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Analysis Study of Fuzzy C-Mean Algorithm Implemented on Abnormal MR Brain Images

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Abstract: *The MR brain image analysis is used to extract clinical information that improve diagnosis and treatment of disease. Brain tumors are one of the most common brain diseases. Clustering is a process for segmenting and classifying objects. There are many clustering strategies such as the hard clustering scheme and the fuzzy clustering scheme, each of them has its own special characteristics. In this work Fuzzy C-Mean clustering was implemented to segment three abnormal brain MR images, and the performance of it was analyised. This algorithms was applied to cluster the images into different clusters number: 5-9 with different values of membership grade: 0.50-0.90 with steps of 0,05 for each cluster number. The percentage of the unclassified pixels that were produced from implementing FCM algorithm with different configuration was calculated. The minimum values of the objective function of the FCM algorithm for different number of clusters and for different membership grade values were also calculated. The results showed that an optimal number of clusters that corresponds to optimal segmentation error is depending on the slice condition. In this experiment, the optimal cluster number was found to be 6. The fluctuation around this number is affected also by the anatomical structure of the slice. In addition, it can be concluded that the objective function may not be the superior criterion for the judgments of goodness, where it may be a few number of pixels with high uncertainty is the source of high error.*

Keywords: *MRI, Brain Tumor, Clustering, and Fuzzy C-Mean.*

I. Introduction

Medical imaging techniques like MRI, CT, US and PET are tools used for extraction of vital information by medical field specialists. Thus, accurate segmentation that help in image analysis and unerring diagnosis is of immense importance to identify the disease type and location easily. Compared to other medical imaging techniques, MRI has the benefit of having excellent contrast between soft tissues [1]. Detection and extraction of abnormal tissues (tumors) from brain MR images are required implementation of good segmentation and classification processes.

Brain tumors are one of the most common brain diseases, so detection and isolation of brain tumors in MRI are very important in medical diagnosis[2]. Despite numerous efforts and acceptable results in the medical imaging community, accurate and reproducible segmentation and characterization of brain abnormalities is still a challenging and difficult task because of the overlapping among the brain tissues themselves [3], as illustrated in Fig. (1). Most of the suggested segmentation methods, that commonly used for medical images, encounter most likely the same problems. Generally, the segmentation methods for medical images can be divided into three groups: region-based, contour-based and combination of region and boundary based method[3].

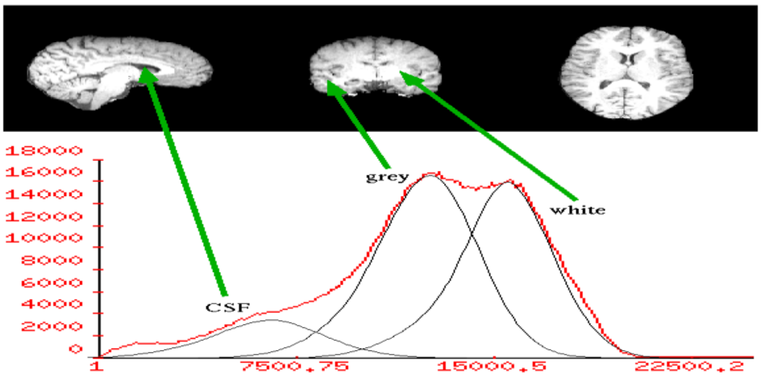

Figure (1): shows the overlapping between the Gaussian Probability Density Function (PDF) of the brain tissues GM, WM and CSF[4].

II. Clustering Techniques

Clustering is a process for segmenting and classifying objects in such a way that samples of the same group are more similar to one another than samples belonging to different groups. Many clustering strategies had been used, such as the hard clustering scheme and the fuzzy clustering scheme, each of them has its own special characteristics. The conventional hard clustering method restricts each point of the data set to exclusively just one cluster. As a consequence, with this approach the segmentation results are often very crisp. But the segmentation utilizing this approach is a difficult task when the image has limited spatial resolution, poor contrast, overlapping intensities, and noise or intensity inhomogeneity variation. To overcome these difficulties the fuzzy set theory was proposed, which produces the idea of partial membership of belonging described by a membership function; fuzzy clustering as a soft segmentation method has been widely studied and successfully applied in image segmentation such as [5-10] .

III. Fuzzy C-Mean Clustering Algorithm

Among the fuzzy clustering methods, Fuzzy C-Mean (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods [10]. The conventional FCM algorithm is efficiently used for clustering in medical image segmentation especially for MRI brain images because the uncertainty of MRI image is widely presented in data, in particular, the transitional regions between tissues are not clearly defined and their memberships are intrinsically vague [11].

In FCM algorithm the data patterns may belong to several clusters, having different membership values with different clusters. The membership value of a data to a cluster denotes similarity between the given data pattern to the cluster. Given a set of n data patterns X= $x_1, \ldots x_k, \ldots x_n$, FCM clustering algorithm is an iterative process to minimize the objective function $J_{FCM}(U,C)$ [12]:

$$J_{FCM}(U,C) = \sum_{k=1}^{n} \sum_{i=1}^{v} (u_{ik})^m d^2(x_k, c_i) \quad \text{. . . . . (1)}$$

Where: x_k is the k[th] d-dimensional data vector, c_i the center of cluster i , u_{ik} is the degree of membership of x_k in the i[th] cluster, m is the weighting exponent, it determines the degree of fuzziness of the final partition, $d\ (x_k, c_i)$ is the distance between data x_k and cluster center c_i , d = || $x_k - c_i$ || , U is (v x n) matrix i.e. U= [u_{ik}], n is the number of data patterns, and v is the number of clusters. The minimization of the objective function $J_{FCM}(U,C)$ can be brought by an iterative process in which updating of degree of membership u_{ik} and the cluster centers, and these are done for each iteration[12]:

$$u_{ik} = \frac{1}{\sum_{j=1}^{v} \left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \quad \text{. . . . . (2)}$$

$$c_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m} \quad \text{. . . . . (3)}$$

Where $\forall\ i$ u_{ik} satisfies: $u_{ik} \in [0, 1]$, $\forall k \sum_{i=1}^{v} u_{ik} = 1$ and $0 < \sum_{k=1}^{n} u_{ik} < n$ [12].

IV. Methodology And Results

The performance of the FCM clustering algorithm will be analysised. This algorithms was implemented on three T1 modalityMRI abnormal images ,with Pinealoma tumor, named as: M9T1,M10T1, and M11T1. The processes involved in this work can be summarized as follows:

1- Cutting the background automatically and smoothing the three images utilizing bilateral filter (see our previous papers [13 , 14]) and the resules are illustrated in Fig. (2).

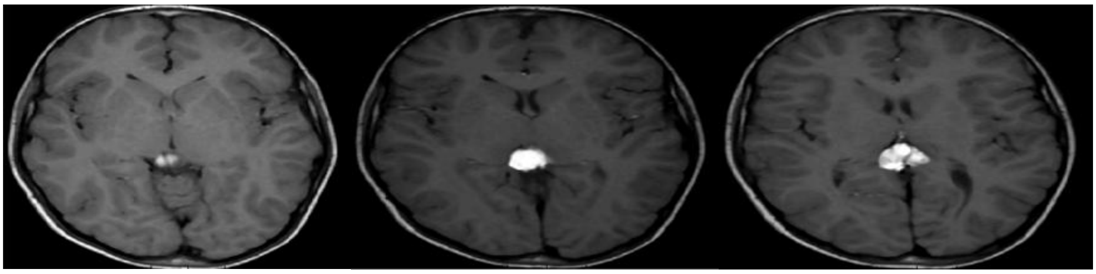

Figure (2): Shows the images M9T1, M10T1 and M11T1 after cutting their background automatically and smoothing them by bilateral filter.

2- Implementing FCM clustering algorithm on the three images to cluster them into five, six, seven, eight, and nine clusters. The algorithm is implemented with different values of membership grade: 0.90, 0.85, 0.80, 0.75, 0.70, 0.65, 0.60, 0.55 and 0.50, for each cluster number. The number of iterations is the same for all cases. The resultant clustered images of the membership grade values (0.90, 0.70 and 0.50) for each clusters number are shown in Figs. (3) - (7).

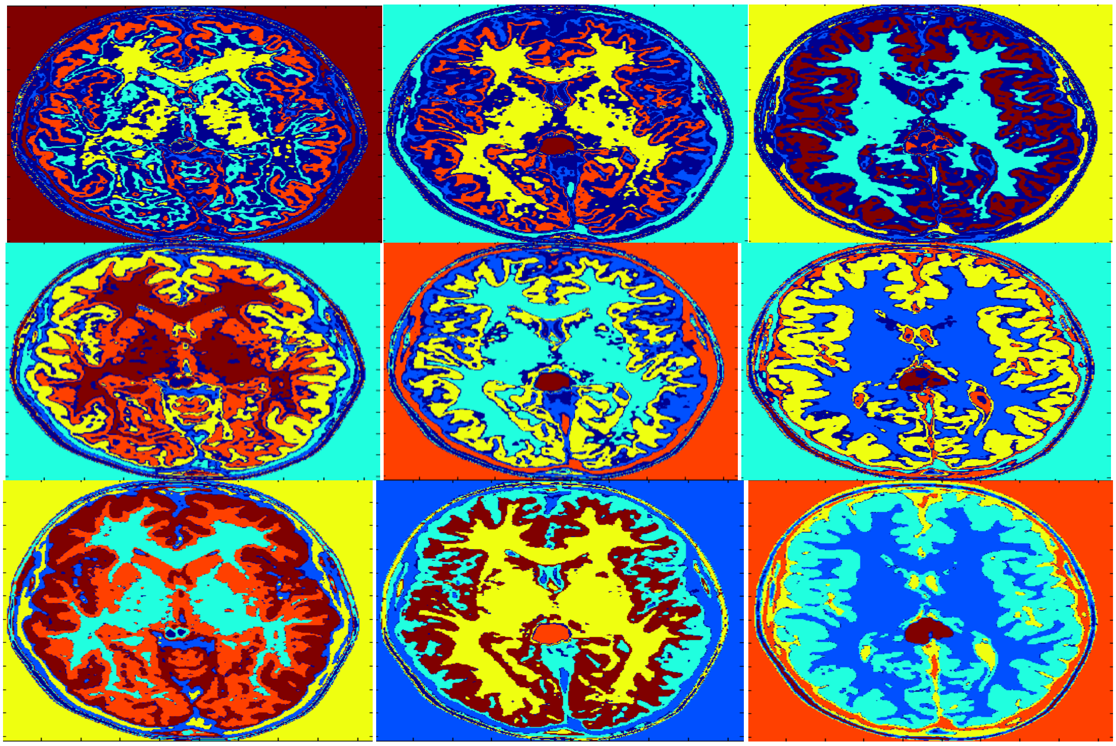

Figure (3): FCM clustered image into **five** clusters with different membership grade (0.90 , 0.70 and 0.50) for M9T1, M10T1 and M11T1 images from left to right.

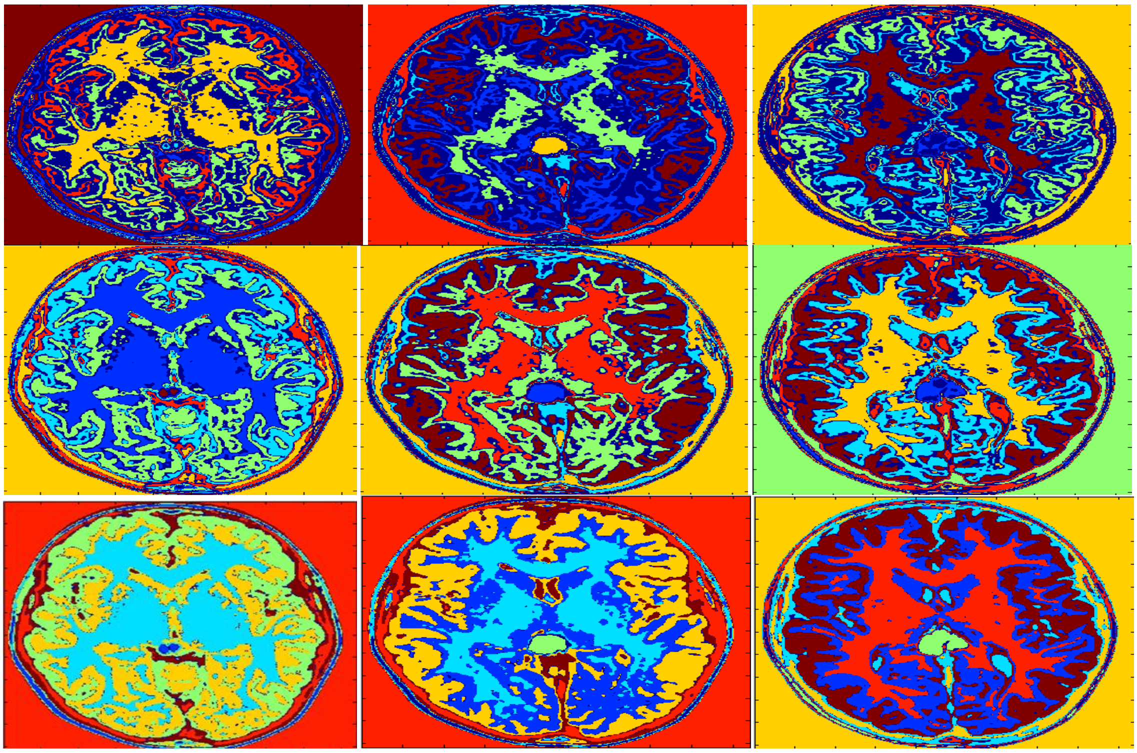

Figure (4): FCM clustered image into **six** clusters with different membership grade (0.90, 0.70and 0.50), for M9T1, M10T1 and M11T1 images from left to right.

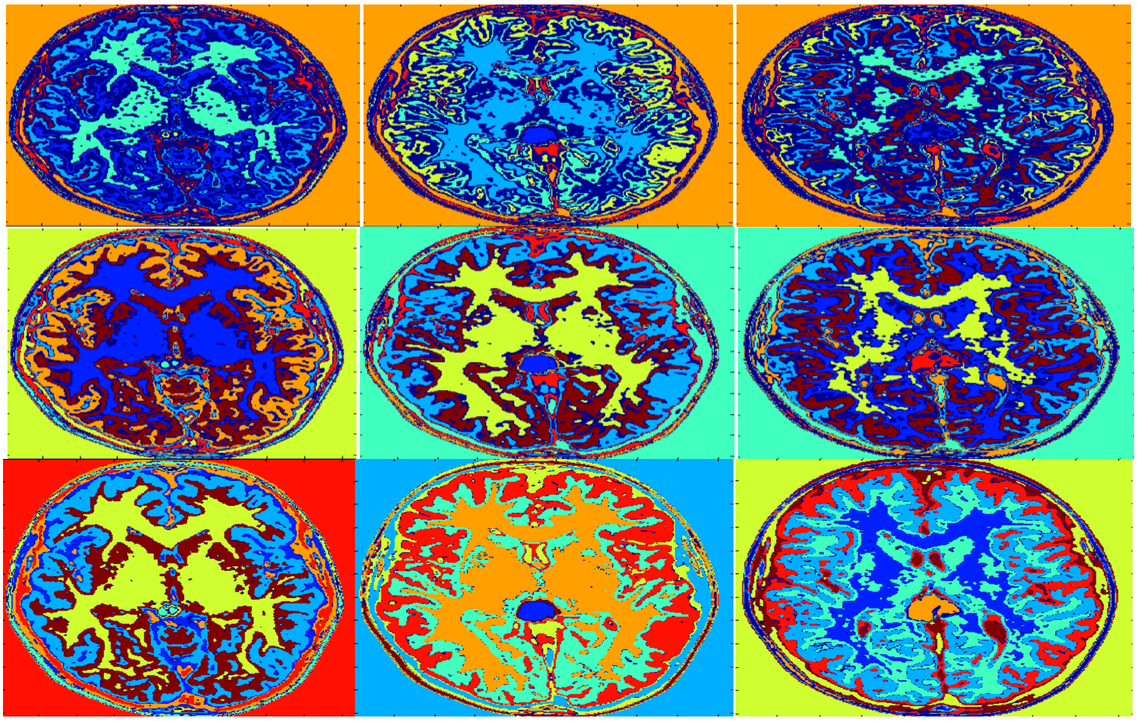

Figure (5): FCM clustered image into **seven** clusters with different membership grade (0.90, 0.70 and 0.50), for M9T1, M10T1 and M11T1 images from left to right.

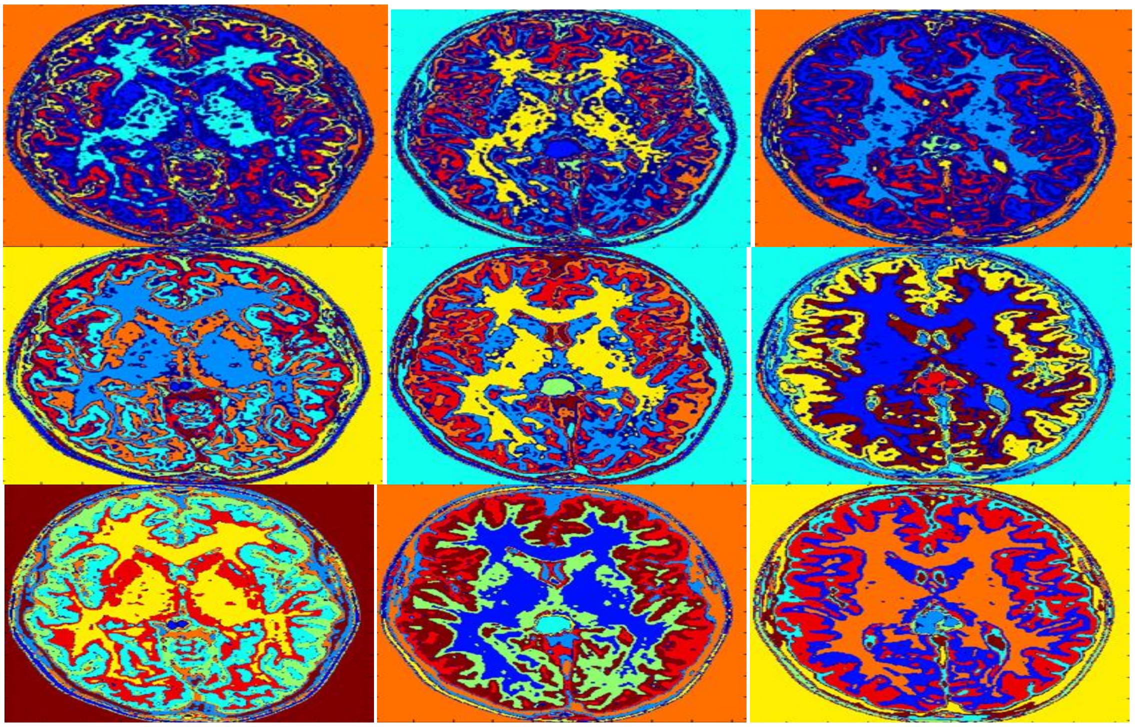

Figure (6): FCM clustered image into **eight** clusters with different membership grade (0.90, 0.70 and 0.50), for M9T1, M10T1 and M11T1 images from left to right.

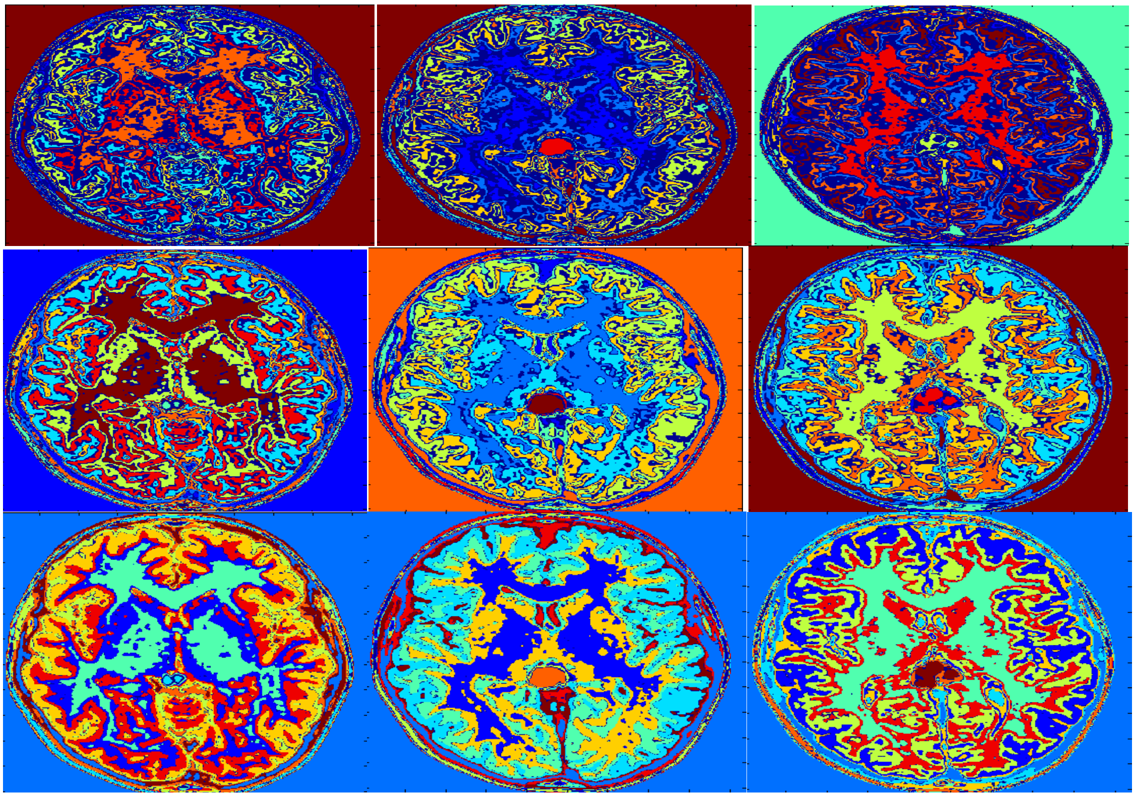

Figure (7): FCM clustered image into **nine** clusters with different membership grade (0.90, 0.70 and 0.50), for M9T1, M10T1 and M11T1 images from left to right.

3- The percentage of the unclassified pixels that are produced from implementing FCM algorithm on the three images with different configuration is calculated. The relation of the three parameters: percentage of the unclassified pixels, number of clusters and membership grade values are given in Fig. (8) and Table (1).

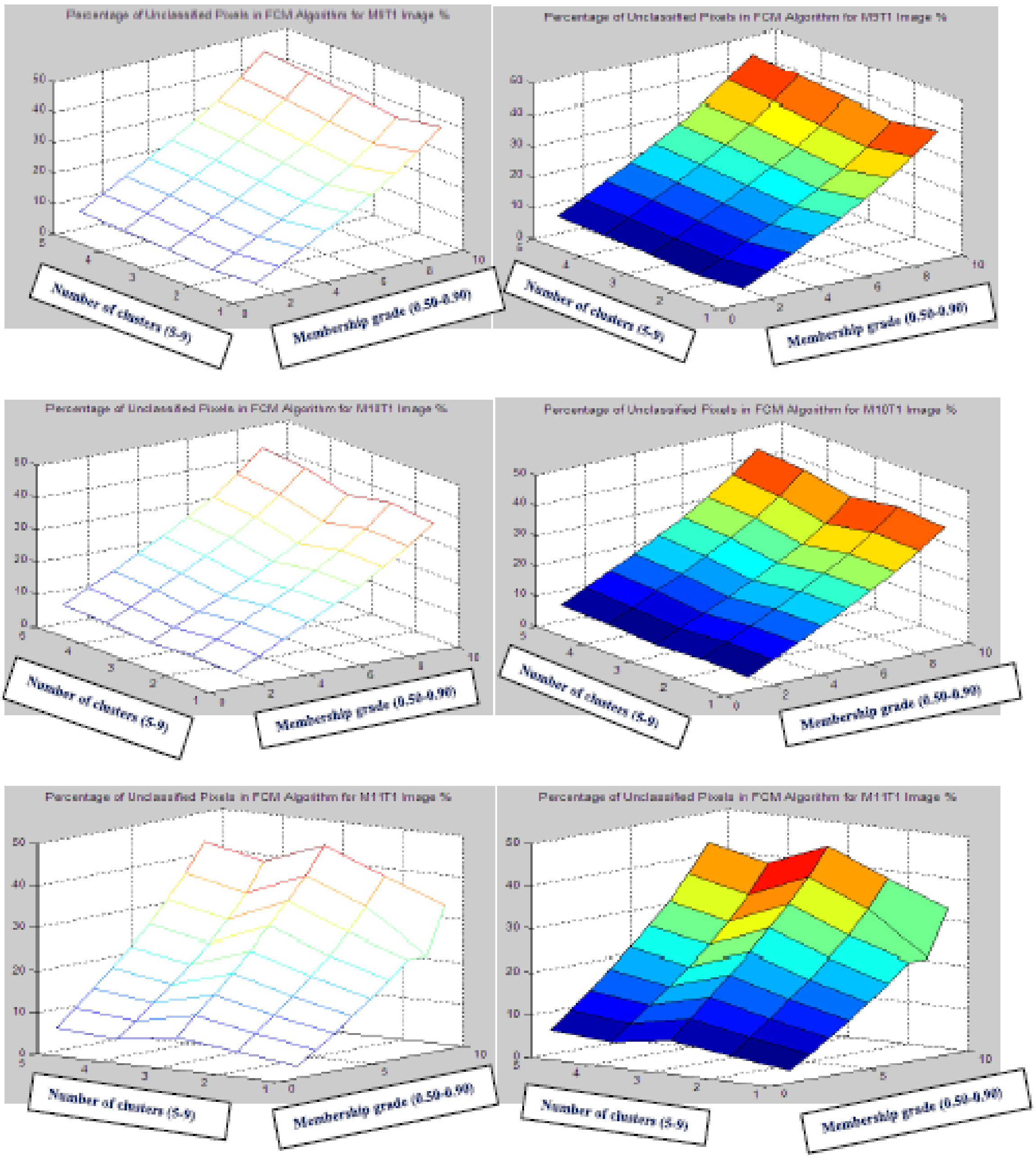

Figure (8): The relation between the percentage of unclassified pixels with the number of clusters and with the membership degree of FCM algorithm for M9T1, M10T1 and M11T1 images from 1st row to the last one respectively.

Table (1): The percentage of the unclassified pixels to the total number of pixels using the FCM algorithm for the clusters numbers of 5, 6, 7, 8, and 9; and for the membership grades from 0.50 to 0.90 with steps of 0.05; for the images M9T1, M10T1 and M11T1.

Image Name	Number of Clusters	Percentage of the Number of Unclassified Pixels (%)								
		Membership Grade								
		0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
M9T1	5	4.990	8.837	12.758	16.796	20.973	25.413	30.302	35.784	42.373
	6	3.852	7.425	11.085	14.811	18.822	23.018	27.635	32.914	39.699
	7	4.520	8.250	12.024	15.922	19.991	24.303	29.080	34.541	41.354
	8	5.267	9.125	13.074	17.126	21.263	25.727	30.606	36.176	42.897
	9	5.693	9.680	13.731	17.880	22.205	26.734	31.686	37.387	44.250

M10T1	**5**	4.465	8.405	12.285	16.227	20.304	24.337	28.922	33.930	39.803
	6	4.895	8.562	12.233	15.970	19.948	24.290	29.019	34.443	41.082
	7	3.880	7.268	10.756	14.272	17.958	21.923	26.371	31.577	38.400
	8	4.924	8.619	12.347	16.141	20.176	24.450	29.328	34.843	41.781
	9	5.458	9.331	13.207	17.078	21.273	25.643	30.525	36.118	42.928
M11T1	**5**	2.832	5.833	8.878	12.200	15.569	19.145	23.280	23.280	34.100
	6	4.665	8.173	11.666	15.393	19.261	23.354	27.840	33.071	39.455
	7	6.484	10.837	15.079	19.374	23.749	28.629	33.583	38.882	45.315
	8	4.459	7.955	11.478	15.093	18.899	23.054	27.638	33.120	39.775
	9	5.556	9.491	13.373	17.405	21.529	25.835	30.706	36.283	42.967

By observing Table (1), it is clear that the unclassified pixels with the highest membership grade vary with clusters number. Increasing cluster number will increase the quality of segmentation. This is not absolutely true (without restriction). There is an optimal number of clusters (segments) that corresponds to optimal segmentation error (i.e. minimum error with high membership function) depending on the slice condition. In this experiment, the optimal cluster number was found to be 6. The fluctuation around this number is affected also by the anatomical structure of the slice. It also indicates that, for high membership grade, error increases due to the high correlation between the brain tissues. Moreover, observing the tumor region in image M11T1 one can see that the tumor area is separated into multiple pieces (segments) instead of single region.

4- The minimum values of the objective function of the FCM algorithm for different number of clusters and for different membership grade values were also calculated and are listed in Table (2) for the same experimental images.

Table (2): The minimum values of the objective function of the FCM clustering algorithm of different clusters numbers for the images M9T1, M10T1 and M11T1.

Image Name	**Minimum Value of the Objective Function of FCM Algorithm ***				
	Five Clusters	**Six Clusters**	**Seven Clusters**	**Eight Clusters**	**Nine Clusters**
M9T1	17.028	8.6380	6.5308	5.1738	4.3264
M10T1	10.237	7.3198	3.9145	3.0592	2.5251
M11T1	11.795	8.8406	7.2467	4.1182	3.4237
***All the values of the Objective Function are multiplying by 10^6.**					

By examining Table (2), it can be concluded that the objective function (error value) decreases with increasing clusters number. Logically, this relation is true, but it does not mean that the segmentation process is better. A heavy weighted pixels may cause a huge error contribution. It can be observed, from Table (4-6), that the objective error of image M10T1 is the lowest. This is because, clusters in this image represent the centers better from the rest; i.e. one can conclude that the objective function is a criterion for calculating the uncertainty of each pixel, it may be not a good criterion where it may be a few number of pixels with high uncertainty is the source of high error.

V. Conclusions

The results showed that there is an optimal number of clusters (segments) that corresponds to optimal segmentation error like 6 and 7 depending on the slice condition. In this experiment, the optimal cluster number was found to be 6, the fluctuation around this number is affected also by the anatomical structure of the slice. The results also indicate that, for high membership grade, error increases due to the high correlation between the brain tissues. It also can be concluded that the objective function, which is a criterion for calculating the uncertainty of each pixel, may be a tricky criterion where it may be a few number of pixels with high uncertainty is the source of high error. So the objective function may not be the superior criterion for the judgments of goodness.

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References

[1]. Selvanayaki K. and Karnan M.,"CAD System for Automatic Detection of Brain Tumor through Magnetic Resonance Image-A Review",International Journal of Engineering Science and Technology 2, PP. 5890-5901, 2010.
[2]. Toga W. A., Thompson P. M., Mega M. S., Narr K. L. and Blanton R. E., "Probabilistic Approaches for AtlasingNormal and Disease-specific Brain Variability", Anatomy and Embryology, Vol.204, No.4, PP. 267–282, 2001.
[3]. Khotanlou H., "3D Brain Tumors and Internal Brain Structures Segmentation in MR Images", Ph. D. thesis in signal and images, ENST, TELECOM Paris Tech, 2008.
[4]. Michael Brady FRS FREng, "Clinical applications of MRI", Department of Engineering Scienc, Oxford University, Michaelmas, 2004.
[5]. Tolias Y. A. and Pans S. M., "Image Segmentation by a Fuzzy Clustering Algorithm Using Adaptive Spatially Constrained Membership Function", IEEE Trans. Systems, Man, Cybernet., Vol. 28, PP. 359-369, 1998.
[6]. Pham D. L. and Prince J. L., "Adaptive Fuzzy Segmentation of Magnetic Resonance Images", IEEE Trans. Medical Imaging Vol. 18, PP.737-752, 1999.
[7]. Noordam J. C., Van Den Broek W. H. A. M. and Buydens L. M. C., "Geometrically Guided Fuzzy C-Means Clustering for Multivariate Image Segmentation", Proc. International Conference on Pattern Recognition, Vol. 1, PP. 462-465, 2000.
[8]. Ahmed M. N., Yamany S. M., Mohamed N., Farag A. and Moriarty A.T., "A Modified Fuzzy C-Means Algorithm for Bias Field Estimation and Segmentation of MRI Data", IEEE Trans. on Medical Imaging, Vol. 21, PP. 193-199, 2002.
[9]. Kwon M. J., Han Y.J., Shin I. H. and Park H.W., "Hierarchical Fuzzy Segmentation of Brain MR Images", International Journal of Imaging Systems and Technology, Vol. 13, PP. 115-125, 2003.
[10]. Yong Yang and Shuying Huang, "Image Segmentation By Fuzzy C- Means Clustering Algorithm With A Novel Penalty Term", Computing and Informatics, vol. 26, PP. 17-31, 2007.
[11]. Zhang D. Q., Chen S. C., Pan Z. S. and Tan K. R.,"Kernel- Based Fuzzy Clustering Incorporating Spatial Constraints for Image Segmentation", Proc. International Conference on Machine Learning and Cybernetics, Vol. 4, PP. 2189-2192, 2003.
[12]. Bezdec J.C., "Pattern Recognition with Fuzzy Objective Function Algorithms", Plenum Press, New York, 1981.
[13]. S.M. Ali, Loay K. Abood, and Rabab Saadoon Abdoon, "Brain Tumor Extraction in MRI images using Clustering and Morphological Operations Techniques", International Journal of Geographical Information System Applications and Remote Sensing Vol.4, No. 1, 2013.
[14]. S.M. Ali, Loay K. Abood and Rabab Saadoon Abdoon, "Clustering and Enhancement Methods for Extracting 3D Brain Tumor of MRI Images", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 3, Issue 9, 2013.