Knowledge based Self Initializing FCM Algorithms for Fast Segmentation of Brain Tissues in Magnetic Resonance Images

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ABSTRACT
This paper presents two robust FCM algorithms to segment the brain tissues from MRI volume. The core regions of human brain are white matter (WM), gray matter (GM), cerebrospinal fluid (CSF) and others known as background (BCK). Usually, to classify the given data, random initial seeds are selected and then the FCM procedure is iterated until the centroids of cluster converge. The first proposed FCM, named as FCM-EXPERT, make use of the expert knowledge about the brain tissue properties to select the initial seed points. Experimental results on brain portions extracted from large MRI database show that this method is faster by 1.3 to 1.7 times than that of the traditional FCM in segmenting brain tissues. FCM-EXPERT has been again modified by making use of the correlation existing between brain regions in adjacent slices of MRI for centroid initialization and named as FCM-EXPERT-E. Experimental results of the second method show that this is faster by 2 to 4 times than that of traditional FCM.

General Terms
Image Segmentation, Clustering, Self Initialization.

Keywords
FCM clustering; brain tissues segmentation; centroid initialization; brain continuity; slice correlation; MRI scans.

1. INTRODUCTION
Segmentation plays an important role in biomedical image processing. It is often the starting point for other processes like analysis, visualization, quantization and modeling. This is a core technique to study about the anatomy and pathology of human organs. In brain diagnostic system, segmentation is essential to study any brain related disorders like seizures, stroke, multiple sclerosis, aneurisms, hemorrohages, brain tumors, brain cancers, brain atrophy, lesions, and sub structural changes. Three main regions of brain, white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) are the important subjects of study in brain diagnostic system. Manual segmentation of these three brain regions by an expert is time consuming, inconsistent and affected by operator bias as the volume of data involved in MRI studies is usually large. Hence an automatic segmentation of brain regions is essential for a physician to speed up their diagnostic process.

Segmentation techniques are broadly classified into two types: supervised and unsupervised [1]. Supervised methods require the user interaction and thus known as semi-automatic. Unsupervised techniques are completely automatic and segment the regions in feature space with a high density. Fuzzy C-Means (FCM) is an unsupervised clustering method. It automatically segments the region of interest (ROI) by classifying a tissue into several classes at the same time but with different degrees [2] [3] [4]. A study [5] revealed that FCM never misses a region and it is the best method for segmenting anisotropic nature of brain volumes that are affected by partial volume effect (PVE).

FCM algorithm employs fuzzy partitioning such that a data point can belong to all clusters with different membership grades between 0 and 1. This method is frequently used in pattern recognition. The aim of FCM is to find cluster centers that minimize a dissimilarity (objective) function. By iteratively updating the cluster centers and the membership grade for each data point, FCM iteratively moves the cluster centers to the “right” location within a data set. But it does not ensure that it converges to an optimal solution in an optimal time, if the cluster centers (centroids) are initialized randomly. The performance of FCM depends on initial centroids of required clusters [6] [7]. Hence the selection of a centroid is important in FCM. For a robust approach there are two ways to select the centroids.

- Run the FCM several times each starting with different initial centroids and select the best initial values for the centroids
- Use application specific expert knowledge and select the initial centroids

The first approach becomes a supervised clustering technique and do not qualify to be a fully automatic method. Further it takes more time to identify the initial centroids. If the details about the data point density of the application are known prior then the second approach is preferable to generate the initial centroids.

Several modifications were proposed for FCM algorithm for medical image segmentation. Most of the existing works generally focused to frame a robust objective function to handle the noisy images [8] [9] [10], bias field estimation [11] [12] and sometimes both [13]. Nowadays advanced scanners are available that produce high resolution and non-artifact form of MRI images. So the modification for FCM algorithm is focused to fully automate its functionality based on the knowledge of the application area. This paper proposes such a modification to initialize the centroids of FCM method for brain tissue segmentation from MRI of head volume.

This paper proposed two FCM methods that generate initial seeds by making use of the expert knowledge about the tissue properties appearing in the MRI of human head scans. FCM is a soft segmentation technique applicable for MRI brain tissues segmentation. The performance of FCM, to obtain an optimal solution depends on the selection of the initial positions of their centroids. In the existing FCM, the number of clusters is usually set by the users and their centroids are initialized randomly. This process generally takes time to reach the optimal solution. In order to accelerate the segmentation process, an application specific knowledge is used to initialize the centers of required clusters. To segment brain portion, the knowledge about the MRI intensity characteristics of brain regions is used to initialize the centroids. In the first method, FCM_EXPERT, the centroids are initialized using the intensity levels of the WM, GM, CSF and BCK. In the second method, FCM_EXPERT_E, the correlation existing between adjacent slices of an MRI volume is utilized. The final centroids obtained for the previous slice is used as initial centroid for the current slice. These methods are then applied on the brain portion extracted from MRI, and segmented the WM, GM and CSF.

The remaining part of this paper is organized as follows. In section 2, the existing FCM algorithm and the proposed methods used for brain tissue segmentation are given. In section 3, the materials used are given. The results and discussion are presented in section 4. The conclusion is given in section 5.

2. METHOD

2.1 Fuzzy C-Means Method (FCM)

FCM based clustering was originally introduced by Jim Bezdek in 1981 [3] [4]. The FCM algorithm attempts to partition a finite collection of elements $X = \{x_1, x_2, ..., x_n\}$ into a collection of c fuzzy clusters with centers V = v_i, i=1, 2,…c and a partition or membership matrix, U = u_{ij}, i=1, 2,…n, j=1, 2,…c where u_{ij} is a numerical value in [0, 1] that tells the degree to which the element x_i belongs to the jth cluster.

The goal of FCM algorithm is to minimize the following objective function:

$$J_m = \sum_{j=1}^{c}\sum_{i=1}^{n} u_{ij}^m d_{ij} \quad , \tag{1}$$

where,

$$d_{ij} = \left\| x_i - v_j \right\| \tag{2}$$

$m \in [1, \infty]$ is a scalar termed as weighting exponent. *m* controls the fuzziness of the resulting clusters and d_{ij} is the Euclidian distance from object x_i to the cluster center v_j. The centroid of the *j*th cluster, v_j is obtained as:

$$v_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \quad , \tag{3}$$

where,

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{d_{ij}}{d_{ik}}\right]^{\frac{2}{m-1}}} \tag{4}$$

The following is the conventional FCM algorithm [3].

Step 1: Select the number of clusters c ($2 \le c \le n$), exponential weight m, initial membership matrix U and the termination/stopping criterion.

Step 2: Compute the cluster centers $v_j,\ j = 1,2,..., c$, according to equation (3)

Step 3: Compute Euclidian distance $d_{ij}, i = 1,2,..., n;\ j = 1,2,..., c$ based on equation (2)

Step 4: Update the membership function $u_{ij}, i = 1,2,..., n;\ j = 1,2,..., c$ using the equation (4)

Step 5: If not converged, go to step 2.

Step 6: Output u_{ij} and v_j, the membership function and centroids of the data.

The FCM algorithm starts by setting values for the number of clusters (c), weighing factor (m), initialization of U and termination criterion as given in step 1. The number of clusters is either supplied by the user during the process or automatically computed by the application. There is no fixed rule for choosing m, however, in many applications m=2 is a common choice. In case of crisp clustering 'm' may be chosen as 1.

The membership function matrix u_{ij}, contains the grade of membership of each object in each cluster. The values 0 and 1 indicate no membership and full membership respectively. Grades between 0 and 1 indicate that the object has partial membership in a cluster. Hence the summation of each row (total grades of an object) should be equal to unity. One more attribute of FCM is that it never leaves any region as blank [5]. These attributes are used to define the characteristics of fuzzy matrix u_{ij} and are defined as follows [6]:

$$u_{ij} \in [0,1] \qquad \forall i = 1,2,\ldots,n; \forall j = 1,2,\ldots,c \tag{5}$$

$$\sum_{j=1}^{c} u_{ij} = 1 \qquad \forall i = 1,2,\ldots,n \tag{6}$$

$$0 < \sum_{i=1}^{n} u_{ij} < n \qquad \forall j = 1,2,\ldots,c \tag{7}$$

The FCM algorithm starts with the initialization of this membership function u_{ij} as given in step 1 of FCM algorithm. In general, this is done by using random number generator and to satisfy the aforesaid three constraints of u_{ij}. Then the matrix u_{ij} is used to generate the cluster centers (step 2 of FCM algorithm).

Several stopping criteria can be used for convergence. The most generalized convergence criteria can be stated as follows:

i. Set the number of iterations as maximum as possible, or

ii. The objective function J_m defined in equation(1) cannot be minimized any further significantly, or

iii. The centroids no longer move in successive iterations.

Among these three criterions, the first two requires a user input in the form of number of iterations and value of error factor respectively. But the third one is a self generated one and does not require any external input. A comparative study [7] between these criteria showed that the third criterion yield results much faster than the other two. So the third is chosen as a stopping criterion for both the existing and proposed FCM methods.

2.2 Proposed Method (FCM-EXPERT)

As explained in the previous section, the performance of FCM algorithm depends on the selection of number of clusters **c** and their centroids **v**. The major ROI of human brain image is GM, WM, CSF and the surrounding background (BCK). Hence for brain tissue segmentation **c** is fixed as 4. The brain tissues are characterized by their intensity values in MRI scans. This expert knowledge is used to initialize the centroids. As the performance of the FCM depends on the initial position of the centroids, they can be initialized by selecting the intensity levels corresponding to the tissues instead of selecting them randomly. This will yield better results and quicken the process. This method is named as FCM-EXPERT.

Imaging characteristics of MRI scans

The images produced by MRI scans are usually gray images with intensity in the range 0-255. The GM of the brain consists of the cortex that lines the external surface of the brain and the gray nuclei deep inside of the brain, including the thalami and basal ganglia. WM is comprised of the neuronal axons that interconnect different regions of the brain and serve as the interface between the brain and the rest of the body. The watery fluid, CSF acts as a cushion for physical shocks. The WM constitutes a connected region that is bordered by GM and CSF as shown in Fig.1. For the display purpose WM is shown in gray color, GM as white color and CSF as black color. In MRI of head scans, the picture of brain organ is usually surrounded by air particles, known as background, BCK in order to make a matrix representation. This BCK is another major ROI in MRI of head scans.

Jeny et al [14] analyzed the intensity characteristics of T1 MRI of head regions and generated a histogram of skull stripped image as shown in Fig.2. In the histogram there are three peaks, the first peak corresponds to CSF, the middle peak corresponds to gray matter and the last peak corresponds to white matter. The three peaks are used in their semi-automatic tool, BrainAssiat™ to separate the brain region. In this paper, the values of these peaks are used to initialize the centroids for the FCM method.

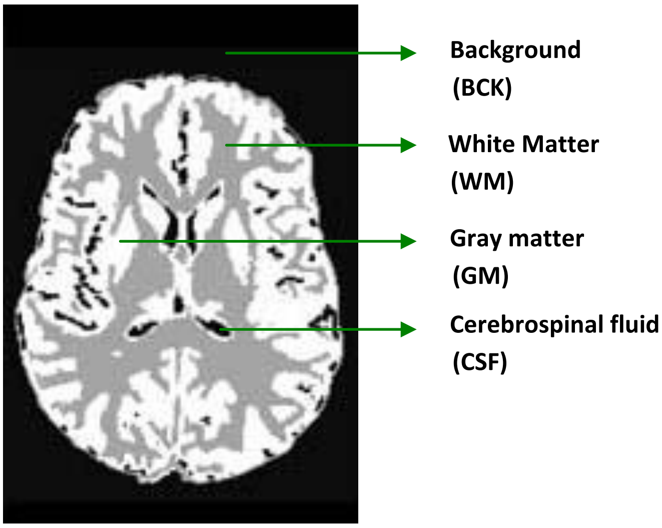

Fig. 1. Segmentation results in MRI of axial head scan

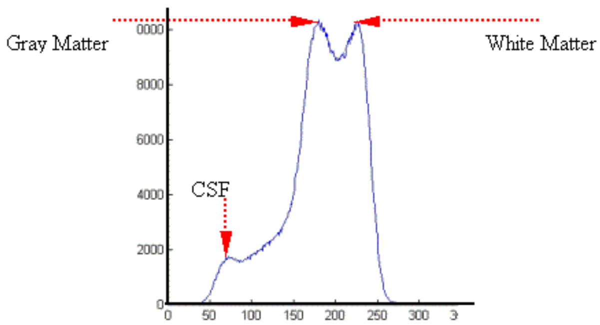

Fig. 2. Histogram of a skull stripped T1 weighted MRI

Initialization of centroids

In the intensity characteristics of MRI brain scans, the brain region lies in four major gray ranges, darkest, dark / dark gray, gray and bright representing BCK, CSF, GM, WM in T1 weighted images and BCK, WM, GM, CSF in T2 weighted images.

Hence the initial centroids for these four regions of gray scale image can be fixed as follow:

- The lowest intensity 0 is considered as cluster center for darkest region, always background (BCK)
- The highest intensity 255 is fixed as centroid for bright region
- In between, an equal interval is assumed based on the peaks of Fig.2 and the values 85 and 170 are taken as centroids for dark gray and gray regions.

Hence the intensity values 0, 85, 170 and 255 are taken as initial centroids for the four regions to start the FCM algorithm in the proposed method, FCM-EXPERT.

The FCM-EXPERT algorithm is given below,

Step 1: Initialize the cluster centroids v_j, $j = 1,2,3,4$ using the given values.

Step 2: Compute Euclidian distance $d_{ij}, i = 1,2,..., n; j = 1,2,3,4$ using equation (2)

Step 3: Compute the membership function u_{ij}, $i = 1,2,\ldots,n; j = 1,2,3,4$ using equation (4)

Step 4: Update the cluster centers v_j, $j = 1,2,3,4$, using equation (3)

Step 5: If none of the centroids(v_j, $j = 1,2,3,4$) changes in step 4, stop; otherwise go to step 2

Step 6: Output u_{ij} and v_j, the membership function and centroids of the data.

2.3 Extension of the proposed Method (FCM-EXPERT-E)

In MRI of head scan, there is a continuity of the brain portion between two adjacent slices. Therefore there should be high correlation between the two adjacent brain areas. Brummer et al., [15] have suggested that this continuity property of brain in a volume could be exploited in neighboring slices to select the ROI. The brain extraction algorithms (BEA) [15] [16] [17] used this concept to extract the brain volume from the MRI volume. This property is used to quicken the proposed FCM-EXPERT method and named it as FCM-EXPERT-E. The flowchart for FCM-EXPERT-E is shown in Fig.3.

The algorithm for FCM-EXPERT-E is given below.

Step 1: Input the MRI of head scans (volume).

Step 2: Extract the brain volume from MRI volume using BEA.

Step 3: Find the middle slice (M) from the MRI brain volume.

Step 4: Divid the brain volume into two sub volumes: lower slices (LS) lying below the M and upper slices (US) lying above M.

Step 5: The LS range is M-1 to bottom-end (BE) of volume and US range is M+1 to top-end (TE) of volume

Step 6: Apply the FCM-EXPERT on the middle slice M by taking initial centroids as 0, 85, 170, 255 and compute the final centroids.

Step 7: Move one slice up in US volume (one slice down in LS volume) by taking the final centroids of the previous slice as initial centroids and apply FCM-EXPERT.

Step 8: Repeat step 7 until TE (BE) is reached.

3. MATERIALS

Twenty datasets of T1 and T2 types obtained from different sources are used for the experiments. Ten T1 coronal volumes of normal subjects were obtained from the 'Internet Brain Segmentation Repository' (IBSR) developed by Centre for Morphometric Analysis (CMA) at Massachusetts General Hospital [19]. Each IBSR dataset has approximately 60 slices per volume with slice thickness = contiguous 3.1 mm and slice matrix = 256×256. Another ten T2 axial datasets consisting of normal and abnormal volumes with brain tumor were taken from the website 'The Whole Brain Atlas' (WBA) maintained by Department of Radiology and Neurology at Brigham and Women's Hospital, Harvard Medical School [20], and from KGS Advanced MR and CT Scans, India. WBA volume consists approximately 25 slices with slice size 256×256 and slice thickness ≈ 5mm. KGS has approximately 20 slices per volume with slice matrix = 448×512 and slice thickness ≈ 7mm along with inter slice gap. KGS scans are much affected by partial volume effect (PVE) artifact.

4. RESULTS/DISCUSSION

The experiments are carried out using the conventional FCM algorithm and the two proposed algorithms FCM-EXPERT and FCM-EXPERT-E on the images chosen from the material pool.

Initially a qualitative performance evaluation of these methods on original MR scan was done. The segmentation results obtained are shown in Fig.4. The first row shows the segmentation results obtained for original MRI of head scan and the second row for skull stripped brain portion of the same slice. For the original image given in row 1 of Fig.4, some of the surrounding non-brain regions like fat, skin, bone and neck portions are misclassified as the required ROIs. But when these methods were applied on brain portion extracted from the original image, the FCM algorithm gave more accurate classifications as given in row 2 of Fig.4. This type of testing was done on several volumes and found that the segmentation on extracted brain produced accurate results. Hence, for further validation, the methods were applied on the brain portion extracted from the MR scans using the brain extraction algorithms [15] [16].

The conventional FCM algorithm and proposed procedures FCM-EXPERT and FCM-EXPERT-E were applied on the datasets of different types of images and orientations taken from the material pool. In each orientation, only the slices with major brain regions were taken for experiments leaving the initial and trailing slices appearing at both ends of the volume. Middle 40 slices out of 60 for IBSR T1 coronal volumes and 10 slices out of 20 for WBA and KGS T2 axial volumes were taken. The conventional FCM algorithm with random initialization was applied on the brain portion in order to find the optimal solution in terms of number of iterations, cluster centers and time taken for processing the images. The values computed are given in Table 1. Then the algorithm FCM-EXPERT with the initial centroids as 0, 85, 170, 255 was applied on the same brain portion. The computed values are given in Table 1. From Table 1, it was noticed that the average number of iterations for the traditional FCM is 19, 21 and 24 for IBSR, WBA and KGS datasets respectively. But the proposed FCM-EXPERT reduced these values to 13, 14 and 18 respectively. Hence the processing times were also reduced considerably. This shows that the proposed FCM-EXPERT is 1.4, 1.72 and 1.32 times faster than the existing FCM for the normal (IBSR), abnormal (WBA) and PVE (KGS) datasets.

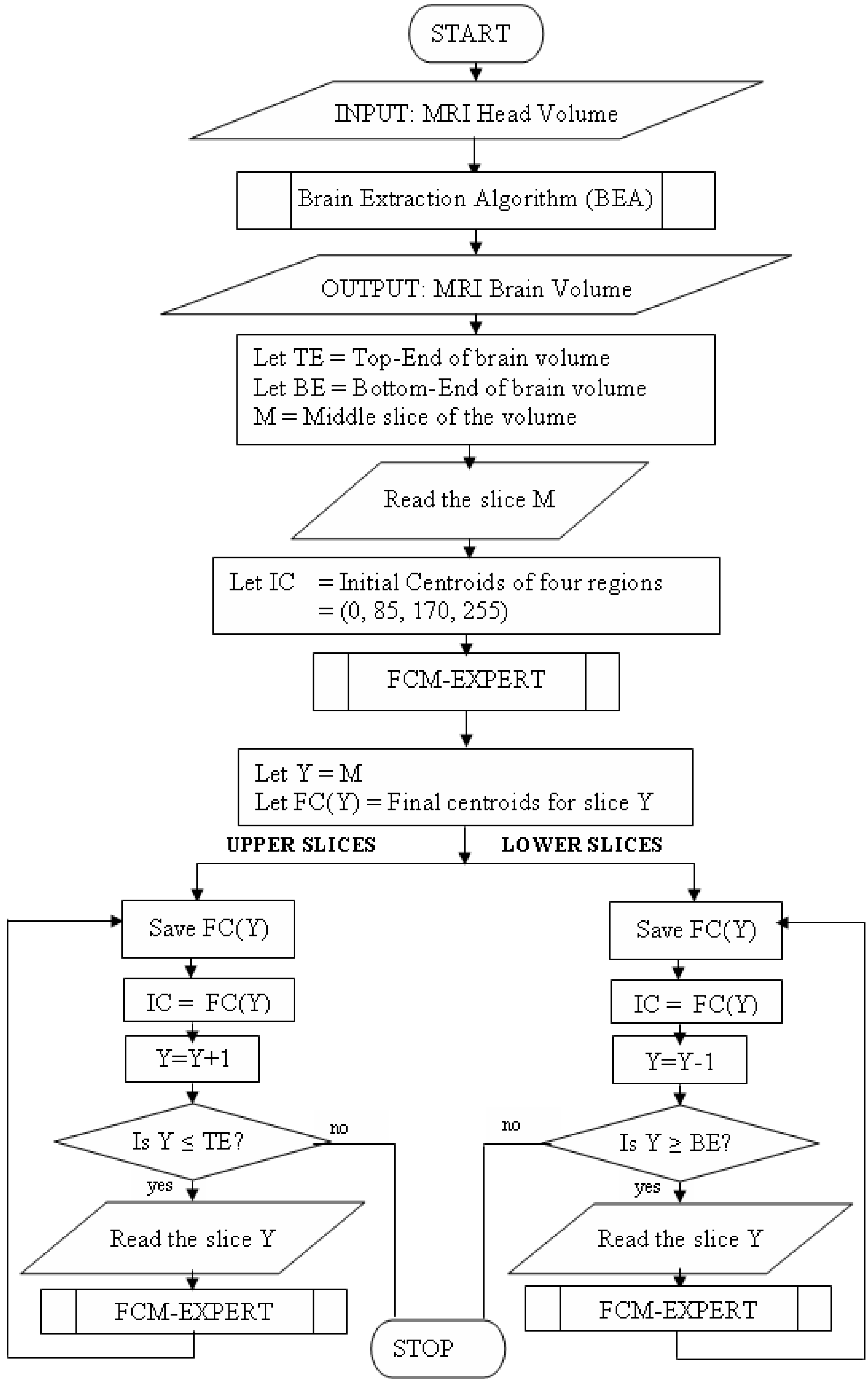

Fig. 3. Flowchart of FCM-EXPERT-E

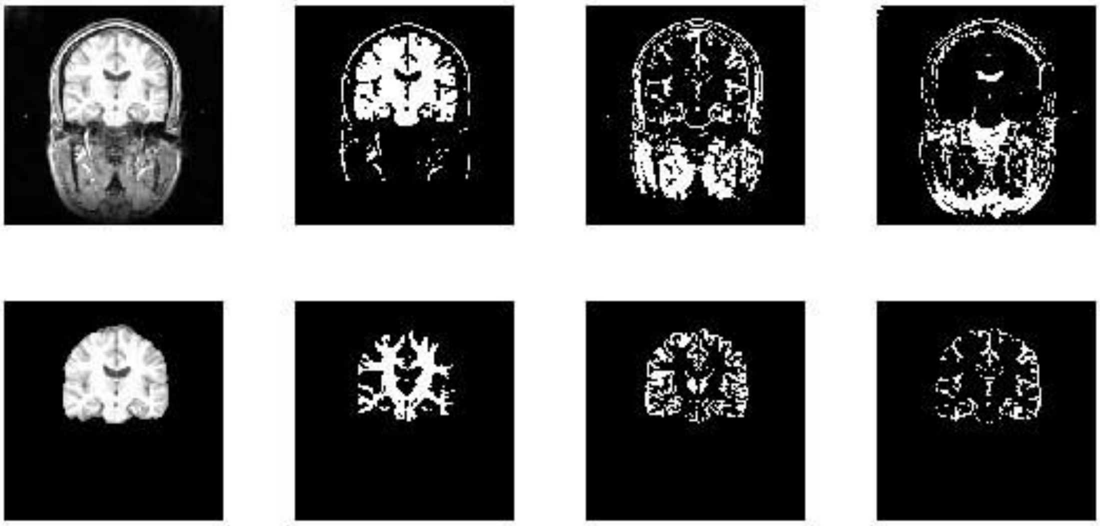

Fig. 4. Segmentation results on raw and extracted brain image. Row 1 shows the segmentation of raw MRI scans and row2 shows the segmentation of the brain portion extracted from the original. Column 1 shows the original head scan and the extracted brain in row 1 and row2. The three ROIs, WM, GM and CSF of head and brain obtained by FCM are in column 2-4 respectively.

Table 1. The average number of iterations, cluster centers and segmentation time of MRI volumes

Data Source	Data set	FCM Method																	
		FCM Conventional						FCM-EXPERT						FCM-EXPERT-E					
		No. iter	Final Centroids				Proc. Time	No. iter	Final Centroids				Proc. Time	No. iter	Final Centroids				Proc. Time
			C1	C2	C3	C4			C1	C2	C3	C4			C1	C2	C3	C4	
IBSR	vol 1	19	0	143	202	249	4.74	14	0	143	202	249	3.33	4	0	144	203	249	0.778
	vol 2	19	0	126	172	217	3.29	10	0	126	172	217	2.11	8	0	127	173	217	1.447
	vol 3	19	0	136	193	243	3.49	13	0	135	192	243	2.37	5	0	137	194	244	0.896
	vol 4	19	0	140	194	248	3.70	13	0	138	193	248	2.40	6	0	140	194	248	1.034
	vol 5	18	0	144	207	248	3.15	14	0	143	206	248	2.65	4	0	144	207	248	0.78
	vol 6	19	0	138	196	246	3.34	13	0	137	195	246	2.24	4	0	139	196	247	0.76
	vol 7	18	0	144	208	250	3.35	14	0	143	208	249	2.55	5	0	144	209	250	0.793
	vol 8	18	0	140	203	249	3.26	13	0	140	203	249	2.47	4	0	141	204	249	0.75
	vol 9	18	0	134	200	247	3.11	13	0	134	199	247	2.23	4	0	135	200	248	0.778
	vol 10	18	0	136	204	249	3.07	13	0	135	203	249	2.26	4	0	136	204	250	0.757
	Avg	**19**	**0**	**138**	**198**	**245**	**3.45**	**13**	**0**	**137**	**197**	**245**	**2.46**	**5**	**0**	**139**	**198**	**245**	**0.877**
WBA	vol 11	20	0	89	128	195	4.85	13	0	90	130	198	2.99	9	0	90	130	197	2.145
	vol 12	21	0	75	114	208	5.10	16	0	76	116	210	3.10	7	0	76	115	210	1.172
	vol 13	23	0	84	124	201	5.00	15	0	84	127	204	3.02	9	0	84	125	203	1.527
	vol1 4	21	0	112	147	208	4.62	9	0	113	150	211	1.68	6	0	112	149	210	1.07
	vol 15	21	0	79	121	187	5.64	15	0	80	124	188	3.84	6	0	80	122	187	1.492
	Avg	**21**	**0**	**88**	**127**	**200**	**5.04**	**14**	**0**	**89**	**129**	**202**	**2.93**	**7**	**0**	**88**	**128**	**201**	**1.481**
KGS	vol 16	23	0	69	97	166	15.10	17	0	70	100	169	11.68	10	0	70	98	167	5.752
	vol 17	21	0	69	97	153	12.89	19	0	70	99	157	11.44	9	0	70	98	156	5.225
	vol 18	26	0	73	103	162	15.33	17	0	74	104	165	10.45	11	0	74	100	159	6.528
	vol 19	23	0	71	100	163	14.26	17	0	72	103	167	10.86	10	0	74	104	164	5.661
	vol 20	25	0	73	98	156	16.59	18	0	74	101	160	11.65	9	0	72	103	166	5.378
	Avg	**24**	**0**	**71**	**99**	**160**	**14.83**	**18**	**0**	**72**	**101**	**164**	**11.22**	**10**	**0**	**72**	**101**	**162**	**5.709**

Table 2. Performance of FCM-EXPERT-E for vol 5 of IBSR

Slices	Slice No	No. of Iter.	C1	C2	C3	C4	Pro. Time (Sec)
Middle Slice (M)	**30**	**15**	**0**	**149**	**210**	**250**	**2.562**
Lower Slices (LU)	**29**	**3**	**0**	**149**	**208**	**251**	**0.531**
	28	4	0	149	209	250	0.703
	27	6	0	143	209	249	1.031
	26	7	0	138	206	249	1.204
	25	4	0	139	205	248	0.703
	24	4	0	138	205	248	0.687
	23	4	0	140	203	248	0.687
	22	4	0	139	204	249	0.703
	21	4	0	137	204	248	0.688
	20	3	0	137	204	247	0.515
	19	5	0	135	203	246	0.875
	18	3	0	136	201	245	0.531
	17	4	0	140	201	243	0.687
	16	4	0	141	200	243	0.703
	15	4	0	143	201	242	0.703
	14	6	0	146	202	242	1.032
	13	4	0	147	204	244	0.688
	12	4	0	146	206	245	0.703
	11	3	0	144	205	246	0.531
Upper Slices (US)	**31**	**5**	**0**	**145**	**208**	**250**	**0.86**
	32	4	0	149	209	250	0.703
	33	5	0	151	210	250	0.86
	34	3	0	153	209	250	0.515
	35	7	0	146	210	250	1.203
	36	5	0	143	209	249	0.875
	37	4	0	143	208	248	0.688
	38	3	0	143	206	248	0.531
	39	4	0	146	205	248	0.687
	40	4	0	147	206	249	0.688
	41	3	0	147	206	249	0.531
	42	6	0	147	210	251	1.156
	43	4	0	151	212	251	0.687
	44	4	0	148	211	251	0.688
	45	3	0	151	211	251	0.532
	46	4	0	151	212	251	0.703
	47	5	0	145	213	251	0.875
	48	4	0	141	213	251	0.703
	49	3	0	140	213	251	0.532
	50	4	0	138	213	250	0.703
Average		**4**	**0**	**144**	**207**	**248**	**0.78**

Finally, the proposed FCM_EXPERT-E was applied on the selected MRI volumes. Table 2 shows the relative change of centroids and iterations for lower slices (LS), upper slices (US) and the middle slice (M) for vol 5 of IBSR. It is observed that only the slice M requires 15 iterations to reach the convergence. The final centroid produced for slice M is used to initialize the adjacent slices 29 and 31, lying above and below it. In this way the resultant centroids of each slice is used to initialize their adjacent slice and executed the FCM-EXPERT-E algorithm.

The average values computed using FCM-EXPERT-E for the selected volumes are given in Table 1. From Table 1, it is noticeable that the average number of iterations for conventional FCM is 19 whereas it is reduced to 13 by proposed FCM_EXPERT and to 5 by FCM_EXPERT-E. The average segmentation time are 0.877 seconds/slice for IBSR, 1.481 seconds/slice for WBA and 5.709 seconds/slice for KGS. This method is 3.93 times faster than conventional FCM and 2.8 times faster than FCM-EXPERT of IBSR volumes. For WBA, it is observed that the proposed method FCM-EXPERT-E is 3.4 times faster than conventional FCM and 1.98 faster than FCM-EXPERT. For KGS datasets, it is found the same trend and the proposed method FCM-EXPERT-E is 2.6 and 1.97 times faster than conventional FCM and FCM-EXPERT. This shows that the proposed FCM-EXPERT-E based segmentation is 3 to 4 times faster for normal volumes, 2 to 3 times faster for abnormal volumes and 2 times faster for PVE volumes than the conventional FCM and FCM-EXPERT method.

The experiments were performed in a 1.73 GHz Intel Pentium dual-core processor, Windows XP with 1GB RAM, using Matlab 6.5.

5. CONCLUSION

The performance of Fuzzy-C-Means (FCM) clustering algorithm depends on the initialization of the seed points. This paper proposed two novel seed initialization methods for the conventional FCM algorithm. The initialization is done based on the domain specific expert knowledge of the MRI of human head scans. In the first method, the seed initialization is done using the WM, GM and CSF properties in MRI. Application of this method on brain portion extracted from publically available T1 and T2 weighted MRI of human head scans show that the first proposed method FCM_EXPERT is faster by 1.32 to 1.72 times than that of the traditional FCM in segmenting WM, GM and CSF. In the second seed initialization method, FCM-EXPERT-E, the correlation existing between the adjacent slices of an MRI volume is exploited. This method is faster by 2 to 4 times than the conventional method in segmenting WM, GM and CSF. The experiments show that a domain specific knowledge can be effectively used to initialize the centroids of FCM method.

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REFERENCES

[1] Jain, A. K., Murty, M. N. and Flynn, P. J. 1999. Data Clustering – A Review, ACM Computing Survey, 31(3), 265-322.

[2] Dunn, J. C. 1973. A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well-Separated Clusters, Journal of Cybernetics, 3, 32-57.

[3] Bezdek, J. C. 1981. Pattern Recognition with Fuzzy Objective Function Algorithms, Plenum Press, New York.

[4] Pal, N.R. and Bezdek, J.C. 1995. On Cluster Validity for the Fuzzy C-Means Model, IEEE Transactions on Fuzzy Systems, 3(3), 370-379.

[5] Somasundaram, K. and Kalaiselvi, T. 2009. A Comparative Study of Segmentation Techniques Used for MR Brain Images, International Conference on Image Processing, Computer Vision, and Pattern Recognition, Las Vegas, Nevada, USA, (July 13-16), 597-603.

[6] Izakian, H. and Abraham, A. 2011. Fuzzy C-means and Fuzzy Swarm for Fuzzy Clustering Problem, Expert Systems with Applications, 38, 1835–1838.

[7] Kalaiselvi, T. and Somasundaram, K. 2010. Fuzzy C-Means Technique with Histogram Based Centroid Initialization for Brain Tissue Segmentation in MRI of Head Scans, IEEE sponsored 2011 International Symposium on Humanities, Science & Engineering Research – SHUSER2011, Kuala Lumpur, Malaysia, (June 5-7), 155-160

[8] Kannan, S.R., Ramathilagam, S., Devi, R. and Sathya, A. 2011. Robust kernel FCM in segmentation of breast medical images, Expert Systems with Application, 38, 4382–4389.

[9] Wang, J., Kong, J., Lu, Y., Qi, M. and Zhang, B. 2008. A modified FCM algorithm for MRI brain image segmentation using both local and non-local spatial constraints, Computerized Medical Imaging and Graphics, 32(8), 685-698.

[10] Chuang, K.S., Tzeng, H.L., Chen, S., Wu, J. and Chen, T.J. 2006. Fuzzy c-means clustering with spatial information for image segmentation, Computerized Medical Imaging and Graphics, 30, 9-15.

[11] Ji, Z.X., Sun, Q.S. and Xia, D.S. 2011. A modified possibilistic fuzzy c-means clustering algorithm for bias field estimation and segmentation of brain MR image, Computerized Medical Imaging and Graphics, 35(5), 383-397.

[12] Ahmed, M.N., Yamany, S.M., Mohamed, N., Farag, A.A. and Moriarty, T. 2002. A Modified Fuzzy C-Means Algorithm for Bias Field Estimation and Segmentation of MRI Data, IEEE Transactions on Medical Imaging, 21(3), 193-199.

[13] Moussaoui, A., Benmahammed, K., Ferahta, N. and Chen, V. 2005. A New MR Brain Image Segmentation Using an Optimal Semi-supervised Fuzzy C-Means and pdf Estimation, Electronic Letters on Computer Vision and Image Analysis, 5(4), 1-11.

[14] Jeny, R., Kannan, K., Thomas, F., Kesavadas, C. and Chandrasekhar, P. S. 2008. MR Brain volume Analysis Using BrainAssist, International Conference on Systematic, Cybernetics and Informatics – ICSCI2008, India, (January 2008).

[15] Somasundaram, K. and Kalaiselvi, T. 2010. Brain Extraction Method for T1 Magnetic Resonance Scans, IEEE International Conference on Signal Processing and Communication, Indian Institute of Sciences (IISc), Bangalore, India, (July 18-21), 1-5.

[16] Somasundaram, K. and Kalaiselvi, T. 2010. Fully Automatic Brain Extraction Algorithm for Axial T2-Weighted Magnetic Resonance Images, Computers in Biology and Medicine, 40(10), 811-822.

[17] Somasundaram, K. and Kalaiselvi, T. 2011. Automatic Brain Extraction Methods for T1 Magnetic Resonance Images using Region Labeling and Morphological Operations, Computers in Biology and Medicine, 41(8), 716-725.

[18] Brummer, M.E., Mersereau, R.M., Eisner, R.L. and Lewine, R.J. 1993. Automatic Detection of Brain Contours in MRI Datasets, IEEE Transactions on Medical Imaging, 12(2), 153-166.

[19] http://www.cma.mgh.harvard.edu/ibsr/index.html

[20] http://www.med.harvard.edu/AANLIB/home.html