A New Fuzzy C-Means for Magnetic Resonance Images (MRIs) Segmentation

E.A. Zanaty[*1], Ashraf Afifi[2]

[*1]Computer Science Dept., College of Science,Sohag University, Sohag, Egypt

[2]Computer Science Dept., College o Computer, 10 Ramdan University, Cairo, Egypt

[*1]zanaty22@yahoo.com; [2]ashrafifi@yahoo.com

***Abstract*- In this paper, a new modified fuzzy c-means algorithm is presented which could improve the medical image segmentation. The proposed algorithm is realized by modifying the objective function of the conventional FCM algorithm with a flexible penalty. This penalty is based on a data shape and data size used for the generation of fuzzy terms. The complexity of the proposed algorithm is reduced using initial seed information into the objective function instead of whole data set.**

The proposed algorithm is applied to magnetic resonance image (MRI) datasets. Compared with the existing approaches, the proposed method can achieve the best accurate results. The results of the conducted experiments show that the efficiency of the proposed method in preserving the regions homogeneity and its robustness in segmenting noisy images is better than other FCM-based methods.

Keywords- Fuzzy Clustering; Modified Fuzzy C-Means; Medical Image Segmentation

I. INTRODUCTION

Because of the advantages of magnetic resonance imaging (MRI) over other diagnostic imaging [1-2], the majority of researches in medical image segmentation pertain to its use for MR images. Fuzzy segmentation methods have considerable benefits, because they could retain much more information from the original image than hard segmentation methods [3]. In particular, the fuzzy c-means (FCM) algorithm [1] assigns pixels to fuzzy clusters without labels. Since the conventional FCM algorithms classify pixels in the feature space without considering their spatial distribution in the image, it is highly sensitive to noise and other imaging artifacts. Many extensions of the FCM algorithm have been proposed to overcome above mentioned problem and reduce errors in the segmentation process [4–11]. They can be broadly grouped into two categories: similarity measure algorithms and modified FCM objective function. Similarity measure algorithms incorporate spatial smoothness into clustering techniques [6-10]. Many researchers have incorporated spatial information into the original FCM algorithm to enhance image segmentation [2, 5, 6, 8, 9, 10, 11, 12, 13, 14]. Shen et al. [7] introduced a new similarity measure that depends on spatial neighborhood information. In the work of Shen et al., the degree of the neighborhood attraction is optimized by a neural network. There are also other methods for enhancing the FCM performance. For example, to improve the segmentation performance, one can combine the pixel-wise classification with pre-processing (noise cleaning in the original image) [8, 10] and post-processing (noise cleaning on the classified data). Xue et al. [10] proposed an algorithm where they firstly denoise images and then classify the pixels using the standard FCM method. These methods can reduce the noise to a certain extent, but still have some drawbacks such as increasing computational time [5], complexity [5, 7, 9] and introducing unwanted smoothing [8, 10]. Liew et al. [15] proposed a spatial FCM clustering algorithm for clustering and segmenting the images by using both the feature space and spatial information. Another variant of FCM algorithm called the robust fuzzy c-means (RFCM) algorithm was proposed by Dzung [16].

Modified FCM objective function adds penalty term into the objective function to constrain the membership values. Based on the traditional FCM objective function, most improved approaches embodied regularization terms to show the increased robustness of the classification of the noisy images. Pham and Prince [17] modified the FCM objective function by introducing a spatial penalty for enabling the iterative algorithm to estimate spatially smooth membership functions. Ahmed et al. [5] introduced a neighborhood averaging additive term into the objective function of FCM. They named the algorithm bias corrected FCM (BCFCM). Liew and Yan [18] introduced a spatial constraint to a fuzzy cluster method where the inhomogeneity field was 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. This way preserves significantly the tissue boundaries. Szilágyi et al. [20] modified the FGFCM (MFGFCM) to improve the precision of segmentation. They proposed EnFCM algorithm to accelerate the image segmentation process. EnFCM is based on a simple fact about images, which is usually overlooked in many FCM-type algorithms. Cai et al. [8] introduced a new local similarity measure by combining spatial and gray level distances. They used their method as an alternative pre-filtering to EnFCM. They named this approach fast generalized FCM (FGFCM). This method is able to extract local information that causes less blur than averaging filter. However, it still has an experimentally adjusted parameter and the precision of the segmentation is not good enough. Kang et al. [21] improved FCM with adaptive weighted averaging filter (FCM AWA). Kang et al. [22] proposed a spatial homogeneity-based FCM (SHFCM). Wang et al. [23] 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 metric. These approaches could overcome the noise impact, but the intensity homogeneity cannot be handled at the same time. FCM-based algorithms are known to be vulnerable to outliers and noise. To address this problem, possibilistic clustering which is pioneered by the possibilistic c-means (PFCM) algorithm [24] is developed. It has shown more robust to outliers than FCM. However, the robustness of PFCM comes at the expense of the stability of the algorithm [25]. The PCM-based algorithms suffer from the coincident cluster problem, which makes them too sensitive to initialization [25]. Many efforts have been presented to improve the stability of possibilistic clustering [26, 27, 28]. However, PFCM estimates the centroids robustly in the case of outliers. This kind of algorithm cannot label the outliers accurately. Some recent results of fuzzy algorithms for improving automatic MRI image segmentation have been presented in [29-32].

Although suppressing the impact of noise and intensity inhomogeneity to some extent, these algorithms still produce misclassified small regions. They still depend on a fixed spatial parameter which needs to be adjusted. Furthermore, the cost of estimating the neighbors for each point in an image is still high. Therefore, these drawbacks will reduce the clustering performance in real applications. This paper addresses these problems for overcoming the shortcomings of existing modified fuzzy methods. In order to reduce the noise effect during segmentation, the new modified fuzzy c-means algorithm is proposed to modify the objective function with an automatic penalty in the conventional FCM algorithm and incorporates the initial seeds into the objective function. This penalty can be varied automatically based on the number of pixels of each region and the exponential weight of the fuzzy membership. The efficiency of the proposed algorithm is demonstrated by extensive segmentation experiments using real MR images and by comparison with other state of the art algorithms.

The rest of this paper is organized as follows. We discuss the limitations of existing fuzzy c-means and its generalization in Section 2. In Section 3, the proposed algorithm is presented. Experimental comparisons are given in Section 4. Finally, Section 5 gives our conclusions.

II. FUZZY C-MEANS ALGORITHMS

Fuzzy c-means clustering (FCM) is a data clustering algorithm in which each datum point belongs to a cluster to determine a degree specified by its membership grade [1-8]. In this section we discuss in more details about the popular fuzzy c-means algorithm and its generalization. We also concentrate on more famous modified fuzzy c-means algorithms which always give good results and are more stable in different applications [5, 6, 8, 21].

A. Fuzzy c-Means Method

Bezdek [1] proposed this algorithm as an alternative to earlier *k*-means clustering. FCM partitions a collection of N vector x_i, $i = 1, \ldots, N$ into C fuzzy groups and finds a cluster centre in each group such that an objective function of a dissimilarity measure is minimized. The major difference between FCM and *k*-means is that FCM employs fuzzy partitioning such that a given datum point can belong to several groups with the degree of belongingness specified by membership grades between 0 and 1. In FCM, the membership matrix $U = [u_{ij}]$ is allowed to have not only 0 and 1 but also the elements with any values between 0 and 1. This matrix satisfies the following constraints:

$$\sum_{i=1}^{C} u_{ij} = 1, \quad \forall j = 1, \ldots, N; 0 \le u_{ij} \le 1, \quad \sum_{j=1}^{N} u_{ij} > 0, \quad , \forall i; \tag{1}$$

The objective function of FCM can be formulated as follows:

$$J_m = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m \left\| x_j - c_i \right\|^2 \tag{2}$$

where C is the number of clusters; c_i is the cluster centre of fuzzy group i and the parameter m is a weighting exponent on each fuzzy membership. Fuzzy partitioning is carried out through an iterative optimization of the above objective function. Updating of membership u_{ij} and the cluster centers c_i is done as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_j - c_i \right\|}{\left\| x_j - c_k \right\|} \right)^{2/(m-1)}} \tag{3}$$

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m} \tag{4}$$

B. Modified Fuzzy c-Means

The modified fuzzy c-means algorithm segments the image more effectively than the previous algorithms because it penalizes the FCM objective function to constrain the behavior of the membership functions to perform segmentation. It has lower misclassification rate than the other algorithms because it reduces the noise effectively.

For example, Ahmed et al. [5] defined the modified objective function of FCM as:

$$J_m = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}{}^{m}\left\|x_j - c_i\right\| + \frac{\alpha}{N_R}\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m}\sum_{r\in N_j}\left\|x_r - c_i\right\|^2 \tag{5}$$

where N_j stands for the set of neighbors that exist in a window around x_j (not including x_j itself), N_R is the cardinality of N_j and the parameter α controls the effect of the penalty term and lies between zero and one inclusive.

The objective function J_m is minimized under the constraint of u_{ij}, c_i and we get:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\dfrac{\| x_j - c_i \|^2 + \dfrac{\alpha}{N_R}\sum_{r\in N_j}\| x_r - c_i \|^2}{\| x_j - c_k \|^2 + \dfrac{\alpha}{N_R}\sum_{r\in N_j}\| x_r - c_k \|^2}\right)^{1/(m-1)}} \tag{6}$$

$$c_i = \frac{\sum_{j=1} u_{ij}^{m}(x_j + \dfrac{\alpha}{N_R}\sum_{r\in N_j} x_r)}{(1+\alpha)\sum_{j=1}^{N} u_{ij}^{m}} \tag{7}$$

In each fuzzy c-means algorithm, the centres c_i and the number of clusters C are given to the algorithm. Iteratively, the fuzzy algorithm works to update the centers and the membership using Eqs. (6), (7). A shortcoming of Eqs. (6) and (7) is that fixing the neighbor term computation and computing the neighbor term will take much time in each iteration step. In fact, the second term $\dfrac{1}{N_R}\sum_{r\in N_j} x_j$ in the numerator of Eq. (7) is a neighboring average gray value around x_j. The image composed of all the neighboring average values around all the image pixels forms a so-called local neighbor average image [6].

In order to reduce the computational complexity, Kang et al. [21] introduced the following objective function that doesn't depend on fixed neighbor term:

$$J_m = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}{}^{m}\left\|x_j - c_i\right\|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^{m}\sum_{r\in N_j}(1-u_{ir})^m$$

The objective function J_m is minimized under the constraint of u_{ij} and we get:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\dfrac{\left\|x_j - c_i\right\|^2 + \dfrac{\alpha}{N_R}\sum_{r\in N_j}(1-u_{ir})^m}{\left\|x_j - c_k\right\| + \dfrac{\alpha}{N_R}\sum_{r\in N_j}(1-u_{ir})^m}\right)^{1/(m-1)}} \tag{8}$$

Because the penalty function does not depend on c_i, so it is identical to that of standard KFCM (Eq. (5)).

Although, Kang et al. [21] presented a new FCM with spatial constraints based on the fuzzy membership of the j^{th} pixel with respect to cluster *i*, this method still suffers the limitation in accuracy [6]. Therefore, Chen and Zhang [6] presented a new image filter named adaptive weighted averaging (AWA) which can be computed in advance. The objective function of Chen and Zhang [6] is as follows:

$$J_m = \sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}{}^m \| x_j - c_i \|^2 + \frac{\alpha}{N_R}\sum_{i=1}^{C}\sum_{j=1}^{N} u_{ij}^m \| \bar{x}_j^* - c_i \|^2$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\| x_j - c_i \|^2 + \alpha \| \bar{x}_j^* - c_i \|^2}{\| x_j - c_k \|^2 + \alpha \| \bar{x}_j^* - c_k \|^2}\right)^{1/(m-1)}} \tag{9}$$

$$c_i = \frac{\sum_{j=1} u_{ij}^m (x_j + \alpha \bar{x}_j^*)}{(1+\alpha)\sum_{j=1}^{N} u_{ij}^m} \tag{10}$$

where $\bar{x}_j^* = \frac{W_j x_j}{N_R}$, W_j is a weighting filter [21]. The modified fuzzy c-means (FCM) algorithms have been proven effective for image segmentation. However, they still have the following disadvantages:

- Although the introduction of local spatial information to the corresponding objective functions enhances their insensitiveness to noise to some extent, they still lack enough robustness to noise and outliers, especially in absence of prior knowledge of the noise;
- In their objective functions, there exists a crucial parameter α used to balance between robustness to noise and effectiveness of preserving the details of the image, it is selected generally through experience;
- The time of segmenting an image is dependent on the image size, and hence the larger size of the image consumes more segmentation time.
- These approaches still depend on a fixed spatial parameter which needs to be adjusted.

The cost of estimating the neighbors for each point in an image is still high.

Generally, every neighboring pixel has different contribution to computing the averaging value of central pixel, because large differences between a central pixel and its neighboring pixels indicate high probability of noise existing within the current neighborhood.

III. THE PROPOSED ALGORITHM

To overcome the limitation of the modified fuzzy methods, we present a novel modified fuzzy c-means algorithm based on a varied parameter that depends on the parameter of fuzziness and special neighborhood. However, a spatial penalty is necessary to be added to the objective function in modified fuzzy c-means to compensate for the intensity in homogeneities of MR image and to allow the labeling of a pixel to be influenced by its neighbors in the image. The penalty γ is automatically selected based on the exponential weight, m and special neighborhood size.

The proposed algorithm starts by finding the initial clustering (*C* clusters) of the whole data set $x_i, i = 1, 2, ..N$ using fuzzy c-means method which presented in Section *A* (see the previous section). Let R_i be the neighbor points of each point x_i. New, we consider the constraint term $\gamma\sum_{k=1}^{C}\sum_{i=1}^{N} u_{ki}^m \| \bar{x}_i - c_k \|^2$ in the objective function where $\bar{x}_i = \sum_{j=1}^{Neig}\frac{x_j}{Neig}$ is the average of neighbors that is surrounded a point x_i, where $Neig$ is the number of neighbors (R_i). The cost of computations can be reduced by decreasing the number of neighbors of each point. For example, one can use the mask 3×3.

The objective function of the proposed method is modified to be:

$$J_m = \sum_{k=1}^{C}\sum_{i=1}^{N} u_{ki}^m \left\| x_i - c_k \right\|^2 + \gamma\sum_{k=1}^{C}\sum_{i=1}^{N} u_{ki}^m \| \bar{x}_i - c_k \|^2 \tag{11}$$

where $u = (u_{ki})_{C\times N}, C = (c_1, c_2, .., c_k)$, $\gamma = \frac{1}{m * N_k}$

This objective function can improve the fuzzy computation to:

- overcome the coincident clusters problem using $\gamma\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\|\bar{x}_i-c_k\|^2$.
- reach the globally optimal cluster vastly using flexible penalty γ.
- reduce the noise effect during segmentation by using special weight $\bar{x}_i$ of a point x_i.

However, the crucial parameter γ is based on the exponential weight, *m*. More datasets are experimented in [35-36], they proved that there is a relation between data shape and *m*. For instance, the triangular shape will fit better if *m*=3 is used, more discussion can be shown in [36]. Therefore we take into account the data shape in the objective function and to be general for all tested data sets. This penalty term also contains spatial neighborhood information, which acts as a regularizer and biases the solution toward piecewise-homogeneous labeling. Such regularization is helpful in segmenting images corrupted by noise. The objective function J_m under the constraint of u_{ki} and c_k can be solved by using the following theorem [5]:

Theorem: Let $X=\{x_i, i=1,2,\dots,N \mid x_i\in R^d\}$ denote an image with *N* pixels to be partitioned into *C* classes (clusters), where x_i represents feature data. The algorithm is an iterative optimization that minimizes the objective function defined by Eq. (11) with the constraints in Eq. (3). Then u_{ki} and c_i must satisfy the following equalities:

$$u_{ki}=\frac{1}{\sum_{L=1}^{C}\left(\frac{\|x_i-c_k\|^2+\gamma\|\bar{x}_i-c_k\|^2}{\|x_i-c_L\|^2+\gamma\|\bar{x}_i-c_L\|^2}\right)^{\left(\frac{1}{m-1}\right)}} \tag{12}$$

$$c_k=\frac{\sum_{i=1}^{N}u_{ki}\left[x_i+\gamma\bar{x}_i\right]}{(1+\gamma)\sum_{i=1}^{N}u_{ki}^{m}} \tag{13}$$

Proof: The minimization of constraint problem J_m in Eq. (6) under constraints can be solved by using the Lagrange multiplier method. Now we define a new objective function with constraint condition (Eq. (3)) as follows:

$$L_m=\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\|x_i-c_k\|^2+\gamma\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\|\bar{x}_i-c_i\|^2+\sum_{i=1}^{N}\lambda_i(1-\sum_{k=1}^{C}u_{ki}) \tag{14}$$

Taking the partial derivative of L_m with respect to u_{ki} and λ_i, we have:

$$\begin{aligned}&\frac{\partial L_m}{\partial u}=\sum_{k=1}^{C}\sum_{i=1}^{N}mu_{ki}^{m-1}\|x_i-c_k\|^2+\gamma m\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m-1}\|\bar{x}_i-c_i\|^2+\sum_{i=1}^{N}\lambda_i(-1)=0\\&\frac{\partial L_m}{\partial\lambda_i}=0\Rightarrow\sum_{k=1}^{C}u_{ki}-1=0\end{aligned} \tag{15}$$

From Eq. (6), we get:

$$u_{ki}=\left(\frac{\lambda_i}{m\|x_i-c_k\|^2+\gamma\|\bar{x}_i-c_k\|^2}\right)^{\frac{1}{m-1}} \tag{16}$$

By substituting from Eq. (15) into Eq. (14), we get:

$$\left(\frac{\lambda_i}{m}\right)^{\left(\frac{1}{m-1}\right)}\sum_{i=1}^{C}\left(\frac{1}{\|x_i-c_k\|^2+\gamma\|\bar{x}_i-c_k\|^2}\right)^{\left(\frac{1}{m-1}\right)}=1$$

$$u_{ki} = \frac{\sum_{L=1}^{C}\left(\|x_i - c_L\|^2 + \gamma\|\bar{x}_i - c_L\|^2\right)^{\left(\frac{1}{m-1}\right)}}{\left(\|x_i - c_k\|^2 + \gamma\|\bar{x}_i - c_k\|^2\right)^{\left(\frac{1}{m-1}\right)}} = \frac{1}{\sum_{L=1}^{C}\left(\frac{\|x_i - c_k\|^2 + \gamma\|\bar{x}_i - c_k\|^2}{\|x_i - c_L\|^2 + \gamma\|\bar{x}_i - c_L\|^2}\right)^{\left(\frac{1}{m-1}\right)}}$$

$$\frac{\partial L_m}{\partial c_k} = 0 \Rightarrow -2\sum_{i=1}^{N} u_{ki}^m \left(x_i - c_k\right) - 2\gamma \sum_{i=1} u_{ki}\left(\bar{x}_i - c_k\right) = 0$$

$$\sum_{i=1}^{N} u_{ki}^m x_i + \gamma \sum_{i=1}^{N} u_{ki}^m \bar{x}_i = (1+\gamma)\sum_{i=1}^{N} u_{ki}^m c_k \Rightarrow \quad c_k = \frac{\sum_{i=1}^{N} u_{ki}\left[x_i + \gamma \bar{x}_i\right]}{(1+\gamma)\sum_{i=1}^{N} u_{ki}^m}$$

The processes of finding the best clusters continue to update the centres c_k and the membership u_{ki} using Eqs. (12) and (13) respectively. The proposed algorithm can be described as follows:

Algorithm:

Initialize the membership matrix u_{ki}^t with random values between 0 and 1 such that the constraints in Equation (1) are satisfied.

Input: initial centres c_k, *i=1,…, C*, the data $c_i, i = 1..N$

Repeat:

Compute: u_{ki} and c_k using Eqs.(12) and (13).

Until: $\|u_{ki} - u^t{}_{ki}\| \le \varepsilon$, where ε a certain tolerance value

Find R_k : extract a pixel that satisfies $\| x_i - c_k \| \le \omega$, ω is a small tolerance.

End Repeat.

IV. EXPERIMENTAL AND COMPARATIVE RESULTS

The experiments were performed on two different sets: one corrupted by 6% salt and pepper noise and the image size is 129×129 pixels which are shown in Fig. 1b, and Fig. 1c, respectively [37-38]. The second set includes simulated volumetric MR data consisting of ten classes as shown in Fig. 1a. The advantages of using digital phantoms rather than real image data for soft segmentation methods include prior knowledge of the true tissue types and control over image parameters such as modality, slice thickness, noise, and intensity in homogeneities. The quality of the segmentation algorithm is of vital importance to the segmentation process. The comparison score *S* for each algorithm as proposed in [36] is defined as follows:

$$S = \left|\frac{A \cap A_{ref}}{A \cup A_{ref}}\right|$$

where *A* represents the set of pixels belonging to a class as found by a particular method and A_{ref} represents the reference cluster pixels.

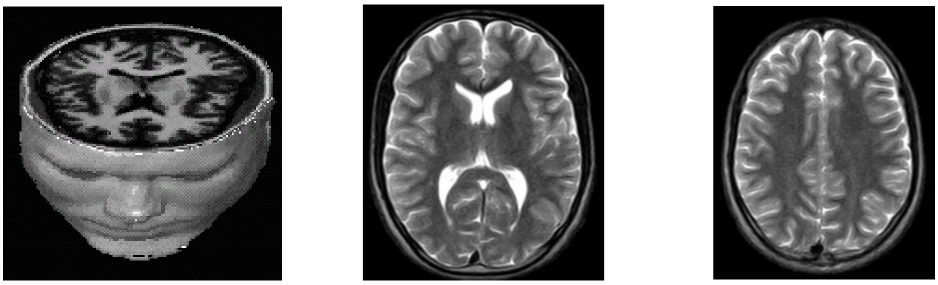

Fig. 1 Test images: (a) 3D simulated data, (b) and (c) two original slices from the 3D simulated data (slice89 and slice 65)

Our tests are focused on applying the proposed method, the standard FCM [1] and most popular modified fuzzy c-means such as: Ahmed et al. [5], Chen and Zhang [6], and Kang et al. [21] on the tested images. The proposed method is found to give better results and is more stable in different data sets. Through our implementation, we set the following parameters: m = 2, λ = 10 and ε = 0.0001. In the seed region growing algorithm, we put the threshold T =5. In the existing methods computations, the parameters α =0.7, r = 2 (i.e., a 3×3 window centered at each pixel) in Kang et al. [21], and N_R (a 3x3 window centered around each pixel, except the central pixel itself) in Chen and Zhang [6].

A. Experiment on the Real Image

We used a high-resolution T1-weighted MR phantom with slice thickness of 1mm, 6% noise and no intensity in homogeneities, obtained from the classical simulated brain database of McGill University [37]. Two slices drawn from the simulated MR data are shown in Figs. 1b and 1c. In this test, beside the proposed method, the standard FCM [1] and most popular modified fuzzy c-means such as: Ahmed et al. [5], Chen and Zhang [6], and Kang et al. [21] are implemented and applied on two slices to prove the efficiency of the proposed method. From the visual inspection, we noted that our proposed approach always gives stable and good results. The results of these methods are presented in Figs. 2-6 for first slice. Figs. 3-11 show the outcome of these methods in case of the second slice. The evaluation accuracy of the existing methods and the proposed method is shown in Table I after applying them into whole brain volume.

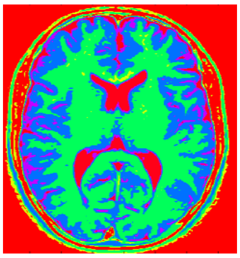

Fig. 2 Results of segmentation using FCM [1].

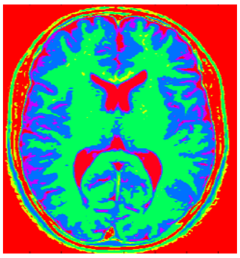

Fig. 3 Results of segmentation using Ahmed et al. method [5].

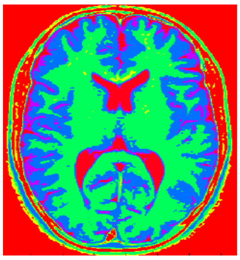

Fig. 4 Results of segmentation using Chen and Zhang method [6].

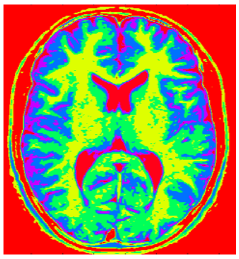

Fig. 5 Results of segmentation using Kang et al. method [21].

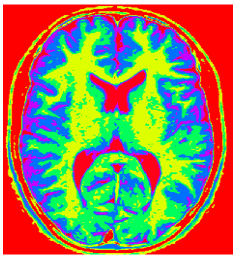

Fig. 6 Results of segmentation using the proposed method.

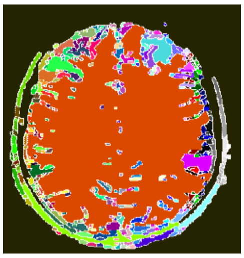

Fig. 7 Results of segmentation using FCM [1].

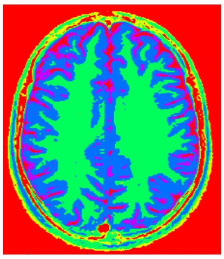

Fig. 8 Results of segmentation using Ahmed et al. method [5].

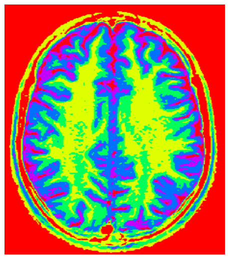

Fig. 9 Results of segmentation using Chen and Zhang method [6].

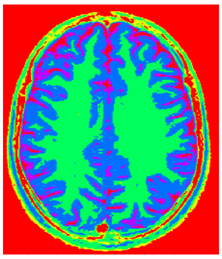

Fig. 10 Results of segmentation using Kang et al. method [21].

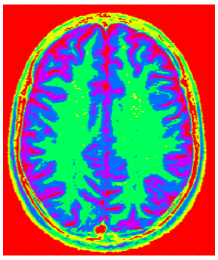

Fig. 11 Results of segmentation using the proposed method.

TABLE I SEGMENTATION ACCURACY (%) OF THE PROPOSED AND THE EXISTING METHODS ON BRAIN CLASSES

Method	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Overall
Standard KFCM	66.87	55.77	59.087	64.0	70.32	37.96	63.99	10.12	90.11	57.581
Ahmed et al. [5]	67.55	61.14	78.83	73.88	67.96	61.87	89.21	15.27	91.97	67.52
Chen and Zhang [21]	79.54	68.55	78.34	82..01	78.65	81.98	80.70	18.54	88.54	71.86
Kang et al. [6]	56.87	60.43	66.98	88.54	76.09	45.98	66.87	16.43	79.09	61.92
The proposed method	83.76	78.45	80.09	90.34	83.56	64.12	89.64	59.34	96.98	80.698

B. Experiment on the Simulated MR Data

Table I shows the corresponding accuracy scores (%) of the proposed and four other methods: standard FCM [1], Ahmed et al. [5], Chen and Zhang [6], and Kang et al. [23] for the nine classes. Obviously, the FCM gives the worst segmentation accuracy for all classes, while other methods give satisfactory results. On the other hand, the method of Ahmed et al. [5], Chen and Zhang [6], and Kang et al. [21] acquire the good segmentation performance in case of Class 9, Class 4, and Class 1 respectively. Overall, the proposed method is more stable and achieves much better performance than the others in all different classes even with misleading of true tissue of validity indexes.

V. CONCLUSION

FCM is a popular clustering method and has been widely applied for medical image segmentation. However, traditional FCM always suffers from noise in the images. Although many researchers have developed various extended algorithms based on FCM, none of them is flawless. A new approach based on proposed modified fuzzy c-means and seed region growing has been proposed in this paper. The proposed algorithm works without any prior information as previous ones. The complexity of the algorithm is reduced using initial seed instead of whole data set. Moreover, the proposed method includes an automatic penalty based on data shape and data size used for the generation of fuzzy terms. In our algorithm, the proposed method incorporates the local spatial context into the standard FCM cluster algorithm. The algorithm is formulated by modifying the objective function of the standard FCM algorithm to allow the labeling of a pixel to be influenced by other pixels and to suppress the noise effect during segmentation. We tested our algorithm on real MRI images with 6% noise. The superiority of the proposed algorithm is demonstrated by comparing its performance with the standard FCM, Ahmed et al. [5], Chen and Zhang [6], and Kang et al. [21]. In addition, quantitative results are also given in our experiments. We noted that the segmentation accuracy of the proposed method is increased over the existing methods between 49% and 7% for one slice and 9% for volumetric MR data (nine slices) over the best one. From the quantitative evaluation and the visual inspection, we can conclude that our proposed algorithm yields a robust and precise segmentation. Finally, we also should point out that although the proposed algorithm can perform better than standard FCM and other poplar modified FCM extension algorithms, it is computationally expensive, and this may limit its applicability to large 3D volume data.

REFERENCES

[1] J.C. Bezdek, “Pattern recognition with fuzzy objective function algorithms,” Plenum Press, NewYork, 1981.

[2] A. Liew, H. Yan, “An adaptive spatial fuzzy clustering algorithm for MR image segmentation,” IEEE Trans. Med. Image., vol. 22, pp.1063-1075, 2003.

[3] M.C. Su and C. H. Chou, “A modified version of the k-means algorithm with a distance based on cluster symmetry,” IEEE Transactions Pattern Analysis and Machine Intelligence, vol.23, no. 6, pp680, 2001.

[4] F. Masulli, A. Schenone, “A fuzzy clustering based segmentation system as support to diagnosis in medical imaging,” Artificial Intelligent Med, vol. 16, no. 2, pp. 29-47, 1999.

[5] M. N. Ahmed, S. M. Yamany, N. Mohamed, A. A. Farag, and T. Moriaty, “A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data,” IEEE Trans. Med. Imag., vol. 21, pp.193-199, 2002.

[6] C. Chen, D. Zhang, “A novel kernelized fuzzy c-means algorithm with application medical image segmentation,” Artificial Intelligence in Medicine, vol. 32, pp. 37–50, 2004.

[7] S. Shen, W. Sandham, M. Granat, and A. Sterr, “MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization,” IEEE Trans. Inf. Technology Biomedicine, vol.9, pp. 459–467, 2005.

[8] 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, pp. 825–838, 2007.

[9] Z. M. Wang, Y. C. Soh, Q. Song, and K. Sim, “Adaptive spatial information-theoretic clustering for image segmentation,” Pattern Recognition Letters, vol. 42, pp. 2029–2044, 2009.

[10] J. H. Xue, A. Piˇzurica, W. Philips, E. Kerre, R. Van de Walle, I. Lemahieu, “An integrated method of adaptive enhancement for unsupervised segmentation of MRI brain images,” Pattern Recognition Letters, vol. 24, pp. 2549–2560, 2003.

[11] E.A. Zanaty, Sultan Aljahdali, “Automatic fuzzy algorithms for reliable image segmentation,” journal, IJCA, vol. 19, no. 3, pp.166-175, Sept. 2012 2011.

[12] E.A. Zanaty, “A new modified fuzzy c-means for segmenting magnetic resonance images (MRIS),” IJICIS Journal, vol.11, no. 2, pp.209-222, 2012.

[13] S. Makrogiannis, G. Economou, S. Fotopoulos, “A region dissimilarity relation that Combines feature-space and spatial information for color image segmentation,” IEEE Trans. Syst. Man Cybern, vol. 35, no. 1, 2005.

[14] A. Z. Cao, Q. Song, “Robust information clustering for automatic breast mass detection in digitized mammograms,” Computer Vision Image Understanding, vol. 109, no. 1, 87–96, 2008.

[15] A. W. C. Liew, S. H. Leung, W. H. Lau, “Fuzzy image clustering incorporating spatial Continuity,” In IEE Proceedings of Vision, Image and Signal Processing, vol. 147, no. 2, pp.185–192, 2000.

[16] Snehashis Roy, Harsh K. Agarwal, Aaron Carass, Ying Bai, Dzung L. Pham, Jerry L. Prince: Fuzzy c-means with variable compactness. ISBI 2008: 452-455.

[17] D. Pham, J. Prince, "Adaptive fuzzy segmentation of magnetic resonance images," IEEE Transactions on Medical Imaging, vol. 18, no.9, 737–752, 1999.

[18] A. W. C. Liew, H. Yan, "An adaptive spatial fuzzy clustering algorithm for 3-D MR image segmentation." IEEE Transactions on Medical Imaging, vol. 22, no. 9, pp. 1063–1075, 2003.

[19] S.C. Chen, D.Q. Zhang, "Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure," IEEE Trans. Syst. Man Cyber net, vol. 34, no. 4, pp. 1907–1916, 2004.

[20] L. Szilágyi, S. M. Szilágyi, Z. Benyó, "A modified FCM algorithm for fast segmentation of brain MR images," In, ICIARLNCS, vol.4633, pp.866–877, 2007.

[21] J. Y. Kang, L. Q. Min, Q. X. Luan, X. Li, J. Z. Liu, "Novel modified fuzzy c-means algorithm with Applications," Digital Signal Processing, vol. 19, no. 2, pp. 309–319, 2009.

[22] B. Y. Kang, D. W. Kim, Q. Li, "Spatial homogeneity-based fuzzy c-means algorithm for Image segmentation," In FSKDLNAI, vol.3613, pp.462–469, 2005.

[23] J. Z. Wang, J. Kong, Y. H. Lu, 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, pp. 685–698, 2008.

[24] R. Krishnapuram, J. M. Keller, " Possibilistic approach to clustering," IEEE Transactions on Fuzzy Systems, vol. 1, no. 2, pp. 98–100, 1993.

[25] M. Barni, V. Cappellini, A. Mecocci, "Comments on a possibilistic approach to clustering," IEEE Transactions on Fuzzy Systems, vol.4, no.3, pp.393–396, 1996.

[26] Z. Ji, Q. Sun, D. Xia, "A modified possibilistic fuzzy c-means clustering algorithm for bias field estimation and segmentation of brain MR image," Computerized Medical Imaging and Graphics, vol.35, no.5, pp.383-397, 2011.

[27] H. Timm, C. Borgelt, C. Doring, R. Kruse, "An extension to possibilistic fuzzy cluster analysis", Fuzzy Sets and Systems," vol. 147, no. 1, pp. 3–16, 2004.

[28] J. S. Zhang, Y. W. Leung, "Improved possibilistic c-means clustering algorithms," IEEE Transactions On Fuzzy Systems, vol. 12, no. 2, pp. 209–17, 2004.

[29] E. A. Zanaty, S. Aljahdali, "Fuzzy algorithms for automatic magnetic resonance image segmentation," International Arab Journal of Information Technology (IAJIT), vol. 7, no.3, pp. 271-279, 2009.

[30] E.A. Zanaty, S. Aljahdali, N. Debnath, "Improving fuzzy algorithms for automatic magnetic resonance image segmentation," Proceedings of seventeenth International Conference of Software Engineering and Data Engineering, pp.60-66, Los Angeles, California, USA, June 2008.

[31] E.A. Zanaty, S. Aljahdali, N. Debnath, "A kernelized fuzzy c-means algorithm for automatic magnetic resonance image segmentation," Journal of Computational Methods in Science and engineering (JCMSE), pp. 123-136, 2009.

[32] L. Zhu, F. L. Chung, S. Wang, "Generalized fuzzy c-means clustering algorithm with improved fuzzy partitions," IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 39, no. 3, pp. 578 - 591, 2009.

[33] D. W. Chakeres, P. Schmalbrock, "Fundamentals of magnetic resonance imaging", Williams &Wilkins, Baltimore, 1992.

[34] A.W.C. Liew, H. Yan, "Current methods in the automatic tissue segmentation of 3D magnetic resonance brain images," Medical Imaging Reviews, vol. 2, pp. 91-103, 2006.

[35] H. Yan, J. C. Gore, "An efficient algorithm for MR image reconstruction without low spatial frequencies", IEEE Trans. Med. Image., TMI-9, pp. 179-184, 1990.

[36] E. A. Zanaty, Ashraf Afifi, "A watershed transformation for detecting distorted brain based on segmenting magnetic resonance images," International Journal of applied mathematics and information Science, vol.5, no.3, xxx, 2011.

[37] Simulated Brain Database, BrainWeb: http://www.bic.mni.mcgill.ca/brainweb/.

[38] DICOM sample image sets: http://pubimage.hcuge.ch:8080/.

E.A.Zanaty is an Associate Professor at Taif University, Saudi Arabia. He received his MSC Degree in computer science in 1997 from South valley University, Egypt. He completed his PhD. studies at TU-Chemnitz, Germany, during the period 2000-2003. His research interests are medical imaging, data reduction, image segmentation, and image reconstruction. In these areas he has published several technical papers in refereed international journals or conference proceedings.

Dr. Zanaty is an Editorial board of several journals and is the member of KACST and IAENG. Moreover he is a supervisor of several PhD and MSC thesis at Sohag, AL-Azhar, Benswef and South valley Universities.

Ashraf Afifi is an assistant professor, faculty of computers and information technology, Taif University, Saudi Arabia. He received his M.sc Degree in digital communication in 1995 from Zagazig University, Egypt. He completed his Ph. D. studies in 2002 from zagazig University, Egypt. His research interests are digital image segmentation and digital communication. In these areas he has published several technical papers in refereed international journals and Conference proceedings.