An Efficient Approach for Medical Image Segmentation using Modified Kernel based Fuzzy Clustering

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Abstract- To distinguish the information of white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) from the magnetic resonance (MR) brain images is essential to investigate the quantification of brain and the alterations in anatomical structures. In addition, it is also required to model the ontogenesis of tumour as they propagate at distinctive rates concording to their surroundings. Hence, it is still a challenging task to segment MR brain images due to the possible noise presence, bias field and impact of partial volume. This article presents an efficient approach for segmenting MR brain images using modified kernel based fuzzy clustering (MKFC) algorithm. In addition, this approach computes the weight of each picture element based on local mutation coefficient (LMC). Further, it is also proposed that the input MR brain image is denoised using non-linear anisotropic filtering (NLAF). Simulation outcome shown that the proposed segmentation approach performed quite superior to the existing segmentation algorithms in terms of both ocular and quantitative analysis.

Keywords: *MR brain image, tumour, data clustering, image segmentation, fuzzy-c means algorithm, non-linear anisotropic filtering and gaussian kernel.*

I. INTRODUCTION

Image segmentation is one of the important extensive way of classifying the pixel values of an image appropriately in decision-oriented applications. It partitions an image into even and non-overlapping areas depending on some similarity measure. It is one of the most challenging tasks in image processing and a very important pre-processing step in the fields of computer vision, image analysis, pattern recognition, medical image processing, remote sensing and geographical information system [1]. It is broadly used by customer display schemes to improve the eminence of image processing techniques and has two elementary properties of image. They are 1) intensity values comprising of discontinuity that denotes the immediate or unexpected variations in intensity as boundaries and 2) similarity that denotes to segregate a digital image into areas according to some pre-specified similarity principle. It plays a vital part in the field of medical applications, since the medical images. In clinical diagnosis, medical imaging plays a crucial role which helps in understanding and analysis of the organs. Medical imaging is a technique to create an internal image of a human body for clinical or medical purpose. Medical images are obtained by using different modalities that includes X-ray, computed tomography (CT), positron emission tomography and magnetic resonance imaging (MRI).

Segmentation is an indispensable step in medical image analysis which helps in identifying appropriate therapy for abnormal changes in tissues and organs. However, segmentation of these sorts of image become difficult due to the factors like unknown noise, intensity inhomogeneity, and partial volume influence. In the literature, so many algorithms have been implemented and published for the medical image segmentation. Image segmentation is classified into several categories based on their specific application nature since it is a primary processing stage in many real-time applications. Histogram thresholding is one of the approaches for segmenting an image, in which the segmentation is done by separating the objects form the background based on the considerable threshold in the gray levels of an image [2, 3]. However, this is computationally expensive, and the histograms of an image doesn't have clearly defined valley points which often makes the selection of threshold quite difficult. Later, edge-based segmentation approaches are proposed, which detects the edges based on several edge operators like canny [4], sobel and prewitt [5,6]. These methods usually suffer from over or under segmentation induced by improper selection of threshold. Afterwards, region-based techniques [7] aimed at iteratively building regions in the image until a certain level of stability is reached, which begins from well-chosen seeds and then expand the region of seed by annexing their homogeneous neighbours. This process is iterated until all the pixels in the image have been classified. However, this sort of approaches requires a manual interaction to obtain a seed point.

Later years, clustering-based segmentation approaches [8] are employed to overcome several limitations of above-mentioned approaches. Clustering is an algorithm, which clusters the number of colors or elements into several clusters based on the similarity of color intensities and gray intensities of an image. The major motive of clustering a medical image is dominant colors extraction from the images. By extracting the information from images such as texture, color, shape and structure, the image segmentation can be very important to simplify. Clustering algorithms are broadly classified into hierarchical and partitional clustering [9,10]. Hierarchical clustering algorithm generates a hierarchical tree of clusters called dendrogram which can be either divisive or agglomerative [9]. The partitional clustering algorithm gives a single C partition of objects, with a predefined C number of clusters. Among partitional clustering approaches, fuzzy c-means (FCM) is a well-known method and very popular clustering scheme [10] and [11], which segment an image into several partitions based on the membership function, which is utilized to decide the closely related picture elements in an image with positive and negative membership values.

Afterwards, many alterations have been done to the basic FCM clustering [12-15]. Though it produces accurate outcome of segmentation, it requires higher computational time to segment an image as it relies on the value of membership function for each picture element. In medical images, uncertainty occurs in terms of vagueness in imprecise gray levels, object boundary and so on. While defining membership function, hesitation arises due to the presence of uncertainty in gray levels. Unfortunately, classical FCM clustering techniques fail to handle this hesitation. To handle this hesitation, Xu et al. proposed higher order fuzzy set called intuitionistic fuzzy set (IFS) [15]. IFS consider both membership (μ) and non-membership (v) values. In traditional fuzzy set, the non-membership degree is equal to the complement of the membership degree, but in IFS non-membership the degree is less than or equal to the complement of the membership degree due to the index of intuitionism or hesitation degree. Further, a review on wide range of FCM clustering techniques is addressed in [16]. Author in [17] presented an FCM clustering approach that employs the membership function values based on the probability. Recently, Kumar et al. implemented a novel FCM clustering for medical image segmentation which operates based on weighted spatial kernel that produces spatial information to eliminate uncertainty in finding exact location in the medical images [18].

However, the segmentation methods in the literature were failed to deal with local spatial property of images which leads to strong noise sensibility. Further, the medical images mainly suffer from intensity inhomogeneity and noise caused due to radio frequency (RF) coil used in the procedure of image acquisition. Therefore, correction of intensity inhomogeneity as well as removal of noise is always desirable before segmentation of medical images. Thus, medical image segmentation is still a challenging problem since they are influenced by numerous factors like

(1) Noise caused in the procedure of image acquisition
(2) Poor contrast and intensity inhomogeneity physically linked to the RF MR signal
(3) Partial impact of volume being the combination of various tissue signals in the same picture element, induced by the resolution of an image.

Generally, the current brain MR image segmentation algorithms suffer from one or more of the following shortcomings: lack of robustness to outliers, high computational cost, prior adjusting of crucial or many parameters, limited segmentation accuracy in the presence of high-level noise, and loss of such image details like cerebrospinal fluid (CSF). Therefore, this article implements a new framework for segmentation of medical images with better accuracy over several segmentation approaches discussed previously.

The rest of this paper is organized as follows. Section 2 describes the background of FCM clustering algorithm. Our proposed segmentation framework is explained in section 3. Section 4 describes the results and discussion of proposed and conventional medical image segmentation approaches with clinical MR images. Finally, conclusions and future work are presented in sections 5 followed by the references.

II. FUZZY C-MEANS CLUSTERING

Initially, FCM was implemented by J.C. Dunn in 1973 and later it is enhanced by J.C. Bezdek in 1981. It is quite similar to that of another clustering approach named K-means:

- First, select cluster quantity k.
- Now, allocate random coefficients to every picture element in an image for being in the clusters.
- Iterate the similar procedure till the convergence obtained i.e., the difference between couple of iterations not more than the value of assigned sensitivity threshold:
- Calculate the centroid for every cluster Compute the centroid for each cluster.
- Next, compute their coefficients of being in the cluster for every picture element in an image.

A. *Algorithm*

Regarding the provided criterion, FCM is employed to partition a finite accumulation of n elements $X = \{x_1, x_2, \cdots, x_n\}$ into $v = \{v_1, v_2, \cdots, v_c\}$ fuzzy clusters accumulation. For a given finite set of information, FCM returns v and a matrix of partition $W = w_{ij} \in [0,1], i = 1,2,\cdots,n$ and $j = 1,2,\cdots,c$, where every w_{ij} element evidence the degree to which element x_i, adjunct to cluster k_j.

The FCM aims to understate following function:

$$arg \min_{K} \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left\| x_i - v_j \right\|^2 \quad (1)$$

Where

$$w_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|} \right)^{2/m-1}} \quad (2)$$

$$v_j = \frac{\sum_{i=1}^{n} w_{ij}^{m} x_i}{\sum_{i=1}^{n} w_{ij}^{m}} \quad (3)$$

Clustering with K-means also aims to minimize the objective function given in eq. (1). FCM dissents from the objective function of K-means by the membership values

w_{ij} summation and the fuzzifier, $m \in R$ with $m \geq 1$, which decides the cluster fuzziness level. Improved m led to tiny w_{ij} values, and thus, fuzzier clusters. In the limit $m = 1$, w_{ij} converge to 0 or 1, which results a crisp partitioning. Ideally, the value of m fixed to 2 in the domain knowledge absence. Then FCM understates the variance of intra-cluster as well but has the similar issues as K-means; the minimum is a local minimum, and the outcome relies on the initial weight's selection.

Therefore, further enhancement is required to set the cluster quantity adaptively that will upgrade the segmentation performance of FCM clustering approach [11]. Traditional FCM clustering discussed above is quite sensitive to the noise as the objective function in eq. (1) does not comprise any local info. Further, in presence of noise, the segmentation accuracy will also be mitigated. To defeat this issue, Ahmed et al. [19] added a term for the adjacent pixel's spatial information to the objective function as given below,

$$J_{\mathrm{M-FCM}} = \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left\| x_i - v_j \right\|^2 + \frac{\beta}{N_R} \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left(\sum_{r \in N_i} \left\| x_r - v_j \right\|^2 \right) \tag{4}$$

Where adjacent picture elements spatial info is controlled by the parameter β $(0 < \beta \leq 1)$, set of picture elements close to pixel i is denoted as N_i and N_R is the quantity of N_i.

However, this approach is computationally expensive as the local adjacent term has to be computed in every stage of iteration, which is later overcome by Chen and Zhang [20] by replacing the term $1/N_R \sum_{r \in N_i} \left\| x_r - v_j \right\|^2$ in eq. (4) with the $\left\| \bar{x}_i - v_j \right\|^2$, where $\bar{x}$ is the filtered image grayscale that could be computed once in advance, and employed a function of kernel to substitute the traditional Euclidean distance. The improvement could be in two forms i.e., one is by adopting average filter and the second is by employing median filter. Their objective function is as follows:

$$J_{\mathrm{FCM}_{A,M}} = \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left\| x_i - v_j \right\|^2 + \beta \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left\| \bar{x}_i - v_j \right\|^2 \tag{5}$$

Although there is an enhancement in the segmentation accuracy, this approach is sensitive to the noise of higher levels and several kinds. In summation, β is set manually with concern and needs anterior info regarding noise.

Yang and Tsai [21] proposed a Gaussian kernel-based FCM method with the parameter η_j calculated in every Computational and Mathematical Methods in Medicine 3 iteration to replace α for every cluster. Like [20], this method has two forms: GKFCM_1 and GKFCM_2 for average and median filters, respectively. The parameter η_j is estimated using kernel functions:

$$\eta_j = \frac{\min_{j' \neq j} \left(1 - K(v_{j'}, v_j) \right)}{\max_k \left(1 - \mathrm{K}(v_k, \bar{x}) \right)} \tag{6}$$

where K is the kernel function. The replacement of β with η_j could yield better results than [20]. However, for good estimation of η_j, cluster centers should be well separated which might not be always true; hence the algorithm has to iterate many times to converge. Moreover, the learning scheme requires many patterns and numerous cluster centers to find the optimal value for η_j.

To handle the adjusting of parameter issue, Krinidis and Chatzis [22] proposed the FLICM algorithm with a fuzzy factor that combined both spatial and grayscale information of the adjacent pixels. Although FLICM algorithm enhances robustness to noise and artifacts, it is slow since the fuzzy factor must be calculated in each iteration. Moreover, it is heavily affected by spatial Euclidean distance from the central pixel to its neighbouring pixels to lose small image details due to the smoothing effect.

To enhance the FLICM algorithm, Gong et al. [23] developed KWFLICM algorithm with a trade-off weighted fuzzy factor to control the local neighbour relationship and replaced the Euclidean distance with kernel function. The trade-off weighted fuzzy factor combines both the local spatial and grayscale information [23]. Because of the trade-off weighted fuzzy factor, its computational cost increases substantially. In addition, the algorithm is unable to preserve small image details.

Moreover, to the abovementioned shortcomings, Szilagyi [24] pointed out serious theoretical mistakes in FLICM and KWFLICM. It was shown that the iterative optimization nature of FLICM and KWFLICM did not minimize their objective functions; instead, they iterated until the partition matrices converged. Furthermore, their objective functions intended to employ local contextual information but theoretically failed and were not even suitable for creating a valid partition [24].

To this end, a new way to modify the existing FCM clustering is explored with adaptive regularization for contextual information. The proposed framework employed a new parameter to control the effect of pixel neighbours based on LMC. A weighted image is devised that combines the local contextual information with respect to the LMC and the non-linear anisotropic filtered grayscale that is calculated once in advance to reduce the computational cost. To improve segmentation accuracy and robustness to outliers, a gaussian kernel function is employed to replace the Euclidean distance metric.

III. PROPOSED METHODOLOGY

This section explains the proposed segmentation framework for medical images. In general, parameter β employed in conventional FCM approaches is set in advance to assure the suitable contextual info quantity. In truth, the level of noise alters from one window to another, so, invariable β for each pixel is not suitable. Further, it requires anterior knowledge regarding noise that is almost impossible in real-time nature. Thus, adaptive computation of β is essential concording to the picture element being processed.

A. Computation of Weights

Weights of each pixel is computed by employing the LMC, which is referred as a ratio of local variance of each pixel $\left(L_{\mathrm{var}_i}\right)$ to the local average of each pixel $\left(L_{\mathrm{avg}_i}\right)$. The average filtering with local window is utilized to calculate L_{avg_i} and L_{var_i} is attained by applying the standard deviation filtering to the input image. Then the LMC is defined as follows:

$$\mathrm{LMC}_i = \frac{L_{\mathrm{var}_i}}{{L_{\mathrm{avg}_i}}^2} \tag{7}$$

Now, exponential function, $\mathcal{E}_i$ is employed for $\mathrm{LMC}_i$and local accumulation of LMC_i to compute the weights, w_i in each picture element. Further, an inflexion parameter ϕ_i, is utilized to assign weights to every picture element as follows:

$$\phi_i = \begin{cases} \xi + w_i, & L_{\mathrm{avg}_i} > x_i \\ \xi - w_i, & L_{\mathrm{avg}_i} < x_i \\ 0, & L_{\mathrm{avg}_i} = x_i \end{cases} \tag{8}$$

For the pixels with larger L_{avg_i}, the parameter ϕ_i assigns higher values. When L_{avg_i} is equal to x_i then ϕ_i will be zero, which behaves like the traditional FCM clustering algorithm. ξ denote the positive constant probably 2 that trade-off the rate of convergence and capacity to hold back the details. In eq. (5), parameter β is replaced with the inflexion parameter expressed in eq. (8).

Algorithm 1: MKFC-NLAF

Step 1: Initialize the parameters $v, w^{(0)}, t = 0$ and $m = 2$

Step 2: Select and read an MR brain image which is to be segmented

Step 3: Compute weights of every picture element by employing LMC_i as expressed in eq. (7)

Step 4: Compute the inflexion parameter ϕ_i, as mentioned in eq. (8)

Step 5: Apply NLAF approach to smooth input MR brain image at similar kind of regions while holding back the non-similar kind of regions i.e., edges which is quite difficult in medical images.

Step 6: Using eq. (13), compute the modified kernel based on gaussian function.

Step 7: Finally, compute the number of cluster centres and new membership function values.

Step 8: Evaluate the obtained segmented outcome using quality metrics like Jaccard index and running time.

B. Non-linear Anisotropic Filtering

The NLAF process will smooth a given image at homogeneous regions while preserving the nonhomogeneous regions (edges) using partial differential equations (PDE). It overcomes the drawbacks of non-linear isotropic filtering, which uses inter-region smoothing. So, edge information is lost. In contrast, NLAF uses intraregional smoothing to generate coarser resolution images. At each coarser resolution edges are sharp and meaningful. The NLAF equation uses flux function to control the diffusion of an image x as,

$$x_t = \mathbb{F}(m,n,t)\Delta x + \nabla\mathbb{F} \cdot \nabla x \tag{9}$$

Where $\mathbb{F}(m,n,t)$is flux function, Δ is a Laplacian operator, ∇ is a gradient operator and t is time or scaling constant.

We can also term (9) as heat equation. Forward-time-central space (FTCS) scheme is used to solve this equation.

The solution for this PDE is

$$x_{i,j}^{t+1} = x_{i,j}^t + \zeta\left[\mathbb{F}_N \cdot \overline{\nabla}_N x_{i,j}^t + \mathbb{F}_S \cdot \overline{\nabla}_S x_{i,j}^t + \mathbb{F}_E \cdot \overline{\nabla}_E x_{i,j}^t + \mathbb{F}_W \cdot \overline{\nabla}_W x_{i,j}^t\right] \tag{10}$$

In above eq., $x_{i,j}^{t+1}$is the coarser resolution image at $t+1$ scale which depends on the previous coarser scale image $x_{i,j}^t$. ζ is a stability constant satisfying $0 \le \zeta \le 1/4$. Nearest neighbour differences in north, south, east and west directions denoted as $\overline{\nabla}_N, \overline{\nabla}_S, \overline{\nabla}_E, \overline{\nabla}_W$ respectively. They are defined as

$$\overline{\nabla}_N x_{i,j} = x_{i-1,j} - x_{i,j}$$

$$\overline{\nabla}_S x_{i,j} = x_{i+1,j} - x_{i,j}$$

$$\overline{\nabla}_E x_{i,j} = x_{i,j+1} - x_{i,j}$$

$$\overline{\nabla}_W x_{i,j} = x_{i,j-1} - x_{i,j}$$

Similarly, the flux functions are denoted as $\mathbb{F}_N$, $\mathbb{F}_S$, $\mathbb{F}_E$ and $\mathbb{F}_W$respectively.

$$\mathbb{F}^t{}_{N_{i,j}} = g\left(\left\|(\nabla x)^t{}_{i-1/2,j}\right\|\right) = g\left(\left|\overline{\nabla}_N x_{i,j}^t\right|\right)$$

$$\mathbb{F}^t{}_{S_{i,j}} = g\left(\left\|(\nabla x)^t{}_{i+1/2,j}\right\|\right) = g\left(\left|\overline{\nabla}_S x_{i,j}^t\right|\right)$$

$$\mathbb{F}^t{}_{E_{i,j}} = g\left(\left\|(\nabla x)^t{}_{i,j+1/2}\right\|\right) = g\left(\left|\overline{\nabla}_E x_{i,j}^t\right|\right)$$

$$\mathbb{F}^t{}_{W_{i,j}} = g\left(\left\|(\nabla x)^t{}_{i,j-1/2}\right\|\right) = g\left(\left|\overline{\nabla}_W x_{i,j}^t\right|\right)$$

In above eq., g (·) is a monotonically decreasing function with g (0) = 1. Different functions can be used for g (·). But Perona and Malik [] suggested two functions as mentioned below

$$g(\nabla x) = e^{-\left(\frac{\|\nabla I\|}{\varepsilon}\right)^2} \tag{11}$$

$$g(\nabla x) = \frac{1}{1+\left(\frac{\|\nabla I\|}{\varepsilon}\right)^2} \tag{12}$$

These functions offer a trade-off between the smoothing and texture preservation. First function is useful if the image consists of high-contrast edges over the low-contrast edges. Second function is useful if the image consists of wide regions over the smaller regions. Both functions consist of a free parameter ε, which is used to decide the validity of a region boundary based on its edge strength.

C. Modified Kernel Function

In practice, measurement of distance is computed by the Euclidean distance metric due to its simplicity and inexpensiveness. But it is tender to fluster and outliers. To address this, kernel functions are implemented in recent days, which are capable to externalize the information into a space of high-dimension where the info could be differentiated to greater extent. To obtain this, kernel function is assumed to map a linear algorithm into no-linear one by employing a dot multiplication. The kernel width is computed as,

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(d_i - \bar{d})^2}{N-1}} \qquad (13)$$

Where, d_i denotes that the absolute distance values from each pixel i to the average of all pixels and mean of all distances is denoted as $\bar{d}$.

IV. RESULTS AND DISCUSSION

This section describes the experimental analysis of proposed segmentation framework with comparison to the conventional segmentation approaches. Simulated Brain Database (SBD) [25] is considered for testing the proposed medical image segmentation approach, where the SBD comprises a realistic MR volume set generated by an MR imaging simulator with their ground truths of WM, GM and CSF available. Fig. 1 disclose that the segmentation of T1-weighted axial slice (number 100) with 217 × 181 pixels corrupted with the noise of 7% and grayscale nonuniformity of 20% into WM, GM, and CSF while the running time and Jaccard index values are demonstrated in Table 1. As given in Table 1, besides classical FCM, proposed framework consumes less running time over the other segmentation approaches presented in literature. Further, T1-weighted axial slice number, denoted as Brats1 with the size of 240×240. From black to white are, respectively, background, CSF, GM, and WM. It should be noted that clustering is carried out only for CSF, GM, and WM, with the pathology region being considered as background. The obtained segmented results are shown in Fig. 2, where the proposed segmentation method obtained a better separation of WM, GM and CSF as compared to the approaches presented in literature like classical FCM [11], Ahmed et al. [19], Yang et al. [21] and Gong et al. [23]. The performance measurement with running time is disclosed in Fig. 3.

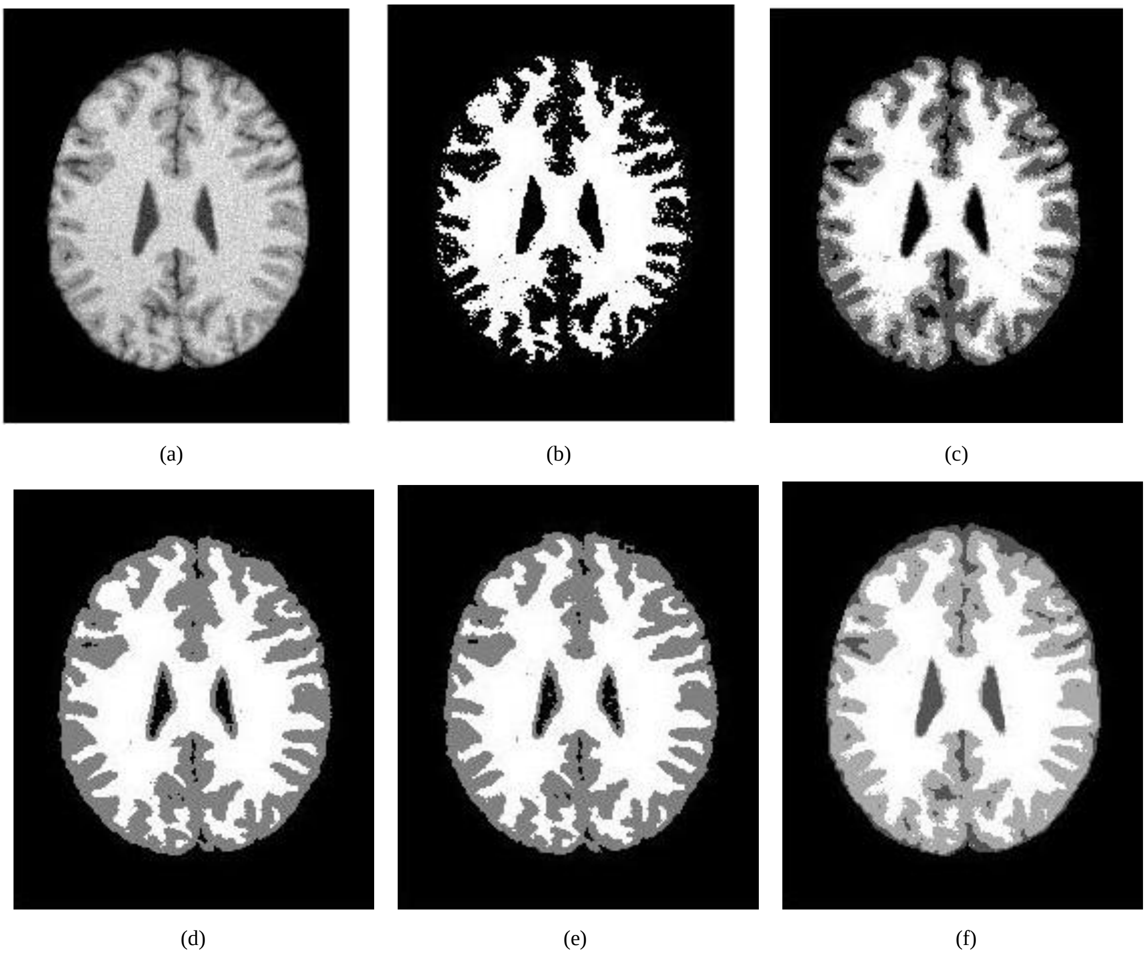

Fig. 1 Segmented outcome of T1-weighted axial slice (number 100) from SBD with 7% noise and 20% grayscale nonuniformity (a) original image (b) classical FCM [11] (c) Ahmed et al. [19] (d) Yang et al. [21] (e) Gong et al. [23] (f) our method

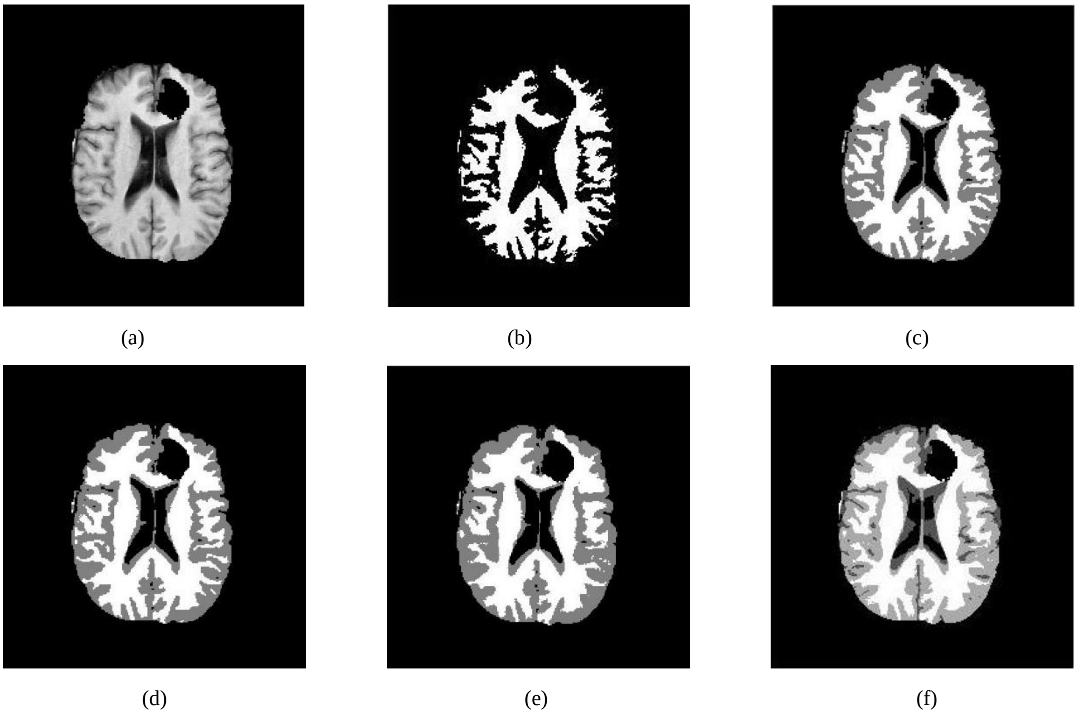

Fig. 2 Segmented outcome of Brats1 image. (number 80) from SBD with 7% noise and 20% grayscale nonuniformity (a) original image (b) classical FCM [11] (c) Ahmed et al. [19] (d) Yang et al. [21] (e) Gong et al. [23] (f) our method

Table 1. Obtained quality metric values with the proposed and existing segmentation approaches for Fig. 1

	Classical FCM [11]	Ahmed et al. [19]	Yang et al. [21]	Gong et al. [23]	Our method
Jaccard index	0.59	0.79	0.84	0.865	**0.94**
Execution time (in sec)	14.58	10.59	9.11	139.47	**3.18**

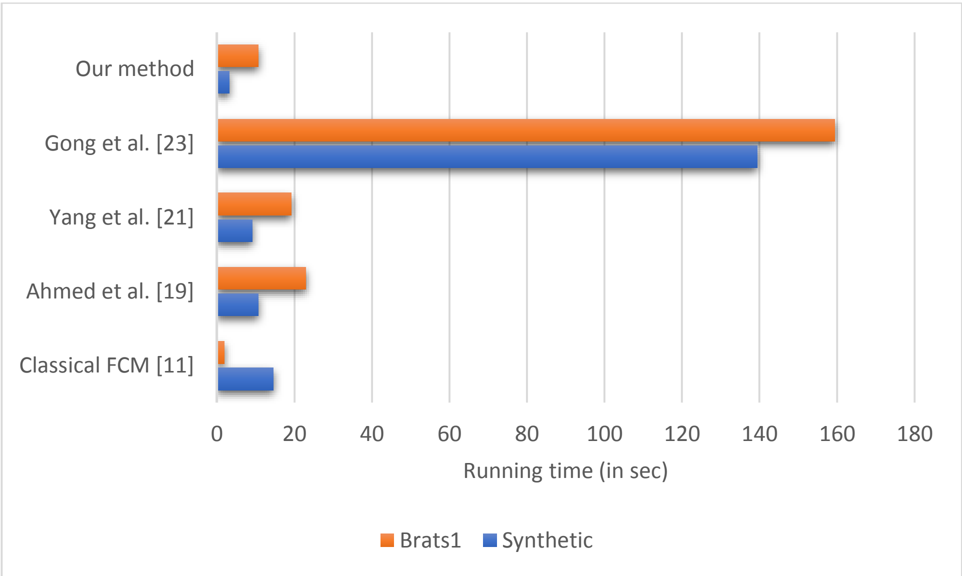

Fig. 3 Performance measure of proposed and existing segmentation approaches with running time

V. CONCLUSIONS

This article proposed an efficient approach for segmenting MR brain images using MKFC algorithm. In addition, this approach computes the weight of each picture element based on LMC. Further, it is also utilized NLAF for smoothing of input MR brain image to preserve the edge details. Simulation outcome shown that the proposed segmentation approach performed quite superior to the existing segmentation algorithms in terms of both ocular and quantitative analysis.

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