Improving Fuzzy C-Means for MRIs Segmentation

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Abstract: In this paper, a new modified fuzzy c-means algorithm is presented that 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 performance of the proposed algorithm is tested on noisy real images. 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.

1. Introduction

Because of the advantages of magnetic resonance imaging (MRI) over other diagnostic imaging [1-2], the majority of researches in medical image segmentation pertains 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[19-22]. 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

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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 produces 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.

2. The fuzzy c-means algorithm

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].
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:

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

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:

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

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

$$c_i = \frac{\sum_{j=1} u_{ij}^{m}\left(x_j + \dfrac{\alpha}{N_R}\sum_{r\in N_j} x_r\right)}{(1+\alpha)\sum_{j=1}^{N} u_{ij}^{m}} \quad (2)$$

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. (1), (2). A shortcoming of Eqs. (1) and (2) 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 $\dfrac{\sum_{R\in N_j} x_j}{N_R}$ in the numerator of Eq. (2) 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:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\dfrac{\left\|x_j - c_i\right\|^2 + \dfrac{\alpha}{N_R}\sum_{r\in N_j}(1-u_{ir})^m}{\left\|x_j - c_k\right\| + \dfrac{\alpha}{N_R}\sum_{r\in N_j}(1-u_{ir})^m}\right)^{1/(m-1)}} \quad (3)$$

Because the penalty function does not depend on c_i, so it is identical to that of standard KFCM (Eq. (1)).
Although, Kang et al. [21] presented a new FCM with spatial constraints based on the fuzzy membership of the jth 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:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\dfrac{\| x_j - c_i \|^2 + \alpha \| \bar{x}_j^{*} - c_i \|^2}{\| x_j - c_k \|^2 + \alpha \| \bar{x}_j^{*} - c_k \|^2}\right)^{1/(m-1)}} \quad (4)$$

$$c_i = \frac{\sum_{j=1} u_{ij}^{m}\left(x_j + \alpha \bar{x}_j^{*}\right)}{(1+\alpha)\sum_{j=1}^{N} u_{ij}^{m}} \quad (5)$$

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.

3. 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 partitioning the image into C regions of intensity by known the minimum and maximum values of intensity. The median point of each region R_k (including points $x_i, i = 1, 2, .., N_k$, N_k is the number of points of R_k) is selected to be as an initial centre of the region, and then both region and centre are fed to the method. While the constraints term $\gamma\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\sum_{x_i\in R}^{N_k}\|x_i-c_k\|^2$ is only considered in the objective function if a point x_i belongs to a region R_k , k=1,2,…, C with initial center c_k , i.e. we only estimate this term if $x_i \in R_k$ .The cost of computations can be reduced using a region and not neighbors for all points.

The objective function of the proposed modified fuzzy c-means is modified to:

$$J_m=\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\|x_i-c_k\|^2+\gamma\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\sum_{x_i\in N_k}^{N_k}\|x_i-c_k\|^2 \qquad (6)$$

Where u_{ki} of $C \times N$ $c_1, c_2, \ldots, c_k$ is centers of R_k , $\gamma = \frac{1}{m * N_k}$

However, the crucial parameter γ is based on the exponential weight, *m*. More datasets are experimented in [33-34], 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 [32]. 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 $X = \{x_i, i = 1, 2, .., N / x_i \in R^d\}$ denotes 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_{ij} and c_i must satisfy the following equalities:

$$u_{ki}=\frac{1}{\sum_{L=1}^{C}\left(\frac{\|x_i-c_k\|^2+\gamma\sum_{x_i\in R_k}^{N_k}\|x_i-c_k\|^2}{\|x_i-c_L\|^2+\gamma\sum_{x_i\in R_k}^{N_k}\|x_i-c_L\|^2}\right)^{\left(\frac{1}{m-1}\right)}} \qquad (7)$$

$$c_k=\frac{\sum_{i=1}^{N}u_{ki}\left[x_i+\gamma\sum_{x_i\in R_k}^{N_k}x_i\right]}{(1+\gamma)\sum_{i=1}^{N}U_{ki}^{m}} \qquad (8)$$

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:

$$L_m=\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\|x_i-c_k\|^2+\gamma\sum_{k=1}^{C}\sum_{i=1}^{N}u_{ki}^{m}\sum_{x_i\in R_k}^{N_k}\|x_i-c_k\|^2+\sum_{i=1}^{N}\lambda_i(1-\sum_{k=1}^{C}u_{ki})$$

Taking the partial derivative of Lm with respect to uki and λ_i and then setting them to equal to zero, we have

$$\frac{\partial L_m}{\partial U_{ki}}=0\Rightarrow mu_{ki}^{m-1}\|x_i-c_k\|^2+\gamma mu_{ki}^{m-1}\sum_{x_i\in R_k}^{N_k}\|x_i-c_k\|^2+\lambda_i(-1)=0 \quad (9)$$

$$\frac{\partial L_m}{\partial \lambda_i}=0\Rightarrow\sum_{k=1}^{C}u_{ki}-1=0 \qquad (10)$$

From Eq. (6), we get:

$$u_{ki} = \left(\frac{\lambda_i}{m\|x_i - c_k\|^2 + \gamma \sum_{x_i \in R_k}^{N_k} \|x_i - c_k\|^2} \right)^{\frac{1}{m-1}} \qquad (11)$$

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

$$\left(\frac{\lambda_i}{m}\right)^{\left(\frac{1}{m-1}\right)} = \frac{1}{\sum_{L=1}^{C} \left(\|x_i - c_i\|^2 + \gamma \sum_{x_i \in R_k}^{N_k} \|x_i - c_k\|^2 \right)^{\left(\frac{-1}{m-1}\right)}}$$

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

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

$$\sum_{i=1}^{N} u_{ki}^m x_i + \gamma \sum_{i=1}^{N} u_{ki}^m \sum_{x_i \in R_k}^{N_k} x_i = (1+\gamma) \sum_{i=1}^{N} u_{ki}^m c_k \Rightarrow$$

$$\frac{\partial L_m}{\partial c_k} = 0 \Rightarrow -2 \sum_{i=1}^{N} u_{ki}^m (x_i - c_k) - 2\gamma \sum_{i=1} u_{ki} \sum_{x_i \in R_k}^{N_k} (x_i - c_k) = 0$$

$$c_k = \frac{\sum_{i=1}^{N} u_{ki} \left[x_i + \gamma \sum_{x_i \in R_k}^{N_k} x_i \right]}{(1+\gamma) \sum_{i=1}^{N} u_{ki}^m}$$

The process of finding the best clusters are continue to update the centres c_k and the membership u_{ki} using Eqs.(12) and (13) respectively. The R_k neighbors of the centres c_k can be obtained using a region growing algorithm [35-36] with an initial seed c_k under a small threshold T. Also one can find R_k by extracting the neighbors around c_k using a large mask 5×5 .

Algorithm:

Initialize the membership matrix u_{ki}^t with random values between 0 and 1.

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

Repeat:

Compute: u_{ki} and c_k using Eqs.(7)and (8).

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

Find R_k : extract a pixel that satisfy $\| x_i - c_k \| \le T$ (in mask 5×5)

End Repeat

4. 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. 1(b), and Fig. 1(c), respectively [37]. The second set includes simulated volumetric MR data consisting of ten classes as shown in Figure (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 inhomogeneities. The quality of the segmentation algorithm is of vital importance to the segmentation process. The comparison score S for each algorithm as proposed in [4] 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.

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 5×5 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].

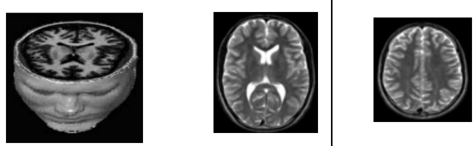
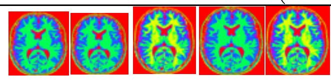
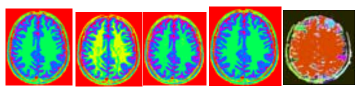


Fig.(1): Test images: (a) 3D simulated data, (b) and (c) two original slices from the 3D simulated data (slice89 and slice 65).



a b c d f

Fig. (2): Results of segmentation of first T1-weighted MR at various noise levels: a) 0%, b) 1%, c) 3%, d) 5%, f)7%.



a b c d f

Fig. (3): Results of segmentation of second T1-weighted MR at various noise levels: a) 0%, b) 1%, c) 3%, d) 5%, f)7%.

Table 2. 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
6	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

4.1 Experiment on the real image

We used a high-resolution T1-weighted MR phantom with slice thickness of 1mm 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. 1(b) and 1(c). In this test, the proposed technique is applied to two T1-weighted MR at various noise levels (0%, 1%, 3%, 5% and 7%) and 20% spatial RF levels as shown in Figures 3, 4.

To prove the efficiency of proposed algorithm, the mean segmentation accuracy (MSA) is evaluated for two T1-weighted at different noise levels. Table 1 shows MSA of the proposed algorithm applied to MRI image with various noise levels (0%,3%,5% and7%) and 20% RF levels. The obtained results show that the proposed algorithms are very robust to noise and intensity homogeneities and inhomogeneities. The best MSA is achieved for low noise and RF levels, for which values of MSA are higher than 0.93. According to Table 1, the proposed technique is stable at 90% at noise level 7% and RF 200%, this result is satisfactory for segmenting the WM tissues.

Table 1. Segmentation accuracy (%) of the proposed at various noise levels (0%, 1%, 3%, 5% and 7%) and 20% spatial RF levels.

Noise/RF	20%
0%	0.98
1%	0.98
3%	0.97
5%	0.95
7%	0.93

4.2 Experiment on the simulated MR data

Table (2) 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. [21] 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 classes 9, 4, and 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.

5. 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 are 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.

The proposed method have been experimented using two weighted MR images at noise levels (0%, 3%, 5% and 7%) and 20% RF levels. These test images showed that the segmentation of brain MRI obtains excellent performances, the average exceeding 93% at large noise factor. We have noted that the proposed algorithm is succeeded to segment real images which have noise levels from 0% to 7% and RF levels from 20%.

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 thatalthough the proposed algorithm can perform better thanstandard FCM and other poplar modified FCM extension algorithms, it is computationally expensive, and this may limit its applicability to large 3D volume data.

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