MR Brain Image Segmentation Using Spatial Fuzzy C- Means Clustering Algorithm

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ABSTRACT

A conventional FCM algorithm does not fully utilize the spatial information in the image. In this research, we use a FCM algorithm that incorporates spatial information into the membership function for clustering. The spatial function is the summation of the membership functions in the neighborhood of each pixel under consideration. The advantages of the method are that it is less sensitive to noise than other techniques, and it yields regions more homogeneous than those of other methods. This technique is a powerful method for noisy image segmentation.

Keywords: fuzzy c-means; spatial information; image segmentation; clustering; mri brain image.

تجزئه صور الرنين المغناطيسي باستخدام المنطق المضبب المكاني (sFCM)

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ألخلاصه

ان خوارزميه المنطق المضبب الاعتياديه (FCM) لاتستخدم جميع المعلومات المكانيه للpixel وذلك يوثر سلبا في تقسيم الصوره بسبب وجود الضوضاء. في هذه البحث نستخدم خوارزميه (Spatial Fuzzy C-Mean) التي تتطلب تضمين المعلومات المكانيه للمعادله العضويه(membership function) للpixel التي تستخدم في تجزئه الصوره, والتي تحسب من خلال جمع ال(membership function)- في محيط كل pixel .فائده هذه الطريقه هي قله التحسس للضوضاء الذي في الصوره بالنسبه لبقيه طرق التجزئه ,وتكون المجاميع الناتجه عن هذه الطريقه متجانسه بحيث تعتبر هذه الخوارزميه هي الطريقه الفعاله لتجزئه الصور المشوشه.

الكلمات الرئيسية: المنطق المضبب , المعلومات المكانيه , تجزئة الصوره, التقسيم , صور الدماغ الرنينية

1. INTRODUCTION

The underlying objective of medical image segmentation is to partition it into different anatomical structures, thereby separating the components of interest, such as Brain tumors, from their background. Computerized medical image segmentation is a challenging problem, due to poor resolution and weak contrast. Moreover the task is often made more difficult by the presence of noise and artifacts, due to instrumental limitations, and patient movement.

In this paper, segmentation process is applied on Magnetic resonance imaging (MRI) Brain images, MRI is a noninvasive method for imaging internal tissues and organs, and it represents crucial diagnostic imaging technique for the early detection of abnormal changes in tissues and organs. It possesses fairly good contrast resolution for different tissues, and high spatial resolution and slice selection at any orientation.

Fuzzy c-means (FCM) is an unsupervised clustering technique that has been successfully applied to feature analysis, clustering, and classification in the fields such as astronomy, geology, medical imaging, target recognition, and image segmentation. An image can be represented in various feature spaces, and the FCM algorithm classifies the image by grouping similar data points in the feature space into clusters. This clustering is achieved by iteratively minimizing a cost function those dependents on the distance of the pixels to the cluster centers in the feature domain.

The pixels on an image are highly correlated, i.e., the pixels in the immediate neighborhood possess nearly the same feature data. Therefore, the spatial relationship of neighboring pixels is an important characteristic to improve the performance of FCM, many techniques have been developed.

Wang, et al., 2004. proposed a feature-weight assignment method is improved the performance of FCM clustering. **Mohamed, et al., 1999.** modified the fuzzy c-mean (MFCM) clustering algorithm where the membership value was chosen to tolerate the resistance. In this method, the spatial influence on the center pixel is considered as an explicit modification of its membership value to tolerate the resistance. **Liew, et al., 2000.** presented a spatial fuzzy clustering algorithm that exploits the spatial contextual information into image data, where the influence of the neighboring pixels is suppressed in nonhomogeneous regions of the image. **Das, et al., 2006.** proposes a particle swarm based segmentation algorithm for automatically grouping the pixels of an image into different homogeneous regions using spatial information.

The aim of this research is to introduce an improved segmentation method for FCM clustering. In a standard FCM technique, a noisy pixel is wrongly classified because of its abnormal feature data. Improved method incorporates spatial information, and the membership weighting of each cluster is altered after the cluster distribution in the neighborhood is considered. This scheme greatly reduces the effect of noise and biases the algorithm toward homogeneous clustering.

2. SPATIAL FUZZY C-MEANS CLUSTERING

Clustering techniques are mostly unsupervised methods that can be used to organise input data into groups based on similarities among the individual data items. The Fuzzy C-Means algorithm (often abbreviated to FCM) is an iterative algorithm that finds clusters in data and which uses the concept of fuzzy membership. Instead of assigning a pixel to a single cluster, each pixel will have different membership values on each cluster. This method was developed by Dunn in 1973 and improved by Bezdek in 1981 and it is widely used in image segmentation.

The Fuzzy C-Means attempts to find clusters in the data by minimizing an objective function given in the equation below **Chuang,et al., 2006.**

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^{m} \parallel x_{j} - v_{i} \parallel^{2} \qquad (1)$$

J is the objective function and it reduces at each iteration. It means the algorithm is converging or getting closer to a good separation of pixels into clusters. N is the number of pixels in the image, C is the number of clusters used in the algorithm, (m >1) is a weighting factor that controls the fuzziness of the resultant segmentation, in this research m = 2, u_{ij} represents the membership function of pixel X_j in the ith cluster, V_i is the ith cluster center, , and $\parallel X_j - V_i \parallel$ is the Euclidean distance between X_j and V_i .the membership functions are subject to the following constraints: $\sum_{i=1}^{c} u_{ij}=1$; $0\leq u_{ij} \leq 1$; $0< \sum_{j=1}^{N} u_{ij} < N$

The cost function is minimized when pixel closes to the centeroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far from the centeroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent on the distance between the pixel and each individual cluster center in the feature domain. The membership functions and cluster centers are updated iteratively **Li, et al., 2011.**

$$u_{ij} = \sum_{k=1}^{c} \left(\frac{\parallel x_j - v_i \parallel}{\parallel x_j - v_k \parallel} \right)^{\frac{-2}{(m-1)}} \qquad (2)$$

And

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \qquad (3)$$

One of the problems of standard FCM algorithms in image segmentation is the lack of spatial information. Since image noise and artifacts often impair the performance of FCM segmentation, because neighboring pixels possess similar feature values, and the probability that they belong to the same cluster is great so it would be attractive to incorporate spatial information into a standard FCM algorithm **Chuang, et al., 2006.**

To exploit the spatial information, a spatial function is defined as

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ij} \qquad (4)$$

Where NB (x_j) represents a square window centered on pixel x_j in the spatial domain. A 5x5 window was used in this research. Just like the membership function, the spatial function h_{ij} represents the probability that pixel x_j belongs to *i*th cluster. The spatial function of a pixel for a cluster is large if the majority of its neighborhood belongs to the same cluster. The spatial function is incorporated into membership function as follows:

$$u'_{ij} = \frac{u_{ij}^{p} h_{ij}^{q}}{\sum_{k=1}^{c} u_{ij}^{p} h_{ij}^{q}} \qquad (5)$$

where p and q are parameters to control the importance of both functions. In a homogenous region, the spatial functions fortify the original membership, and the clustering result remains unchanged. However, for a noisy pixel, this formula reduces the weighting of a noisy cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions can easily be corrected. The spatial FCM with parameter p and q is denoted $\mathrm{sFCM}_{p,q}$.Note that $\mathrm{sFCM}_{1,0}$ is identical to the conventional FCM **Soesanti, eta al.**

The flow chart of the sFCM algorithm is shown in **Fig. 1**

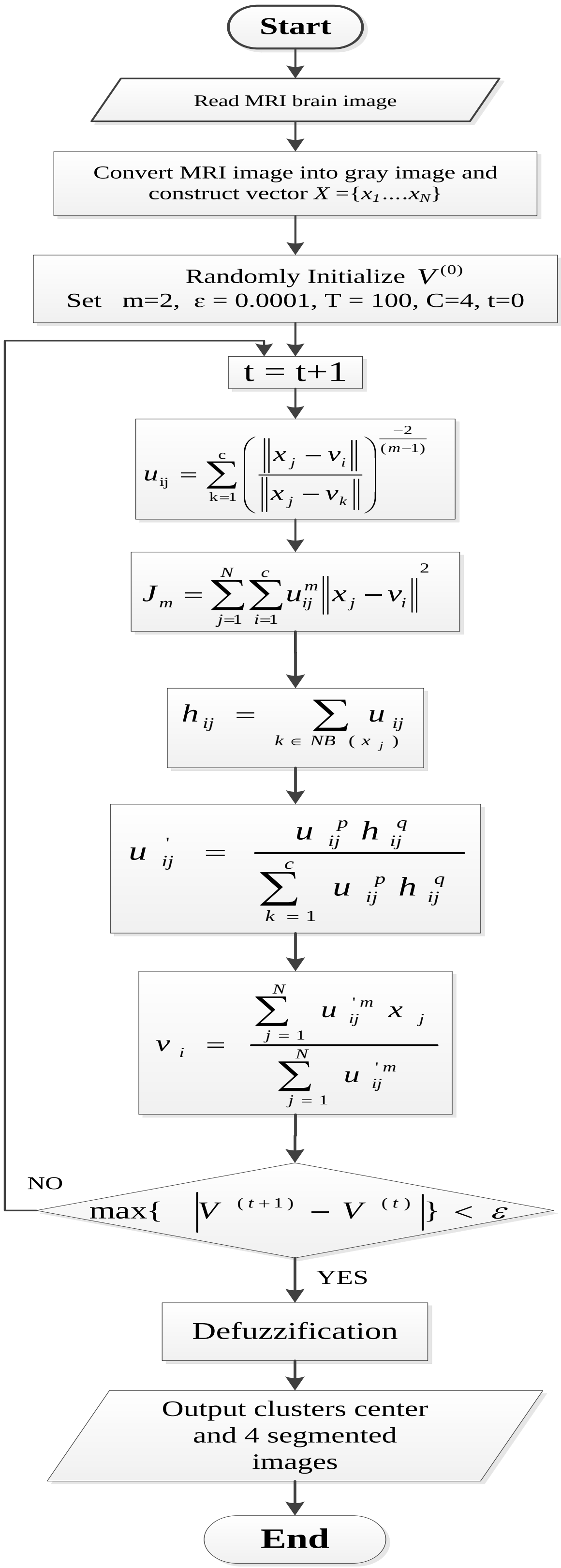

Figure 1. The flow chart of sFCM algorithm.

3. VALIDITY FUNCTIONS FOR FUZZY CLUSTERING

1. Clustering validity functions based on partition coefficient and partition entropy.

Fuzzy partition used in this paper to evaluate the performance of clustering in a quantitative way. The representative functions for the validity function based on the fuzzy partitions are partition coefficient Vpc and partition entropy Vpe which are defined as follows **Sayadi, et al., 2007.** :

$$V_{pc} = \frac{\sum_j^N \sum_i^c u_{ij}^2}{N} \tag{6}$$

and

$$V_{pe} = \frac{-\sum_j^N \sum_i^c \,[u_{ij} * \log u_{ij}]}{N} \tag{7}$$

The idea of these validity functions is that the partition with less fuzziness means better performance. In both equation (6) and (7), u_{ij} (i = 1, 2,…c; j = 1, 2,… N) is the membership of data point j in cluster i. As a result, the good clustering is achieved when ($\frac{1}{c} \leq v_{pc} \leq 1$) and ($0 \leq v_{pe} \leq 2$), the best clustering is when the value V_{pc} is maximal or V_{pe} is minimal **Xiao, et al., 2010.**

2. Clustering validity functions based on geometric sample structure.

The idea of validity functions based on measuring geometric data structure is that samples within one partition should be compact and samples between different clusters should be separate. To quantify the ratio of total variation within clusters and the separation of clusters, Xie and Beni proposed Xie-Benie validity function V_{xb} and it is defined as follows **Xiao, et al., 2010.**

$$V_{xb} = \frac{-\sum_j^N \sum_i^c u_{ij}^2 \, \|x_j - v_i\|^2}{N * (\min_{i \neq k} \{ \|v_k - v_i\|^2 \})} \tag{8}$$

An optimal clustering result generates samples that are within one cluster and samples that are separated between different clusters. Minimised V_{xb} is expected to lead to a good partition.

Partition coefficient and partition entropy is a class of validation functions that uses only the membership function to evaluate the partitioning of the clusters. Their disadvantages are that it does not take into account the geometrical properties of the data and it depends monotonically on the number of clusters while Xie-Beni validity function however quantifies the performance of the clustering by taking into account the total variation within each clusters and the separation between-cluster.

4. RESULT AND DISCUSSION

A complete program using MATLAB programming language and CPU Core 2 Duo (1.83 GHz) for this process. **Fig. 2** shows the 512 x 416 grayscale original MRI Brain image with tumor.

The spatial function modifies the membership function of a pixel according to the membership statistics of its neighborhood. Both sFCM techniques reduce the noise effect, because no similar cluster is present in the neighborhood, the weight of the noisy cluster is greatly reduced with sFCM. Furthermore, the membership of the correct cluster is enhanced by the cluster distribution in the neighboring pixels. As a result, both sFCM techniques effectively correct the misclassification caused by the noise and makes the segmented images more homogeneous.

The MR images used in this paper are obtained from AL-KADEMYA HOSPITAL for male patient (year birth:1950).

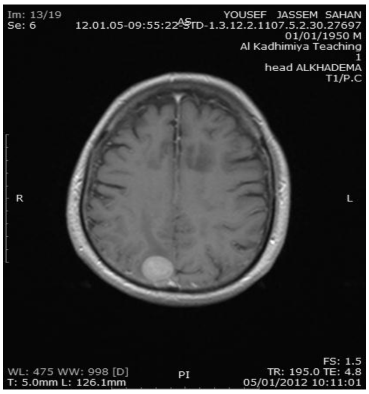

Figure 2. T1 weighted image.

Fig.3 to **Fig.6** shows the result of segmentation of image shown in **Fig. 2** by applying spatial FCM algorithm with parameter (p=1,q=1) on T1 weighted image.

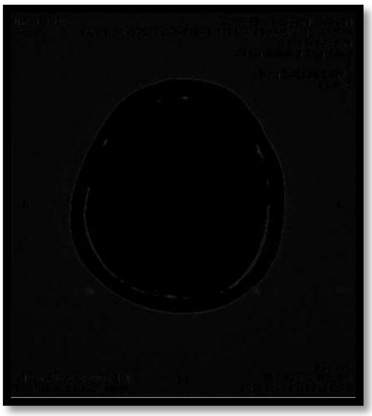

Figure 3. Cluster 1 of $\mathrm{FCM}_{1,1}$ algorithm.

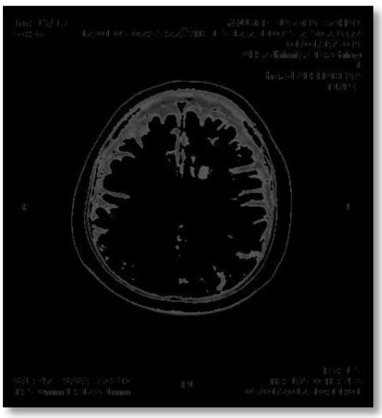

Figure 4. Cluster 2 of $FCM_{1,1}$ algorithm.

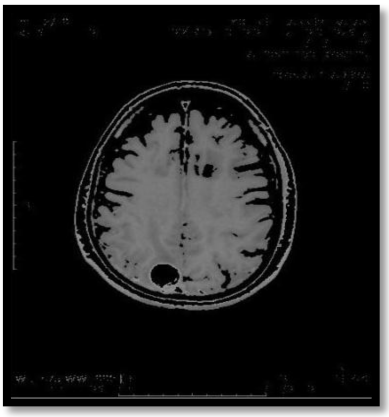

Figure 5. Cluster 3 of $\mathrm{sFCM}_{1,1}$ algorithm.

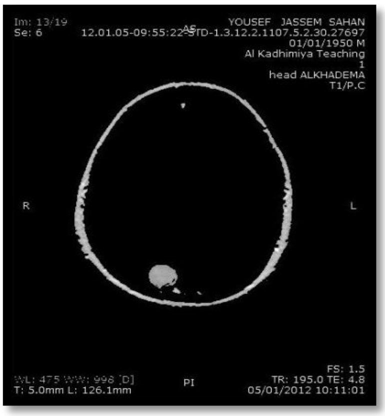

Figure 6. Cluster 4 of $\mathrm{FCM}_{1,1}$ algorithm.

Different gray levels were taken for initialization of the clusters centers as shown in table 1 while table 2 shows the optimized clusters centers obtained from the iteration of the $FCM_{1,1}$ algorithm.

Table 1. Selected clusters centers.

40	90	140	200

Table 2. optimized clusters center.

7.2124	68.1943	112.0011	187.8991

The plot shown in **Fig .7** shows how the iterative optimization of the objective function is carried out with the up-dating of the membership function u_{ij} and the clusters centers c_{ij}.

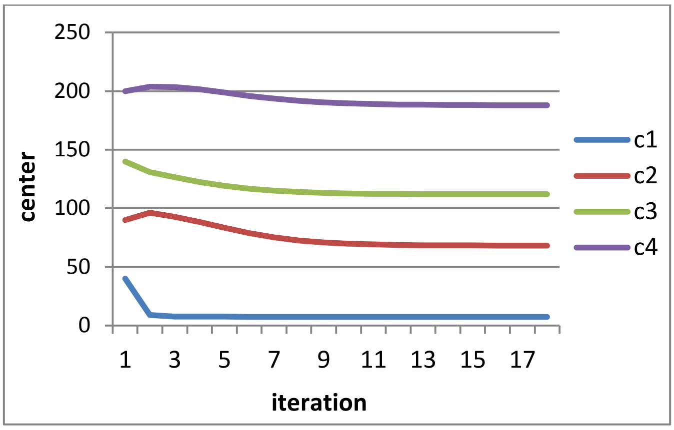

Figure 7. Iterative optimization of cluster center for $\mathrm{FCM}_{1,1}$ algorithm.

Fig. 8 shows the bars graph of the four clusters.

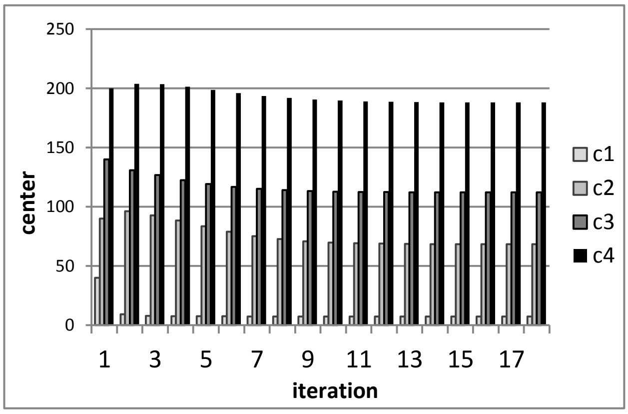

Figure 8. Bar graph for cluster variation in each iteration for $\mathrm{FCM}_{1,1}$ algorithm.

Fig.9 to **Fig.12** shows the result of segmentation of image shown in **Fig. 1** with parameters (p=0, q=2).

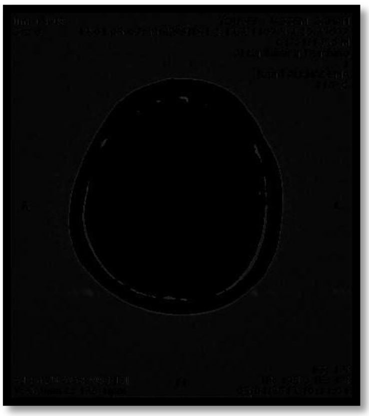

Figure 9. Cluster 1 of $FCM_{0,2}$ algorithm.

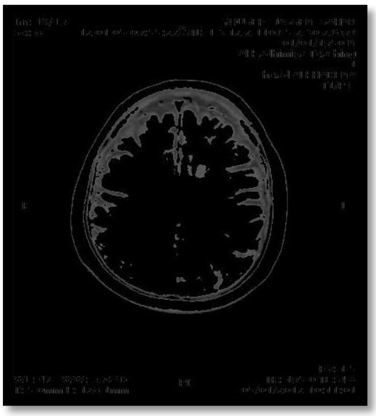

Figure 10. Cluster 2 of $FCM_{0,2}$ algorithm.

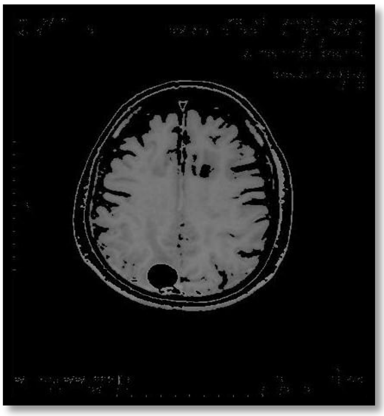

Figure 11. Cluster 3 for $s\mathrm{FCM}_{0,2}$ algorithm.

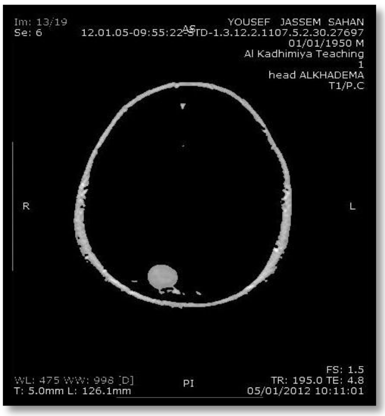

Figure 12. Cluster 4 of $FCM_{0,2}$ algorithm.

In table 3 shown Deferent gray levels were taken for initialization of the clusters centers while table 4 shows the optimized clusters centers obtained from the iteration of the $FCM_{0,2}$ algorithm.

Table 3. Selected clusters centers.

40	90	140	200

Table 4. Optimized clusters center.

11.3708	69.9816	110.8312	165.8091

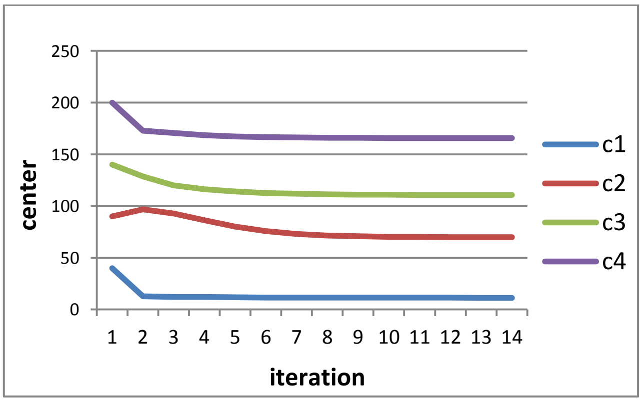

Figure 13. Iterative optimization of cluster center for $\mathrm{sFCM}_{0,2}$ algorithm.

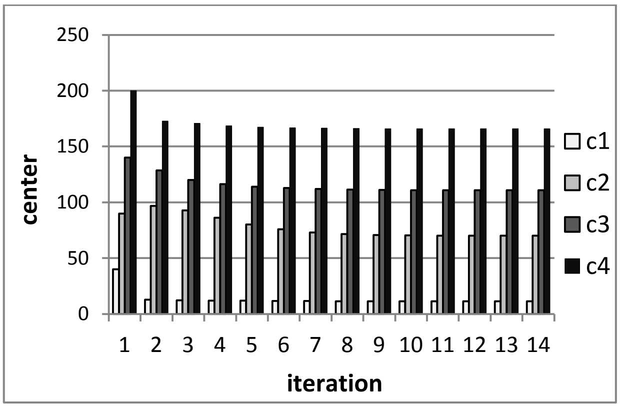

Figure 14. Bar graph for cluster variation in each iteration for $\mathrm{sFCM}_{0,2}$ algorithm.

Three basic tissue classes found on a healthy brain MR image: white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF).

Both sFCM techniques reduce the overlap of gray matter with white matter cluster, because the spatial function modifies the membership statistics of its neighborhood. Such neighboring effect biases the solution toword piecewise-homogeneous labeling, this make the segmented images more homogeneous. The sFCM algorithm with a higher q (>1) parameter shows a better smoothing effect, but disadvantages of using higher spatial weighting (q) are the blurring of some of fine details. This is difficult to judge from the results so used the cluster validity functions. Table.5 tabulates the validity functions used to evaluate the performance of sFCM clustering. In this cases, the validity functions based on the fuzzy partition were better for the $sFCM_{1,1}$ (p=1, q=1) than $sFCM_{0,2}$ (p=0, q=2). For V_{pc} (V_{pe}), the $sFCM_{1,1}$ is greater (smaller) than $sFCM_{0,2}$, and the validity function based on feature structure showed increased for $sFCM_{0,2}$. V_{xb} Measured the compactness in the feature domain. The sFCM modifies the partition on the basis of spatial distribution and causes deterioration of compactness in feature domain so V_{xb} is increased for $sFCM_{0,2}$ more than $sFCM_{1,1}$.

Table5. Cluster validity function.

Type	Vpc	Vpe	Vxb
$sFCM_{1,1}$	**0.9622**	**0.0675**	**0.0041**
$sFCM_{0,2}$	**0.9377**	**0.1125**	**0.042**

5. CONCLUSIONS

In this paper, spatial fuzzy c mean was applied in segmenting an actual MRI data set. This method improved the segmentation result, by incorporates the spatial information into the membership function to improve the segmentation results. The membership functions of the neighbors centered on a pixel in the spatial domain are enumerated to obtain the cluster distribution statistics; these statistics are transformed into a weighting function and incorporated into the membership function. This neighboring effect reduces the noise effect and makes the clustering more homogeneous.

The result of $sFCM_{1,1}$ (p=1, q=1)algorithm shows good segmentation result better than $sFCM_{0,2}$ because higher spatial weighting (q) cause blurring of some fine details, also using cluster validity function to evaluate the performance of both method show the best clustering is achieved using $sFCM_{1,1}$ algorithm with maximum value of V_{pc} (1.28% larger than $sFCM_{0,2}$), and minimum value of V_{pe} (25% less than $sFCM_{0,2}$), minimum value of V_{xb} (82.21% less than $sFCM_{0,2}$)

The results show that the method effectively segmented MRI brain images with spatial information, and the segmented abnormal MRI brain images can be analyzed for diagnosis purpose.

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7. NOMENCLATURE

C	Cluster Number
h_{ij}	Spatial Function
J_m	Objective Function
m	Fuzziness Factor
N	No. Of Pixels In Image
NB (x_j)	A Square Window Centered On Pixel
P, q	Parameter control the importance of spatial function and membership function
t	Iteration
T	Max Number Of Iteration
X	Vector Of Data Set
x_j	Individual Pixel
μ_{ij}	Membership Function Of Pixel
μ'_{ij}	Membership Function With Spatial Information
v_i	Cluster Center