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# Improved Fuzzy C-Means for Brain Tissue Segmentation Using T1-Weighted MRI Head Scans

Bantrotu Raghavendra(158r1a0429), Ch Shashank(158r1a0440), Chanagani Deepthi(158r1a0442), Chanti Jyothsna (158r1a0444)

**Department of ECE, C M R Enginnering college,Hyderabad, Telangana, INDIA**

***Abstract :-***

*Brain tissue segmentation of Magnetic Resonance Imaging (MRI) is an important and one of the challenging tasks in medical image processing. MRI images of brain are classified into two types: classifying tissues, anatomical structures. It comprised into different tissue classes which contain four major regions, namely Gray matter (GM), White matter (WM), Cerebrospinal fluid (CSF), and Background (BG). The present study of proposed method is an improved fuzzy c-means (FCM) clustering for tissue segmentation using T1-weighted head scans. The proposed method improved by modifying the objective function, cluster center and membership value for updating criterion. The quantitative measures of results were compared using the metrics Dice Coefficient (DC) and processing time. The DC value of proposed method attained maximum value while compared to conventional FCM. The proposed method is very efficient and faster than FCM for brain tissue segmentation from T1-weighted head scans.*

***Keywords:*** *Brain MRI, Clustering, Fuzzy c-means, Image Segmentation.*

## 1. Introduction

Image segmentation is the process of partitioning a digital image into non-overlapped, consistent regions that are homogeneous attributes with respect to some characteristics like gray level, color, tone or texture, motion etc. Image segmentation is an important and challenging problem and used in various applications like object recognition, traffic control systems, geographicalimaging and medical imaging [1] [2]. Several image segmentation approaches have been proposed and it is classified into edge detection, thresholding, clustering and region based methods. The proposed work is focused on the region based approach using fuzzy c-means (FCM) clustering. FCM clustering algorithm is a soft segmentation method that retains more information from the input images. It is proved to be the best method for the anisotropic nature of volumes [3] Segmentation of brain tissues in MRI (Magnetic Resonance Imaging) images plays a significant role in medical image analysis and related operations. Medical imaging provides effective and non-invasive mapping of human soft tissue anatomy. In the field of medicine, good segmentation assists clinicians and patients by providing important information for 3-D visualization, surgical planning and early disease recognition [4]. The diagnostic capability of medical experts improved significantly with the arrival of medical imaging techniques such as computed tomography (CT), positron emission tomography (PET), magnetic resonance (MR) images and single photon emission computed tomography (SPECT). MR images of brain are

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classified into two types: classifying tissues, anatomical structures. It comprised into different tissue classes that contain four major regions, namely gray matter (GM), white matter (WM), cerebrospinal fluid (CSF), and background (BG) [5]. In recent years, many approaches have been developed to the brain tissue segmentation and analysis. Benaichouche et al. [6] proposed an improvement method for image segmentation using the FCM clustering algorithm. This algorithm is widely experimented in the field of image segmentation with very successful results. This proposed method, named improved spatial fuzzy c-means (IFCMS) compared to the most used FCM-based algorithms of the literature. Sayed et al. [7] proposed a summarized hybrid techniques for the classification of the MR human brain tissue. The hybrid technique consists of three methods, feature extraction, dimensionality reduction, and classification. FCM used to classify the subjects as normal or abnormal MRI images. Ahmed et al. [8] proposed a summarized hybrid approach for classification of brain tissues in MRI based on genetic algorithm (GA) and support vector machine (SVM). A wavelet based texture feature set derived for classification. The optimal texture features are extracting from normal and tumor regions by using spatial gray level dependence method (SGLDM). The optimal feature set extracted by applying GA. The feature set containing five features and they were inputs to the SVM classifier. This algorithm is advance, to replace the neighborhood term of FCM_S. Thus the execution times of both FCM_S1 and FCM_S2 are considerably reduced.

Shasidhar et al. [10] proposed a FCM algorithm and proved to be superior over the other clustering approaches in terms of segmentation efficiency. In this paper, the application of modified FCM algorithm for MR brain tumor detection is explored. Feature vector space is used for the segmentation technique. Comparative analysis in terms of segmentation efficiency and convergence rate is performed between the conventional FCM and the modified FCM. The modified FCM algorithm is a fast alternative to the traditional FCM technique.

Yambal and Gupta [11] proposed a survey for the brain tumor detection using segmentation methods. It is based on hierarchical self-organizing map (SOM). The proposed method used FCM technique with histogram based centroid initialization for brain tissue segmentation in MRI of heads scans, FCM algorithm is used in various tasks of pattern recognition, data mining, image processing, gene expression, data recognition etc,. Modifying and generalizing the FCM algorithm is a prevailing research stream in fuzzy clustering in recent decades. Low depth of field is a method used to give special importance to a part of image which is essential or which has to be focused. In SOM, the first part consists of capturing an image form the database and the second part consists of accurately identify the principle structures in these image volumes.

Hussian [12] proposed a method named improved fuzzy possiblistic c-means (IFPCM). The proposed method combines the FCM and possiblistic c-means (PCM) functions without considering any spatial constraints on the objective function. It is realized by modifying the objective function of PCM algorithm. This proposed algorithm is evaluated and compared with the most popular modified probabilistic c-means techniques via application to simulated MRI brain images corrupted with noise. The quantitative results suggested that the proposed algorithm yields better segmentation results than the others for all tested images.

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that minimize dissimilarity (objective) function [18] [19]. The objective function is,

$$J_m = \sum_{j-1}^{n} \sum_{i-1}^{c} u_{ij}^{m} \; d_{ij}^{2}(x_j, c_i)$$

where, m - [1, ∞] is a weighting exponent

uR ij R- [1,0] is the degree of membership function matrix

dR ij R(xR jR,cR iR) - is the Euclidean distance between element

xR jR and center of cluster

cR i R c - is the number of cluster n - is the number of data

The updated membership functions are defined as follows [5], $\mu ij$ =

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$$\mu_{ij} = \frac{1}{\sum_{l=1}^{c}\left(\frac{d\left(x_j,\ c_i^{(k-1)}\right)}{d\left(x_j,\ c_l^{(k-1)}\right)}\right)^{\frac{2}{m-1}}}$$

$$c_i^{(k)} = \frac{\sum_{j=1}^{N}\left(\mu_{ij}^{(k)}\right)^{m} x_j}{\sum_{j=1}^{N}\left(\mu_{ij}^{(k)}\right)^{m}}$$

This condition will stop if the improvement of the objective function over the previous iteration is below critical value, ε [1, 0]. This algorithm is iteratively updating the centers and membership grades for each data point. FCM iteratively moves the cluster centers to the right location within a data set. The detailed FCM algorithm is given below.

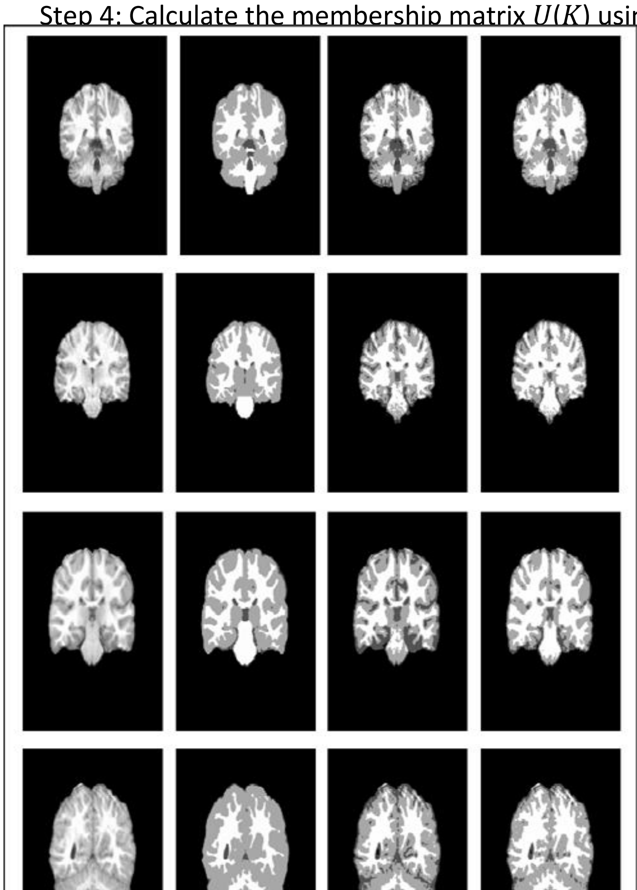
Requirement: Set values for the number of clusters C, the degree of fuzziness m > 1 and the error ∑.

Step 1: Initialize randomly the centers of clusters $ci$ (0) .

Step 2: k ← 1

Step 3: repeat

Step 4: Calculate the membership matrix $U(K)$ using



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database [20]. Both qualitative and quantitative validations were used for the performance evaluation. Experiments were done by taking the MRI brain image applied to the qualitative validation in the form of visual inspection with some of the sample T1-weighted images MRI and results are shown in Figure 1. The original images are shown in column 1, the corresponding ground truth images are in column 2, the results of FCM in column 3 and the results of proposed method are in column 4. The proposed method gives better results than the conventional FCM method.

Figure 1. Original images are in column 1, corresponding ground truth images are in column 2, results of FCM are in column 3 and results of proposed method are in column 4. For the quantitative validation, the performance is checked against two parameters. They are Dice Coefficient (DC) and processing time. The parameter DC is used to verify the similarity between the ground truth and

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the result of proposed work. The value for DC ranges from 0 to 1 where 0 for no agreement and 1 for exact agreement.

The DC is given by:

D(A, B) = 2|A∩B| |A|+|B| (13)

where, A represents the ground truth image and B represents the proposed result image.

Table 1 shown the DC value of conventional FCM and proposed method calculates with 18 IBSR volumes. The proposed method gives the average values for GM is 0.84, WM is 0.86 and CSF is 0.13. The proposed method gives better results while compared to the conventional FCM clustering. The graphs given in Figure 2 shows the quantitative representation of DC value for FCM and IFCM with bar representation. In Figure 3, the X axis represents MRI volume number considered for experiment and Y axis represents the processing time of FCM and IFCM.

**Table 1. DC values of GM, WM and CSF for conventional FCM and Improved FCM.**

| Volume Id | FCM | | | Improved FCM | | |
|---|---|---|---|---|---|---|
| | CSF | GM | WM | CSF | GM | WM |
| IB_1 | 0.17 | 0.77 | 0.78 | 0.22 | 0.74 | 0.80 |
| IB_2 | 0.26 | 0.77 | 0.80 | 0.29 | 0.79 | 0.83 |
| IB_3 | 0.08 | 0.76 | 0.83 | 0.12 | 0.85 | 0.89 |
| IB_4 | 0.07 | 0.73 | 0.85 | 0.08 | 0.84 | 0.89 |
| IB_5 | 0.08 | 0.71 | 0.79 | 0.09 | 0.81 | 0.85 |
| IB_6 | 0.10 | 0.66 | 0.84 | 0.14 | 0.83 | 0.92 |
| IB_7 | 0.06 | 0.85 | 0.88 | 0.14 | 0.87 | 0.90 |
| IB_8 | 0.06 | 0.83 | 0.89 | 0.14 | 0.84 | 0.88 |
| IB_9 | 0.13 | 0.82 | 0.84 | 0.17 | 0.87 | 0.87 |
| IB_10 | 0.08 | 0.85 | 0.94 | 0.14 | 0.87 | 0.95 |
| IB_11 | 0.08 | 0.85 | 0.88 | 0.14 | 0.86 | 0.90 |
| IB_12 | 0.15 | 0.87 | 0.83 | 0.18 | 0.84 | 0.85 |
| IB_13 | 0.08 | 0.77 | 0.83 | 0.03 | 0.85 | 0.88 |
| IB_14 | 0.04 | 0.78 | 0.84 | 0.03 | 0.85 | 0.86 |
| IB_15 | 0.02 | 0.78 | 0.85 | 0.10 | 0.84 | 0.86 |
| IB_16 | 0.10 | 0.73 | 0.73 | 0.11 | 0.80 | 0.71 |
| IB_17 | 0.05 | 0.76 | 0.81 | 0.08 | 0.84 | 0.84 |
| IB_18 | 0.09 | 0.74 | 0.75 | 0.14 | 0.82 | 0.79 |
| Average | **0.09** | **0.78** | **0.83** | **0.13** | **0.83** | **0.86** |

Then average processing time of each method isconverted into percentage (%) using the below equation.

$$Time\ difference\ (\%) = {}^{HT-LT} * 100 \quad (14)$$

where HT is representing the higher time and LT isrepresen

**Table 2.** Processing time for conventional FCM andImproved FCM.

| Volume Id | FCM (sec) | Improved FCM (sec) |
|---|---|---|
| IB_1 | 223.48 | 192.02 |
| IB_2 | 247.63 | 177.46 |
| IB_3 | 221.38 | 215.73 |
| IB_4 | 252.63 | 255.87 |
| IB_5 | 186.14 | 181.84 |
| IB_6 | 215.08 | 211.62 |
| IB_7 | 206.03 | 199.06 |
| IB_8 | 201.44 | 196.95 |
| IB_9 | 233.22 | 225.26 |
| IB_10 | 207.36 | 209.18 |
| IB_11 | 213.36 | 207.97 |
| IB_12 | 209.84 | 217.49 |
| IB_13 | 252.79 | 241.40 |
| IB_14 | 259.28 | 226.92 |

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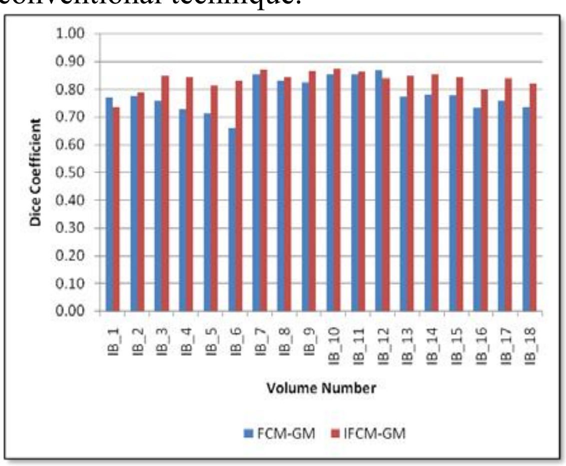
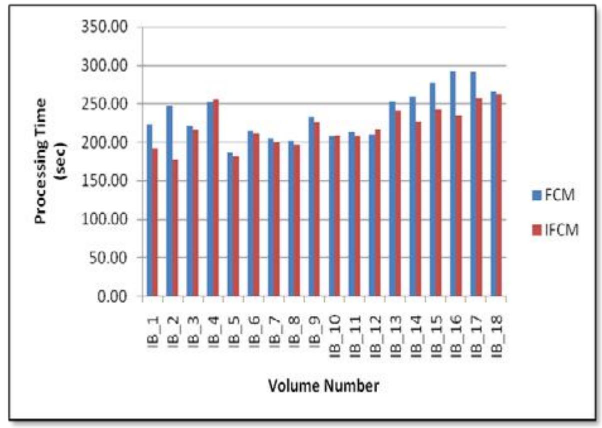
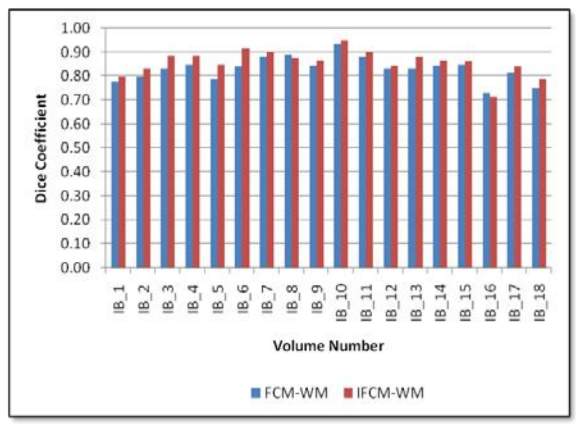
| | | |
|---|---|---|
| **IB_15** | 277.34 | 242.80 |
| **IB_16** | 292.24 | 235.88 |
| **IB_17** | 291.51 | 256.69 |
| **IB_18** | 266.15 | 263.26 |
| **Average** | **236.49** | **219.86** |

Table 2 is shown the processing time taken by conventional FCM and improved FCM for the 18 IBSR volumes. The proposed method takes minimum time while compared to conventional FCM clustering. In Figure 4, X axis represents the volume numeral Y axis represents the processing time in seconds. After applying the average processing time values in above equation (14), the proposed method is 7% faster than the conventional FCM. Our proposed method is fast as well as given satisfied results for T1-weighted images while compared with existing conventional technique.

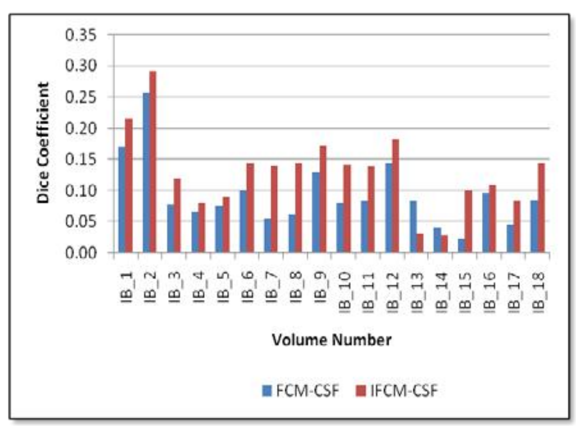



(a)




(b)




(c)

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**Figure 2.** DC Measurement Graph (a) GM values for FCM and IFCM (b) WM values for FCM and IFCM and
**(c) CSF values for FCM and IFCM**

**References**


[1] R.C. Gonzalez and R.E. Woods, "Digital Image Processing", Pearson Education, Inc., Publications, 2009.

[2] M. Sonka, V. Hlavac, and R. Boyal, "Digital Image Processing And Computer Vision", Cengage Learning, 2008.

[3] T. Kalaiselvi and P. Nagaraja, "A Rapid Automatic Brain Tumor Detection Method for MRI Images using Modified Minimum Error Thresholding Technique" International Journal of Imaging Systems and Technology, Vol.25, No.1, 2015, pp. 77–85.

[4] T. Kalaiselvi and P. Nagaraja, "Brain Tumor Segmentation of MRI Brain Images through FCM clustering and Seeded Region Growing Technique", International Journal of Applied Engineering Research, Vol.10, No.76, 2015, pp. 427-432,

[5] K. Somasundaram and T. Kalaiselvi, "Fully Automatic Method to Identify Abnormal MRI Head Scans using Fuzzy Segmentation and Fuzzy Symmetric Measure", ICGST International Journal on Graphics, Vision and Image Processing (GVIP), Vol.10, No.3, 2010, pp1-9,.

[6] K.M.M.Rao and V.D.P.Rao," Medical Image Processing", http://www.drkmm.com

[7] EL.Sayed A., E.L.Dashan,Abdel- Badeeh, M.Salem and Tamer H.Youns, "A Hybrid Technique for automatic MRI brain Images Classification", Vol.4, No.1, 2009, pp. 947-964.

[8] Ahmed Kharrat, Karim Gasmi and Mohamed Ben Meassoun, Nacera Benamrane and Mohamed Abid, "A Hybrid approach for automatic Classification of Brain using Genetic Algorithm and Support Vector Machine", Leonardo Journal of Sciences, Issue-7, 2010, pp.71-82.

[9] Weiling Cai Songcan Chen and Daoqiang Zhang., "Fast and Robust Fuzzy C-Means Clustering Algorithms Incorporating Local Information for Image Segmentation", Pattern Recognition, Vol.40, Issue 3, 2007, pp. 825–838

[10] A.N. Benaichouche, H. Oulhadj, and P. Siarry., "Improved Spatial Fuzzy C-Means Clustering for Image Segmentation using PSO Initialization, Mahalanobis Distance and Post-Segmentation Correction ", Digital Signal Processing Vol.23,2013, pp. 1390–1400.

[11] M. Shasidhar, V.Sudheer Raja, and B. Vijay Kumar., "MRI Brain Image Segmentation Using Modified Fuzzy C-Means Clustering Algorithm", International Conference on Communication Systems and Network Technologies, 2011.

[12] M.Yambal and H.Gutpta, "Image Segmentation using Fuzzy C-means Clustering-A Survey", International Journal of Advanced Research in Computer and Communication Engineering, Vol.2, 2013.

[13] Hussian AbouSora, Said Ghoniemy, Sayed A. Banwan, E.A.Zanaty, Ashraf Afifi.," Improved Fuzzy Possiblistic c- Means (IFPCM) Algorithms for Magnetic Resonance Images Segmentation", Journal of Global Research in Computer Science, Volume 4, No. 1, 2013, pp. 2927-2929.

[14] P.Vasuda and S.Satheesh., "Improved Fuzzy C-Means Algorithm for MR Brain Image Segmentation", (IJCSE) International Journal on Computer Science and Engineering Vol. 02, No. 05, 2010, pp.1713-1715.

[15] A. W. C. Liew and H. Yan," An adaptive spatial fuzzy clustering algorithm for 3-D MR image segmentation", IEEE Transactions on Medical Imaging, Vol. 22, No. 9, 2003, pp.

ISSN: 2057-5688

1063–1075.

[16] W. Cai, S. Chen and D. Zang, “Fast and robust fuzzy c means clustering algorithms incorporating local information for image segmentation”, Pattern Recognition, Vol. 40, 2007,pp. 825–838,

[17] J. Z. Wang, J. Kong, Y. H. Lu, and M. Qi, B. X. Zhang, "A modified FCM algorithm for MRI brain image segmentation using both local and non-local spatial constrains", Computerized Medical Imaging and Graphics, Vol.31, No.8, 2008, pp. 685–698.

[18] Bezdek, J.C.Hall and L.O.Clarke, “Review of MRI image Segmentation Techniques Using Pattern Recongnition Technique”, Vol.20, 1993, pp. 1033-1048.

[19] Ghanshyam D.Parmar and Suman K.Mitra, “Effectiveness Analysis of Fuzzy Unsupervised Clsutering Algorithms for Brain Tissue Segmentation in Single Channel MR Image”, International Journal of Bio-science and Bio-technology, Vol.3, No.2, 2011, pp. 39-46.

Internet Brain Segmentation Repository, Center for Morphometric Analysis at Massachusetts General Hospital.
http://www.cma.mgh.harvard.edu/ibsr/index.html

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