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

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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, geographical imaging 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 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 efficient in classification of normal or abnormal human brain with high sensitivity, specificity and accuracy rates.

Chen and Zhang [9] proposed two variants, FCM_S1 and FCM_S2, which simplified the neighborhood term of the objective function of FCM_S. These two algorithms introduce the extra mean-filtered image and median-filtered image respectively, which can be computed in 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.

Vasuda and Satheesh [13] proposed an FCM and MFCM method and that can be successively segmented a tumor provided the parameters are chosen properly. The modified FCM algorithm yields superior convergence rate. The tumor identification and the investigation are carried out for the potential use of MRI data for improving the tumor shape and 2D visualization of the surgical planning.

Liew and Yan [14] introduced a spatial constraint to a fuzzy cluster method where the inhomogeneity field modeled by a B-spline surface. The spatial voxel connectivity was implemented by a dissimilarity index, which enforced the connectivity constraint only in the homogeneous areas. In this way, this proposed method preserves significantly the tissue boundaries. Cai et al. [15] proposed a new local similarity measure by combining spatial and gray level distances. They used their method as an alternative pre-filtering to an enhanced FCM algorithm. Wang et al. [16] incorporated both the local spatial context and the non-local information into the standard FCM cluster algorithm. They used a novel dissimilarity measure in place of the usual distance metrics.

The proposed work is an automatic method for brain tissue segmentation that overcomes the above said problems and works efficiently for T1-weighted MRI head scans. The proposed method is an improved FCM clustering for segmentation of brain tissues from T1-weighted MRI head scans. The proposed method introduces spatial parameter for minimizing the objective function of conventional FCM. Then new weighting parameter introduces for centroid initialization. The proposed method gives better results for segmenting brain tissues are GM, WM and CSF. The experimental results are demonstrated the robustness and efficiency of the proposed segmentation technique.

The rest of the paper is organized as follows. The conventional FCM is explained in section 2, the proposed improved FCM is explained in section 4, the results and discussion are given in section 4 and the conclusion is given in section 5

2. Conventional Fuzzy c-means

FCM algorithm is one of the most popular fuzzy clustering methods widely used in various tasks of pattern recognition, data mining, image processing, gene expression data recognition etc. FCM is a data clustering technique in which a dataset is grouped into *n* clusters with every data point in the dataset belonging to every cluster to a certain degree. This algorithm divides the image space into smaller regions or units called clusters and by definition, such regions are to be disjoined. It is based on fuzzy portioning that makes the data point belongs to all groups with different membership grades between 0 and 1. The aim of FCM clustering is to find the cluster centers that minimize dissimilarity (objective) function [18] [19]. The objective function is,

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

where,
m - [1, ∞] is a weighting exponent
u_{ij} - [1,0] is the degree of membership function matrix
$d_{ij}\,(x_j, c_i)$ - is the Euclidean distance between element x_j and center of cluster c_i
c - is the number of cluster
n - is the number of data

The updated membership functions are defined as follows [5],

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

$$c_i^{(k)} = \frac{\sum_{j=1}^{N}\left(\mu_{ij}^{(k)}\right)^{m} x_j}{\sum_{j=1}^{N}\left(\mu_{ij}^{(k)}\right)^{m}} \quad (3)$$

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 $c_i^{(0)}$.
Step 2: k ← 1
Step 3: repeat
Step 4: Calculate the membership matrix $U^{(K)}$ using the centers $c_i^{(k-1)}$ by the equation (2)
Step 5: Update the centers $c_i^{(k)}$ using $U^{(K)}$ by the equation (3)

Step 6: k ← k + 1
Step 7: until $\left\| C_i^{(k)} - C_i^{(k-1)} \right\| < \epsilon$
Step 8: return C_i the centers of clusters and the membership degrees u_{ij}

3. Improved Fuzzy c-means

The proposed work is an automatic method to segment the brain tissues from T1-weighted head scans. It relies on the information provided in the T1-weighted image changed for identifying the tissues portion. This proposed work modifying the conventional FCM for fast segmentation of the tissue regions from T1-weighted image head scans. The improvements over the FCM method are explained in the following sections [10] [17].

In the segmentation process, the objective function of the traditional FCM algorithm does not take into accounts any spatial information. The FCM clustering process is related only on the grey levels independently on pixels of image in segmentation. Ahmed et al [8] considered the spatial information of the image and proposed a constrained objective function accordingly to as given below.

$$J = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} d^2(x_j, c_i) + \frac{\alpha}{N_R} \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} \sum_{r \in N_i} d^2(x_r, c_i) \quad (4)$$

where,

N_i - stands for the set of neighbors falling into a window around.

x_k and N_R - is its cardinality. The parameter in the second term α controls the effect of the penalty.

Chen and Zhang [16] proposed a object function to improve the robustness to noise and reduce the time calculation, The enhanced equation is:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} d^2(x_j, c_i) + \alpha \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m}\, d^2(\bar{x}_j, c_i) \quad (5)$$

where,

$\bar{x}_j$ - is the *j*th pixel of the filtered image

α - is a parameter that allows adjusting the impact of the local variance on the reallocation of pixels. Its value is determined experimentally and set to 0.65.

The proposed method introduces spatial parameter for minimizing the objective function of conventional FCM.

$$\boldsymbol{J = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} d^2(x_j, c_i) + \alpha \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} d^2(x_j, c_i)} \quad (6)$$

where α is the spatial function of the proposed method.

This spatial function approach is computed as follows:

$$\boldsymbol{P_i = \frac{f_i}{N}} \quad (7)$$

where,

P_i – is the probability of given image
f_i – is the number of i^{th} pixels
N – is the total number of pixels.

$$\alpha = max(P_i) \quad (i = 1\ to\ 255) \quad (8)$$

IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 3 Issue 7, July 2016
ISSN (Online) 2348 – 7968 | Impact Factor (2015) - 4.332
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Normally, the maximum value of probability goes to background pixels for MR images. The proposed method ignores that background pixels probability value (i = 0) for finding the α value from corresponding slice and it controls the effect of the neighbors term. The update of centers of classes and membership degrees are presented in

$$\mathbf{c_i} = \frac{N_g * \sum_{j=1}^{N}(1+\alpha)\, u_{ij}^{m}(x_i)}{\sum_{j=1}^{N}(1-\alpha)(u_{ij})^{m}} \tag{9}$$

$$N_g = \left(\frac{\alpha^2}{n} + \frac{1}{2n}\right) \tag{10}$$

whereN_g is the new weighting parameter introduced in the proposed method for finding the centroid and n ($n = 255$) represents the maximum intensity value of the gray image.

$$\mathbf{u_{ij}} = \frac{1}{(1+\alpha)*2\left[\sum_{k=1}^{c}\left[\frac{d^2(x_j,c_i)}{d^2(x_j,c_k)}\right]^{\frac{2}{m-1}}\right]} \tag{11}$$

The proposed IFCM algorithm is given below:

Step 1: Randomly initialize the membership matrix u = $[u_{ij}]$, $u^{(0)}$ has a constraint equation given by,

$$\sum_{i=1}^{c} u_{ij} = 1, \ \ \forall j = 1,2, \dots n, \tag{12}$$

Step 2: At k-step, calculate the centroids an d objective function using equations (9) and (6) respectively,

Step 3: Update the membership $u^{(k)}$, $u^{(k+1)}$ by using equation (11).

Step 4: If stopping criteria reaches stop; otherwise return to Step 2.

4. Results and Discussion

Our algorithm was implemented in MATLAB2010 on a PC with Intel Pentium Dual-Core 2.30GHz processor and 2GB RAM. For the validation study, the result of the proposed methodology is compared with the corresponding ground truth images from IBSR18 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.

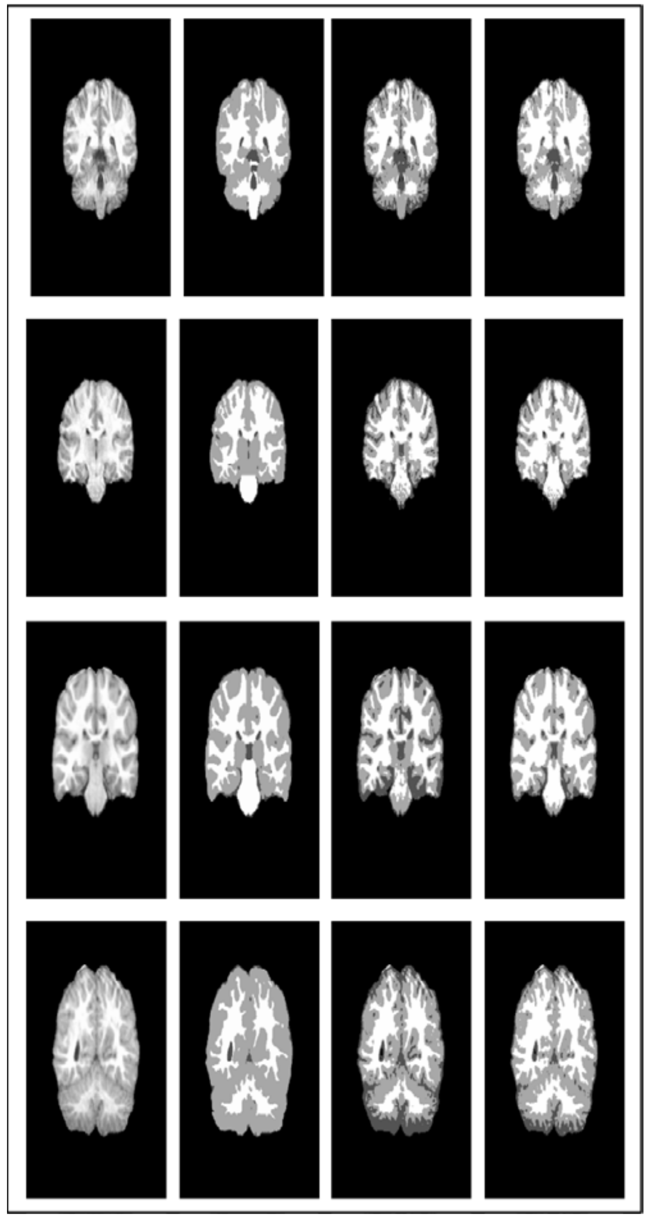

Figure 1. Original images are in column 1, corresponding ground truth images are in column 2, results of FCM are in column 3 and results of proposed method are in column 4.

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

IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 3 Issue 7, July 2016
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The DC is given by:

$$D(A, B) = \frac{2|A \cap B|}{|A| + |B|} \quad (13)$$

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 is converted into percentage (%) using the below equation.

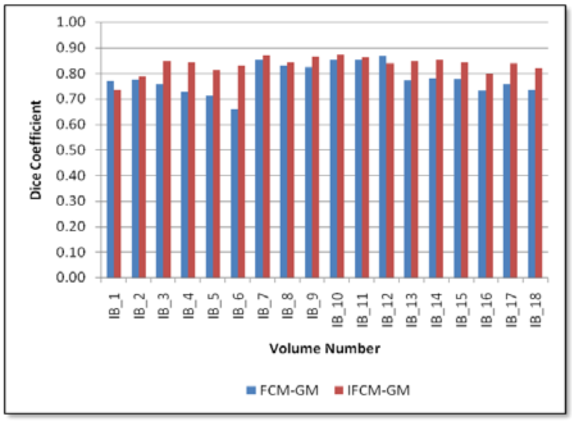
$$Time\ difference\ (\%) = \frac{HT - LT}{HT} * 100 \quad (14)$$

where HT is representing the higher time and LT is represents the lower time.

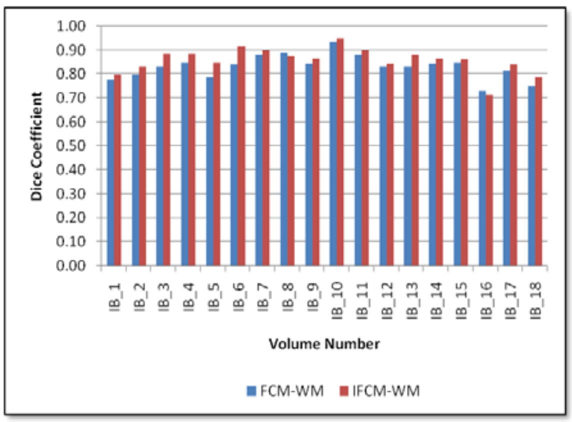
Table 2. Processing time for conventional FCM and Improved FCM.

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
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**

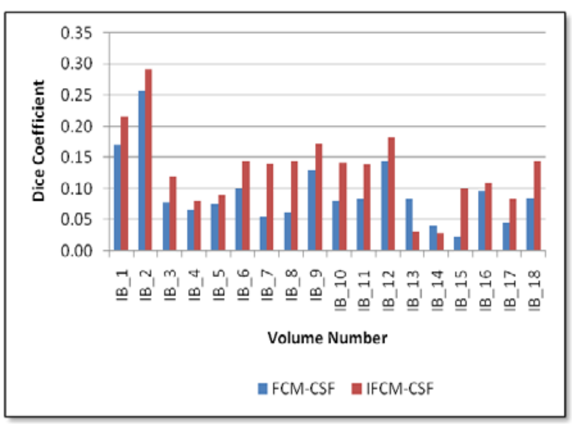
Table 2 is shown the processing time taken by conventional FCM and improved FCM for the 18 IBSR volumes. The proposed method takes minimum time while compared to conventional FCM clustering. In Figure 4, X axis represents the volume numeral Y axis represents the processing time in seconds. After applying 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)

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

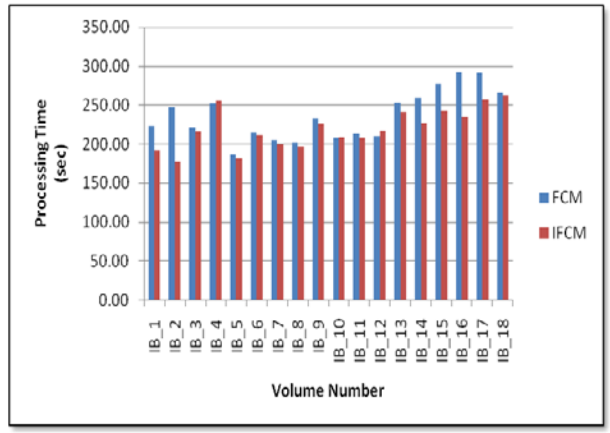


Figure 3. Processing Time for FCM and IFCM

5. Conclusions

The proposed work is brain tissue segmentation using Improved FCM clustering process. The proposed work introduced two parameters for modifying the conventional FCM, namely: spatial function, new weighting parameter. The experimental result of the proposed method is compared with the corresponding ground truth images available from IBSR18 dataset. The DC value of proposed method for GM region is 0.84, WM region is 0.86 and CSF region is 0.13. The proposed method gives better results while compared to the conventional FCM clustering and 7% faster than conventional FCM.

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