{c}\sum_{j=1}^{N}\mu_{ij}^{m} \parallel x_j - a_i \parallel^2 + \frac{\alpha}{N_R}\sum_{i=1}^{c}\sum_{j=1}^{N}\mu_{ij}^{m}\sum_{r=N_j} \parallel x_r - a_i \parallel^2 \quad (10)$$

ALGORITHM

Step-1: Assume

a) $X = \{x_1, x_2 . . ., x_n\}$, x_i ε R(s), the data set

b) $2 \le c \le n$, c as the number of clusters

c) ε > 0, the stopping criterion of algorithm

d) $a = \{a_1, a_2 . . ., a_m\}$, a_i ε R(s), cluster centers

e) Parameter α is made by a trial and error experiments

f) Initialize the membership function μ_0 and let s=1

Step-2: Compute membership function, $\mu_{(s)}$ with prototype, $a_{(s-1)}$ using (12)

$$\mu_s(i,j) = \frac{\left(\left\|x_j - a_i\right\|^2 + \frac{\alpha}{N_R}\sum_{r\in N_j}\|x_r - a_i\|^2\right)^{-\frac{1}{m-1}}}{\sum_{j=1}^{c}\left(\left\|x_j - a_i\right\|^2 + \frac{\alpha}{N_R}\sum_{r\in N_j}\|x_r - a_i\|^2\right)^{-\frac{1}{m-1}}} \qquad (11)$$

Step-3: Update the prototype, $a_{(s)}$ with membership function, $\mu_{(s)}$ using (11)

$$a_s(i) = \frac{\sum_{j=1}^{N}\mu_{ij}^{m}\left(x_j + \frac{\alpha}{N_R}\sum_{r\in N_j}x_r\right)}{(1+\alpha)\sum_{j=1}^{N}\mu_{ij}^{m}} \qquad (12)$$

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Here, Neighbour average gray value around x_j

$$\sum_{k\in N_j} x_k/N_R \quad (13)$$

α=0.8
Where,
x_r-neighbor of x_j
N_{R}- is its cardinality

Step-4: Repeat Steps 2–3 until the following termination criterion is satisfied:

$$\|a_{(s)} - a_{(s-1)}\| < \epsilon \quad (14)$$

2.3 Multiple Kernel Fuzzy C Means [19]

Multiple Kernel Fuzzy C Means is an effective technique for segmenting a brain MR Image. It is an extended technique from the general fuzzy c means algorithm. MKFCM is composed of two or more kernels which are applied to the general kernel FCM and thus MKFCM is formed. This method can also be used to improve the performance of segmentation algorithm and gives better results.
The objective function of the MKFCM is

$$J_{MKFCM} = \sum_{i=1}^{n}\sum_{j=1}^{c} \mu_{ij}^{m}\left(1 - K_{com}(x_i, a_j)\right) \quad (15)$$

ALGORITHM

Step-1: Assume

a. X = {x_1, x_2. . .,x_n}, x_i ε R(s), the data set

b. 2 ≤ c ≤ n, c as the number of clusters

c. ε> 0, the stopping criterion of algorithm

d. $a_0(0)$,$a_1(0)$.....$a_c(0)$the initials of cluster centers

e. s=1; σ – standard deviation.

f. Initialize the membership function μ_0

Step-2: Compute membership function, $\mu_{(s)}$ with cluster centre, $a_{(s-1)}$ using (20)

$$\mu_s(i,j) = \frac{\left(1 - K_{com}(x_j, a_i)\right)^{\frac{-1}{m-1}}}{\sum_{k=1}^{c}\left(1 - K_{com}(x_j, a_i)\right)^{\frac{-1}{m-1}}}, i = 1, \dots, c, j = 1, \dots, n \quad (16)$$

Derivation,
Where

$$K(x_j, a_i) = exp\left(\frac{-\|x_j - a_i\|^2}{\sigma^2}\right) = exp\left(\frac{-\|[x_j, \bar{x}_j] - [a_i, \bar{a}_\iota]\|^2}{\sigma^2}\right) \quad (17)$$

$$K(x_j, a_i) = exp\left(\frac{-|x_j - a_i|^2 + -|\bar{x}_j - \bar{a}_\iota|^2}{\sigma^2}\right) = exp\left(\frac{-\|x_j - a_i\|^2}{\sigma^2}\right) exp\left(\frac{-\|\bar{x}_j - \bar{a}_\iota\|^2}{\sigma^2}\right) \quad (18)$$

$$K(x_j, a_i) = K_{com}(x_j, a_i) \quad (19)$$

Step.3. Update the cluster centers, $a_{(s)}$ with membership function, $\mu_{(s)}$ using (16)

$$a_s(i) = \frac{\sum_{j=1}^{n}\mu_{ij}^{m}\left(K_{com}(x_j, a_i)\right)}{\sum_{j=1}^{n}\mu_{ij}^{m}\left(K_{com}(x_j, a_i)\right)}, i = 1, \dots, c \quad j = 1, \dots, n \quad (20)$$

Step.4. Update If $\|a_{(s)} - a_{(s-1)}\| < \epsilon$, Stop and output. Else s=s+1 and return to step (2).

3. PERFORMANCE METRIC`S

When a clustering result is evaluated based on the data that was clustered itself, this is called internal evaluation. These methods usually assign the best score to the algorithm that produces clusters with high similarity within a cluster and low similarity between clusters. Validity as measured by such an index depends on the claim that this kind of structure exists in the data set. An algorithm designed for some kind of models has no chance if the data set contains a radically different set of models, or if the evaluation measures a radically different criterion.

The following methods can be used to assess the quality of clustering algorithms based on internal criterion:

3.1 β index

The β index [19] is defined as the ratio of the total variation and within – class or cluster variation and is given by

$$\beta = \frac{N}{M} \quad (21)$$

Where

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$$N = \sum_{i=1}^{c} \sum_{j=1}^{n_i} \left\| x_{ij} - \bar{v} \right\|^2 \quad (22)$$

$$M = \sum_{i=1}^{c} \sum_{j=1}^{n_i} \left\| x_{ij} - v_i \right\|^2 \quad (23)$$

$$\sum_{i=1}^{c} n_i = n \quad (24)$$

Where $n_i$is the number of objects in the i^{th} class or cluster (i=1,2,…,c),n the total number of objects, x_{ij} the j^{th} object in cluster i, v_i the mean or centroid of the i^{th} cluster, and $\bar{v}$ the mean on objects. For a given image and c value, the higher the homogeneity within the segmented regions, the higher would be the β value. The value of β increases with c.

3.2 Davies -Bouldinindex

The Davies -Bouldin (DB) Index [20] is a function of the ratio of sum of within-cluster distance to between-cluster separation and is given by

$$\mathrm{DB} = \frac{1}{\mathrm{c}} \sum_{\mathrm{i}=1}^{\mathrm{c}} \max \mathrm{i} \ \neq \mathrm{k} \left\{ \frac{\mathrm{S}(\mathrm{v_i}) + \mathrm{S}(\mathrm{v_k})}{\mathrm{d}(\mathrm{v_i}, \mathrm{v_k})} \right\} \text{for } 1 \leq \mathrm{i}, \mathrm{k} \leq \mathrm{c}. \quad (25)$$

The DB index minimizes the with-in cluster distance $S(v_i)$ and maximizes the between-cluster separation$d(v_i, v_k)$. Therefore, for a given data set and c value, the higher the similarity values within the clusters and the between-cluster separation, the lower would be the DB index value. A good clustering procedure should make the value of the DB index as low as possible.

3.3 Dunn index

Dunn’s index [21] is also defined to identify sets of clusters that are compact and well separated. Dunn’s (D) index maximizes

$$\mathrm{D} = \min \mathrm{i} \left\{ \max \mathrm{i} \ \neq \mathrm{k} \left\{ \frac{d(v_i, v_k)}{S(v_l)} \right\} \right\} \text{for } 1 \leq \mathrm{i}, k, l \leq c. \quad (26)$$

4. PIXEL CLASSIFICATION OF BRAIN MR IMAGES

In this section, the results if different C- Mean algorithms are presented on pixel classification of brain MR images, that is the results of clustering based as only gray values of pixels. The performance of three hybrid algorithms, namely, Gaussian Kernel Fuzzy C Means [GKFCM], Spatially Constrained Fast Kernel Fuzzy C Means[SFKFCM], Multiple Kernel Fuzzy C Means [MKFCM] are compared extensively with that of different C-Mean algorithms. All the algorithms are implemented in Matlab and run in windows and environment with the machine configuration core i5, 1MB cache and 1GB RAM.

The experimentation is done in two parts. In the first part, some real brains MR Images are used. All the brain MR Images have been collected from Aarthi scans, Tuticorin, India. In the second part, the Segmentation results are presented on some benchmark images obtain from Brain Web: Simulated Brain Database (http://brainweb.bic.mni.mcgill.ca/brainweb/). The comparative performance of different C-Means is reported to DB index, Dunn index, and β index reported in previous section.

4.1 Performance on real brain MRimages

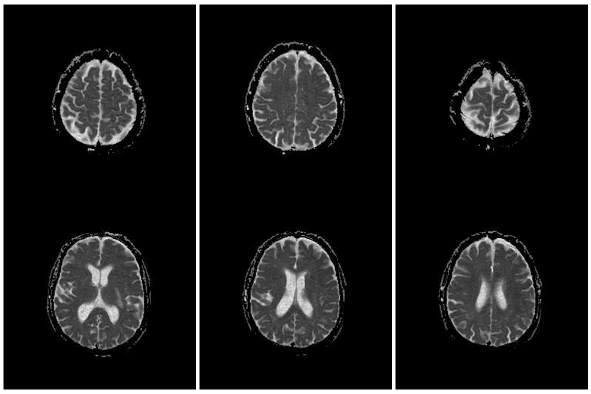
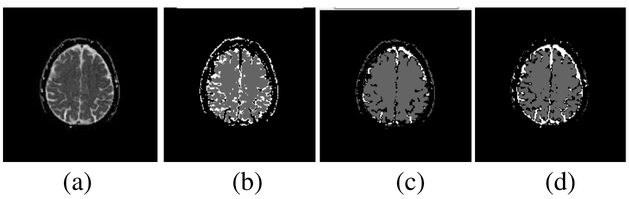


Figure 1. Sample Images of real brain MRI: Real Dataset I, Real Dataset II.

Figure.1 presents examples of some sample of real brain MR Images. Each images is of the size 256 x 180 with 8-bit gray levels. So the number of objects in each data set is 175. Consider Fig.2 as an example, which represents an MR Image (Real Dataset I) along with the segmented images obtained using different Hybrid Fuzzy C-Means algorithms. Table 1depicts the values of DB index, Dunn index, and β index of both MKFCM and SFKFCM for different values of C on the Real Dataset I. The results reported here with respect to DB and Dunn Index confirm that both MKFCM and SFKFCM achieve their best results for c=4 corresponding to three classes or categories such as back ground, gray matter and white matter. Also, the value of β index, as expected, increases with an increase in the value of c. For particular value of c, the performance of the MKFCM is better that of the SFKFCM.



(a) (b) (c) (d)

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Figure 2. Real Dataset I: Original and Segmented versions of different Hybrid Fuzzy C-Means. (a)Original (b) GKFCM (c) SFKFCM (d) MKFCM.

(a) (b) (c) (d)

Figure 3. Real Dataset II: Original and Segmented versions of different Hybrid Fuzzy C-Means. (a)Original (b) GKFCM (c) SFKFCM (d) MKFCM.

Finally Table-2 provides the comparative results of different Hybrid Fuzzy C-Means algorithm on Real Dataset I with respect to the values of DB index, Dunn index, β index, and CPU time (in Milliseconds). The Corresponding segmented images along with the original are presented in Figure-2. The results reported in Figure-2 and Table-2 confirm that the MKFCM clustering Algorithm produce more promising segmented images that do the conventional Methods.Table-3. Compares the performance of different Hybrid Fuzzy C-Means algorithms on Real Dataset II brain MR images with respect to DB, Dunn,β, and CPU time considering c=4. The original images along with the segmented versions of different c-means are shown in Figure-3.All the results reported in Tables 2, 3 and Figures 2, 3 confirm that although each hybrid fuzzy c-means algorithm, generates good segmented images, the values of DB, Dunn, and β index of the MKFCM are better compared to other hybrid fuzzy c-means algorithms.

4.2 Performance of simulated brain MR images

Extensive experimentation is done to evaluate the performance of the MKFCM algorithm on simulated Brain MR Images obtained from Brain Web: Simulated Brain Database.Figures 4, 5 and Figure-6 present the original and segmented images obtained using the MKFCM algorithm for different slice thickness and noise levels. The noise is calculated relative to the brightest tissue.

The results are reported for three different slice thicknesses: 1, 3, and 5 mm, and the noise various from 0 to 9%. Finally, Tables 4, 5, and 6 compare the values of DB, Dunn, and β indices of different c-means algorithms for different slice thickness and noise levels. All the results reported in Figures4, 5 and Fig 6 and Tables 4, 5, and 6 confirm that the MKFCM algorithm generated good segmented images irrespective of the slice thickness and noise level. Also, the performance of the MKFCM algorithm in terms of DB, Dunn, and β indices is significantly better compared to other C-means algorithms.

Table-1. Performance of NWFCM and MKFCM on real dataset I.

Value of c	DB index		Dunn index		β index	
	SFKFCM	MKFCM	SFKFCM	MKFCM	SFKFCM	MKFCM
3	1.58	1.71	1.35	1.35	0.13	0.13
4	4.68	3.08	1.31	1.31	0.13	0.21
5	4.55	5.83	1.35	1.89	0.13	0.13
6	4.59	4.01	0.96	0.94	0.13	0.13
7	6.25	6.26	0.96	0.93	0.13	0.13
8	11.43	9.69	1.23	0.87	0.13	0.13
9	9.73	11.34	0.92	0.92	0.13	0.13
10	13.43	17.19	1.28	1.45	0.13	0.13

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Table-2. Performance of various hybrid fuzzy c-means algorithms for real dataset I.

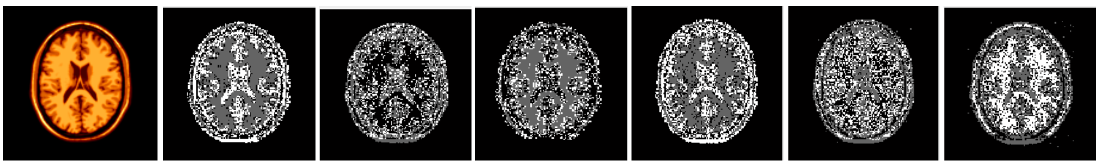
Algorithms	DB index	Dunn index	β index	Time	GM	WM
GKFCM	6.87	1.23	3.04	311	75.48	24.57
SFKFCM	5.87	1.22	3.04	2534	93.20	6.79
MKFCM	5.58	1.41	0.12	573	83.73	16.28

Table-3. Performance of various hybrid fuzzy c-means algorithms for real dataset II.

Algorithms	DB index	Dunn index	β index	Time	GM	WM
GKFCM	1.27	1.84	2.04	940	60.21	39.79
SFKFCM	1.37	1.89	2.04	1909	48.14	51.85
MKFCM	1.14	1.89	0.08	1399	45.90	54.09

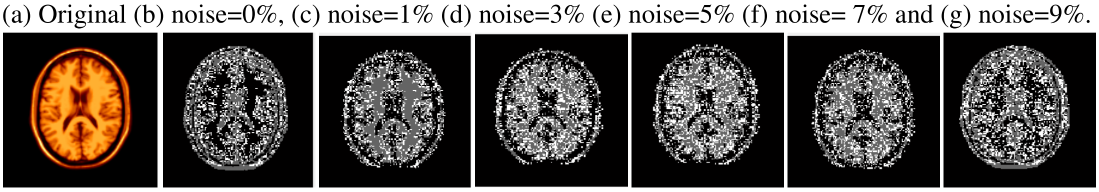
Table-4. Value of DB index for simulated brain MRI.

Slice thickness	Algorithms/Methods	Noise (%)					
		0	**1**	**3**	**5**	**7**	**9**
1	GKFCM	3.35	3.97	4.06	4.78	4.41	4.95
	SFCKFCM	5.25	4.18	4.64	3.25	4.00	3.38
	MKFCM	3.11	4.73	3.68	4.59	4.20	4.92
3	GKFCM	4.74	4.08	5.77	5.64	3.99	5.97
	SFCKFCM	3.78	4.30	3.57	3.79	3.07	3.54
	MKFCM	3.43	3.68	4.94	4.33	3.63	5.15
5	GKFCM	5.32	6.81	4.82	4.50	5.45	3.29
	SFCKFCM	2.98	3.56	2.80	2.47	3.12	3.30
	MKFCM	4.61	5.94	4.56	4.20	3.05	3.65



(a) (b) (c) (d) (e) (f) (g)

Figure 4. Slice thickness=1 mm: original and segmented versions of MKFCM algorithm for different noise levels. (a) Original (b) noise=0%, (c) noise=1% (d) noise=3% (e) noise=5% (f) noise= 7% and (g) noise=9%.



(a) (b) (c) (d) (e) (f) (g)

Figure-5. Slice thickness=3 mm: original and segmented versions of MKFCM algorithm for different noise levels. (a) Original (b) noise=0%, (c) noise=1% (d) noise=3% (e) noise=5% (f) noise= 7% and (g) noise=9%.

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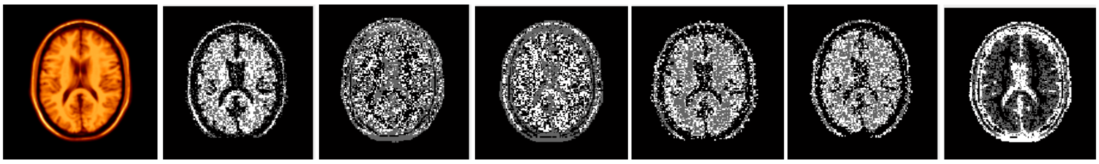

(a) (b) (c) (d) (e) (f) (g)

Figure-6. Slice thickness=5 mm: original and segmented versions of MKFCM algorithm for different noise levels. (a) Original (b) noise=0%, (c) noise=1% (d) noise=3% (e) noise=5% (f) noise= 7% and (g) noise=9%.

Table-5. Value of Dunn index for simulated brain MRI.

Slice thickness	Algorithms/Methods	Noise (%)					
		0	1	3	5	7	9
1	GKFCM	1.42	1.48	1.48	1.34	1.38	0.42
	SFCKFCM	1.44	1.39	1.29	1.44	1.49	1.58
	MKFCM	1.15	1.49	1.45	1.45	1.38	0.42
3	GKFCM	1.26	1.45	1.25	1.36	1.43	1.41
	SFCKFCM	1.43	1.34	1.25	1.42	1.25	1.51
	MKFCM	1.26	1.36	1.25	1.47	1.37	1.41
5	GKFCM	1.29	1.39	1.68	1.60	1.57	1.83
	SFCKFCM	1.29	1.39	1.54	1.55	1.50	1.83
	MKFCM	1.29	1.38	1.68	1.55	1.57	1.79

Table-6. Value of β Index for simulated brain MRI.

Slice thickness	Algorithms/Methods	Noise (%)					
		0	1	3	5	7	9
1	GKFCM	5.34	5.43	5.43	4.87	4.73	4.49
	SFCKFCM	5.34	5.43	5.43	4.87	4.73	4.49
	MKFCM	0.21	0.22	0.20	0.19	0.19	0.18
3	GKFCM	5.37	5.36	5.20	4.94	4.95	4.53
	SFCKFCM	5.37	5.36	5.20	4.94	4.95	4.53
	MKFCM	0.22	0.21	0.20	0.20	0.20	0.18
5	GKFCM	5.42	5.26	4.91	4.76	4.51	5.49
	SFCKFCM	5.42	5.26	4.91	4.76	4.51	5.49
	MKFCM	0.22	0.21	0.20	0.19	0.18	0.22

Table-7. Performance of different c-means algorithms.

Real data	Algorithms	DB index	Dunn index	βindex	Time
Real dataset I	GKFCM	6.86	1.23	3.04	311
	SFCKFCM	5.87	1.22	3.04	2534
	MKFCM	5.58	1.42	0.12	573
Real dataset II	GKFCM	1.27	1.84	2.04	940
	SFCKFCM	1.37	1.89	2.04	1909
	MKFCM	1.14	1.89	0.08	1399

5. EXPERIMENTAL RESULTS

In this section, the performance of different Hybrid Fuzzy C-means algorithms in segmentation of brain MR images is presented. The algorithms compared are GKFCM, SFCKFCM and MKFCM.

5.1Comparative performance analysis

Table-7 compares the performance of different hybrid c-means algorithms on some brain MR images with respected to DB, Dunn and β indices. The segmented versions of different c-means are shown in Figures 6 and 7. All the results reported in Table-7 and Figures6 and 7 confirm that although each c-means algorithm generates good segmented images, the values of DB, Dunn, and β indices of the MKFCM are better compared to other hybrid fuzzy c-means algorithms.

6. CONCULSION AND DISCUSSIONS

The problem of segmenting brain MR images is considered in fuzzy computing framework. A robust segmentation technique is presented in this chapter, integrating the merits of Fuzzy sets, and C-means algorithm, for brain MR images. Some new measures are reported, based on the local properties of MR images, for accurate segmentation. The method, based on the concept of maximization of class separability, is found to be successful in effectively circumventing the initialization and local minima problems of iterative refinement clustering algorithms such as C-means. The extensive experimental results on a set of real and benchmark brain MR images show that the multiple kernel Fuzzy C means clustering algorithm produces a segmented image more promising than do the conventional algorithms.

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