A Spatial Fuzzy C-means Algorithm with Application to MRI Image Segmentation

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***Abstract*—The standard fuzzy C-means (FCM) algorithm does not fully utilize the spatial information for image segmentation and is sensitive to noise especially in the presence of intensity inhomogeneity in magnetic resonance imaging (MRI) images. The underlying reason is that a single fuzzy membership function in FCM algorithm cannot properly represent pattern associations to all clusters. In this paper, we present a spatial fuzzy C-means (SpFCM) algorithm for the segmentation of MRI images. The algorithm utilizes spatial information from the neighbourhood of each pixel under consideration and is realized by defining a probability function. A new membership function is introduced using this spatial information to generate local membership values for each pixel. Finally, new clustering centers and weighted joint membership functions are presented based on the local and global membership functions. The resulting SpFCM algorithm solves the problem of sensitivity to noise and intensity inhomogeneity in MRI data and thereby improves the segmentation results. The experimental results on several simulated and real-patient MRI brain images show that the SpFCM algorithm has superior performance on image segmentation when compared to some FCM-based algorithms.**

Keywords—*image segmentation; MRI brain image; fuzzy c-means; spatial FCM*

I. INTRODUCTION

Image segmentation is an important step in medical image analysis [1] and its goal is to partition an image into a set of disjoint regions or parts that have a strong correlation with the areas or parts corresponding to the objects in the real world. However, manual segmentation is a challenging and time consuming task and prone to error. Its success heavily depends on the expertise of the physician and thereby errors occur in the results and also augmented due to the intrinsic nature of the medical images. Moreover, accurate segmentation is also necessary for detecting and analyzing the diseased or affected regions in medical images. Therefore, computer aided segmentation is very significant to achieve effective results. In literature, several algorithms for magnetic resonance imaging (MRI) image segmentations have been presented [2-4]. Among them, thresholding, region-based segmentation, edge-based segmentation and classification-based segmentation are the most frequently used techniques.

In general, fuzzy segmentation method, especially the fuzzy C-means (FCM) clustering algorithm [5] is more effective with considerable amount of benefits. Unlike hard clustering methods, like k-means algorithm, etc., which assign pixels exclusively to one cluster, the FCM algorithm allows pixels to have relation with multiple clusters with varying degree of memberships. Although the FCM is a very popular unsupervised clustering method, it has some serious drawbacks as it is very sensitive to noise and imaging artifacts. It can also generate local optimal solution due to poor initialization. In order to make the FCM algorithm more robust to noise and outliers for image segmentation, many modified versions of fuzzy clustering approaches have been reported in the past. Pedrycz [6] introduced a conditional fuzzy C-means algorithm guided by an auxiliary or conditional variable. The method reveals a structure within a family of patterns by considering their vicinity in the feature space along with the similarity of the values assumed by a certain conditional variable. Tolias and Panas [7] presented a fuzzy clustering algorithm using adaptive spatially constrained membership functions for image segmentation. Mohamed *et al.* [8] modified the FCM algorithm through the incorporation of spatial information. They have introduced spatial information into the computation of similarity measure to drag a pixel closer to the cluster center if it is in homogeneous region. Ahemed *et al.* [9] introduced the local gray level information by modifying the objective function with another similarity measure for bias field estimation and segmentation of MRI data. Another major contribution with spatial information into the FCM membership function was suggested by Chuang *et al.* [10], known as sFCM algorithm. The spatial function is the summation of the membership function in the neighbourhood of each pixel under consideration.

Recently, Qiu *et al.* [11] suggested a novel algorithm for fuzzy segmentation by introducing two fuzzifiers and a spatial constraint in the membership function. Benaichouche *et al.* [12] presented another improvement of the FCM algorithm by utilizing particle swarm optimization (PSO) initialization, Mahalanobis distance and post segmentation correction. Kannan *et al.* [13] introduced a class of robust non-Euclidean distance measure for the objective function to reduce noise and outliers.

Most of the methods, discussed so far, suffer heavily due to the presence of immense noise and another additional multiplicative noise factor called intensity inhomogeneity (IIH) or bias field in the MRI medical images. The IIH usually refers to the slow, non-anatomic intensity variations of the

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same tissue over the image domain and causes due to imperfection of the image acquisition devices, eddy current, poor magnetic field and patient movement, etc.

In this paper, we present a spatial fuzzy C-means (SpFCM) clustering algorithm that can effectively segment MRI images with the presence of high noise and intensity inhomogeneity. The algorithm utilizes spatial information from the neighbourhood of each pixel under consideration. This is realized by defining a probability function and is estimated from a square neighbourhood window centered to that pixel. Subsequently, by using this spatial information into a new membership function we generate local membership values for each pixel. Finally, new clustering centers and weighted joint membership functions are introduced based on the local and global membership functions.

II. The Fuzzy C-means (FCM) Algorithm

The fuzzy C-means (FCM) algorithm is a fuzzy clustering method based on the minimization of a quadratic criterion where clusters are represented by their respective centers. In the case of image segmentation, it assigns pixels to each category by using fuzzy membership functions. The FCM algorithm was proposed by Dunn (1973) and later improved by Bezdek [5]. Let $\boldsymbol{X}=\{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N\}$ denotes an image with N pixels to be partitioned into C clusters or regions. The algorithm allows partitioning the pixels by iteratively calculating the centers of clusters, $\boldsymbol{v}_i$ and the membership matrix, $\boldsymbol{U}$ through minimizing an objective function, J_{fcm} with respect to these cluster centers and membership values as follows:

$$J_{fcm} = \sum_{i=1}^{C}\sum_{j=1}^{N} \mu_{ij}^{m} d_{ij}^{2} \tag{1}$$

where d_{ij}^2 usually is the Euclidean distance ($d_{ij}^2 = \|x_j - v_i\|^2$) between the jth pixel, x_j and the ith cluster center, v_i, m is any real number greater than 1, μ_{ij} is the degree of fuzzy membership of pixel $\boldsymbol{x}_j$ to the ith cluster.

The objective function is minimized when the large membership values are assigned to the input pixels that are close to their nearest cluster centers and low membership values are assigned when they are far from the cluster centers.

Minimizing the objective function (1) with respect to the constraint $\sum_{i=1}^{C}\mu_{ij} = 1$, we have-

$$\frac{\partial J_{fcm}}{\partial \mu_{ij}} = 0, \text{ and } \quad \frac{\partial J_{fcm}}{\partial v_i} = 0 \tag{2}$$

These lead to the following iterative solutions

$$\mu_{ij} = \frac{1}{\sum_{l=1}^{C}\left(\frac{d_{ij}^{\,2}}{d_{lj}^{\,2}}\right)^{\frac{1}{m-1}}} \tag{3}$$

and

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

III. Spatial Fuzzy C-means (SpFCM) Algorithm

In this paper, the image segmentation process is formulated as a classification problem of pixel intensities into different non-overlapping homogeneous regions. In MRI image, neighbouring pixels have a strong correlation and especially in the regions of blurred tissue boundaries. More specifically, these neighbouring pixels possess similar characteristics and the probability for belonging to the same cluster is great. However, as we go further away from the center pixel in a neighbourhood, this correlation gradually diminishes. To exploit the local spatial information, we have introduced a probability function, f_{ik} for a pixel x_k which represents the probability of its neighbouring pixels that belong to the ith cluster, and is defined as follows:

$$f_{ik} = \frac{\sum_{l=1}^{M} 1 \mid x_l \in N_k \,\&\, x_l \in v_i}{M} \tag{5}$$

where N_k is the square neighbourhood window centered on the pixel x_k in the spatial domain and M is the area of the neighbourhood N_k.

It may be noted that f_{ik} is within the range $0 \le f_{ik} \le 1$. We have tested on several windows and found that a 3×3 window is superior and thereby used throughout this work. This probability function is incorporated in a fuzzy membership function to yield new set of membership values for each pixel in such a way that if the neighbouring pixels share similar characteristics, the center pixel should have higher probability of grouping to the same cluster as of the neighbouring pixels. We call this new membership values as the *local membership values*, which may differ from the global membership values generated by the FCM algorithm. Finally, we have also introduced a weighted joint membership function, which incorporates the local and global membership values to estimate the final membership values and cluster centers. It is also helpful in reducing noise distortion and intensity inhomogeneity in the segmentation of MRI images.

The modified objective function of the FCM-based algorithm using the local spatial information can be summarized and formulated as follows:

$$J_{SpFCM}(Q,U,V) = \sum_{i=1}^{C}\sum_{j=1}^{N}\mu_{ij}^{m}\, d_{ij}^{2} + \alpha \sum_{i=1}^{C}\sum_{j=1}^{N} f_{ij} u_{ij}^{m}\, \bar{d}_{ij}^{2} \tag{6}$$

Subject to the following constraints:

$$\sum_{i=1}^{C} \mu_{ij} = 1, \text{and } \sum_{i=1}^{C} u_{ij} = 1 \quad (7)$$

where the parameters C, N, μ_{ij}, and d_{ij} are the same as of the (1), α reflects the preference of neighbouring effect, u_{ij} represents the *local membership value* of the pixel x_j in the ith cluster, the distance $\bar{d}_{ij}^2$ denotes the Euclidean distance ($\bar{d}_{ij}^2 = \|x_j - v_i\|^2$) between the average intensity $\bar{x}_j$ of the jth pixel's neighbourhood and the cluster center v_i.

If $\alpha = 0$, the formulation (6) reverts to the classic FCM algorithm without any regularization term. However, if $\alpha > 0$, the dependency on the neighbours causes the u_{ij} to be large when the neighbouring membership values of the other clusters are small.

By introducing the Lagrange multipliers λ_1 and λ_2 with respect to the above constraints, the Eq. (6) can be rewritten as an iterative optimization algorithm that minimizes the objective function defined as follows:

$$J_{SpFCM}(Q,U,V) = \sum_{i=1}^{C}\sum_{j=1}^{N} \mu_{ij}^m \, d_{ij}^2 + \alpha \sum_{i=1}^{C}\sum_{j=1}^{N} f_{ij} u_{ij}^m \, \bar{d}_{ij}^2 - \lambda_1\left(\sum_{i=1}^{C} \mu_{ij} - 1\right) - \lambda_2\left(\sum_{i=1}^{C} u_{ij} - 1\right) \quad (8)$$

Minimizing the objective function (8) with respect to the above constraints and the Lagrange multipliers, we have

$$\frac{\partial J_{SpFCM}}{\partial \mu_{ij}} = 0, \quad \frac{\partial J_{SpFCM}}{\partial u_{ij}} = 0, \quad \frac{\partial J_{SpFCM}}{\partial \lambda_1} = 0, \text{ and } \frac{\partial J_{SpFCM}}{\partial \lambda_2} = 0 \quad (9)$$

These lead to the following iterative solutions-

$$\mu_{ij} = \frac{1}{\sum_{l=1}^{C} \left(\frac{d_{ij}^2}{d_{lj}^2}\right)^{\frac{1}{m-1}}} \quad (10)$$

$$v_i = \frac{\sum_{j=1}^{N} \mu_{ij}^m x_j}{\sum_{j=1}^{N} \mu_{ij}^m} \quad (11)$$

and

$$u_{ij} = \frac{\left(f_{ij}\right)^{\frac{1}{m-1}}}{\sum_{l=1}^{C} \left(\frac{\bar{d}_{ij}^2}{\bar{d}_{lj}^2}\right)^{\frac{1}{m-1}}} \quad (12)$$

It may be noted that the two membership values μ_{ij} and u_{ij} may assume same value for a pixel x_j in the homogeneous regions; however, they differ in the blurred heterogeneous regions or the regions of different tissue boundaries. By combining these two membership functions, we have introduced a weighted joint membership function z_{ij} for the pixel x_j, and the associated cluster centers w_i, which incorporate the local and global spatial information and are defined as follows:

$$z_{ij} = \frac{(\mu_{ij})^p (u_{ij})^q}{\sum_{c=1}^{C} (\mu_{cj})^p (u_{cj})^q} \quad (13)$$

$$w_i = \frac{\sum_{j=1}^{N} z_{ij}^m x_j}{\sum_{j=1}^{N} z_{ij}^m} \quad (14)$$

where p and q are the parameters to control the relative importance of both the membership functions.

In a homogenous region, the *local membership function* simply fortifies the global (original) membership function, and the clustering result remains unchanged. However, for a noisy pixel in the blurred heterogeneous region or in the regions of different tissue boundaries, these formulas reduce the weighting of a noisy cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions or spurious blobs can easily be corrected. In the present study, the proposed method provides better results for m=2, p=1 and q=2. The spatial FCM (SpFCM) algorithm with the parameters p and q is denoted as $\text{SpFCM}_{p,q}$. Again, it may be noted that the $\text{SpFCM}_{1,0}$ is identical to the standard FCM.

IV. Experimental Results and Discussion

The performance of the proposed method is evaluated first on simulated and later on real-patient MRI images of human brain. In the comparative study, we have also included the FCM method and a recently proposed competing technique, sFCM [10].

A. Simulated MRI Brain Images

The BrainWeb simulated MRI brain images are acquired from the McConnell Brain Imaging Center of the Montreal Neurological Institute, McGill University [14]. Different combinations of simulated T1-weighted data have been collected. The first set contains images of 9% noise, 40% inhomogeneity, whereas the second set is of 9% noise and 20% inhomogeneity. The third and fourth set contain 7% noise, 40% inhomogeneity and 7% noise, 20% inhomogeneity, respectively. The image resolutions are 181×217×181 voxels and size 1×1×1 mm. The experimental results are first presented in qualitatively and later in quantitatively.

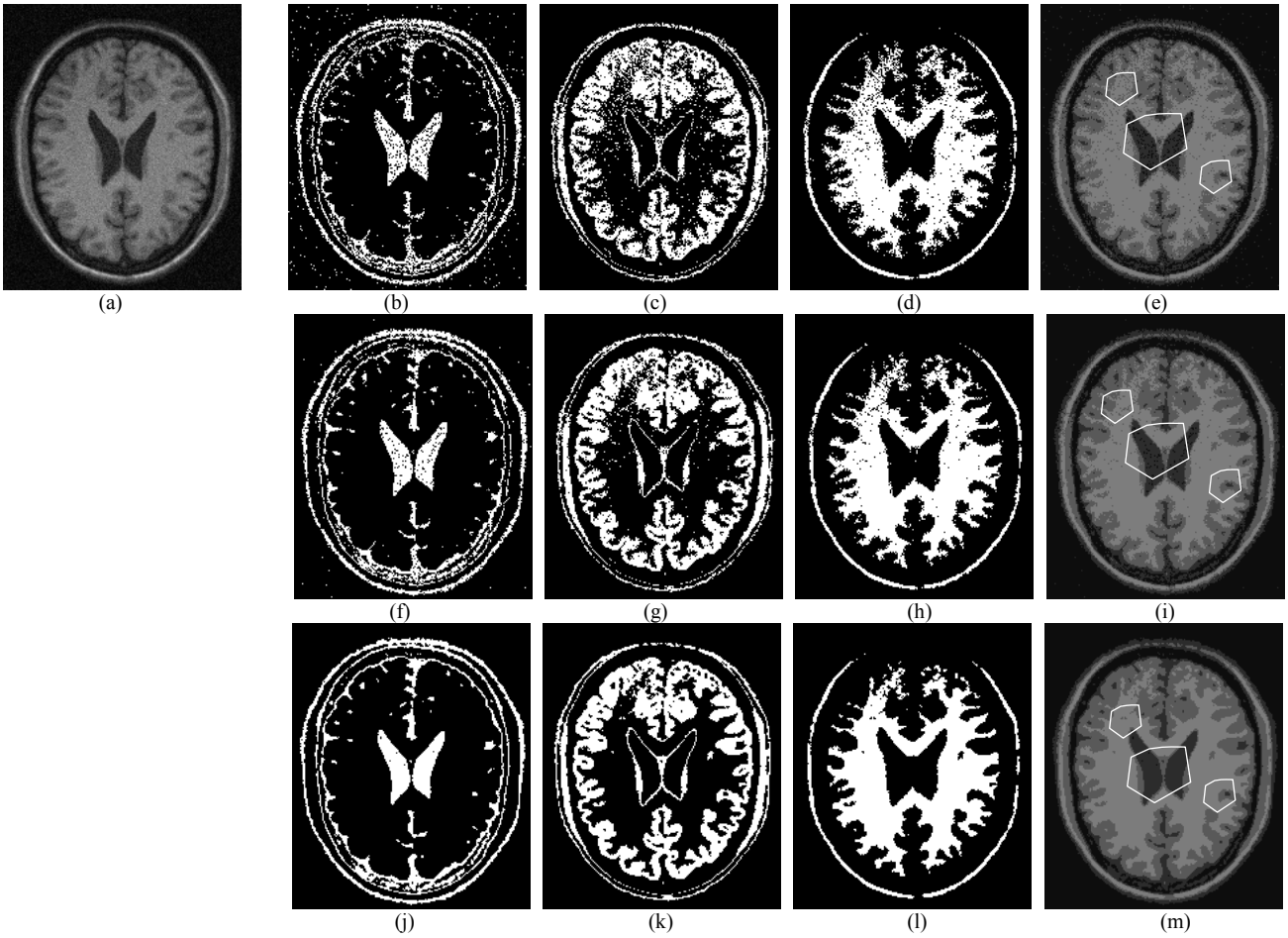

Fig. 1. Qualitative results of segmentation of a T1-weighted simulated MRI brain image (a): original with 9% noise and 40% inhomogeneity. (b)-(e): Segmented regions of the CSF, GM, WM and the total image, respectively by the FCM method; (f)-(i): Segmented regions of the CSF, GM, WM and the total image, respectively by the sFCM method; (j)-(m): Segmented regions of the CSF, GM, WM and the total image, respectively by the SpFCM method.

1) Qualitative evaluation: The qualitative evaluations provide useful information on the target application, the type and quality of the images, the weaknesses of the segmentation method, and the result of the individual step of a method. The qualitative evaluation includes segmentation results, like cerebro spinal fluid (CSF), gray matter (GM), white matter (WM) and the total segmented result. We have tested the performance of the proposed method at various levels of noise and inhomogeneity on T1-weighted simulated MRI brain images from the BrainWeb database and found to be superior to the sFCM and FCM methods. Fig. 1 shows the qualitative results of segmentation of a T1-weighted simulated MRI brain image (slice 95, Fig. 1(a)) with 9% noise and 40% inhomogeneity. Fig. 1(b)-1(e) show the CSF, GM, WM and total segmented results, respectively by the FCM method, Fig. 1(f)-1(i) show the CSF, GM, WM and total segmented results, respectively by the sFCM method and Fig. 1(j)-1(m) show the CSF, GM, WM and total segmented results, respectively by the proposed SpFCM method. It may be observed from the Fig. 1(b)-1(i) that several artifacts are present in the segmented regions of the CSF, WM and GM as marked in white border in Fig. 1(e) and Fig. 1(i). However, these spurious blobs are absent in the segmentation results of the proposed SpFCM method, as shown in Fig. 1(j)-1(m). These results demonstrate the superiority of the SpFCM method over the sFCM and the conventional FCM methods in the presence of high percentage of noise and inhomogeneity in MRI images.

2) Quantitative evaluation: Quantitative evaluation is essential for comparison of the results of different segmentation methods. We have presented two types of quantitative evaluations based on the cluster validity functions and tissue segmentation accuracy. The cluster validity functions are presented in terms of (a) Partition coefficient, (b) Partition entropy and (c) Similarity index. To reduce the influence of the selected images, we have provided the average value of 51 images (slice 50 – slice 100) from each group of simulated MRI brain images for the cluster validity functions and tissue segmentation accuracy.

a) Partition coefficient: Partition coefficient *(V_{pc})* [5], [10], [11] is an important indicator of fuzzy partition and

provides better performance with less fuzziness. The best clustering result is achieved when the V_{pc} is maximal and is defined as follows:

$$V_{pc} = \frac{\sum_{i=1}^{C}\sum_{j=1}^{N} z_{ij}^2}{N} \tag{15}$$

b) Partition entropy: Another important indicator of fuzzy partition is partition entropy *(V_{pe})* [5], [10], [11]. The best clustering result is achieved when the V_{pe} is minimal and is defined as follows:

$$V_{pe} = \frac{-\sum_{i=1}^{C}\sum_{j=1}^{N}\left[z_{ij}\log(z_{ij})\right]}{N} \tag{16}$$

TABLE I. AVERAGE VALIDITY FUNCTIONS FOR T1-WEIGHTED MRI IMAGES

Segmented image	Segmented technique	Validity Functions		
		V_{pc}	V_{pe}	ρ(%)
Noise 9%, IIH 40%	FCM	0.803	0.378	71.176
	sFCM	0.897	0.180	74.356
	SpFCM	**0.968**	**0.052**	**76.729**
Noise 9%, IIH 20%	FCM	0.803	0.378	71.612
	sFCM	0.897	0.180	75.023
	SpFCM	**0.969**	**0.050**	**77.695**
Noise 7%, IIH 40%	FCM	0.821	0.347	75.016
	sFCM	0.910	0.157	76.943
	SpFCM	**0.970**	**0.047**	**77.750**
Noise 7%, IIH 20%	FCM	0.823	0.343	75.653
	sFCM	0.912	0.153	77.723
	SpFCM	**0.972**	**0.046**	**78.678**

c) Similarity index: If A_i and B_i represent the sets of pixels belonging to ith cluster in the segmentation result and in "ground truth", respectively, then the similarity index, ρ [11] is defined as follows:

$$\rho = \frac{1}{C}\sum_{i=1}^{C}\frac{2|A_i \cap B_i|}{|A_i| + |B_i|} \times 100\% \tag{17}$$

ρ is in the range [0, 100] and the optimal clustering result is achieved when ρ=100. Similarity index is a very efficient validity measurement as it compares the segmentation results with the ground truth. Noise and inhomogeneity free image is considered here as the ground truth image.

Table I shows the average values of three validity functions; (a) partition coefficient (V_{pc}), (b) partition entropy (V_{pe}), and (c) similarity index (ρ) for the conventional FCM, sFCM and the proposed SpFCM methods by varying the levels of noise and intensity inhomogeneity (IIH). It may be noted that the average values of V_{pc}, V_{pe} and ρ of the proposed SpFCM method are superior to those of the FCM and sFCM methods and thereby demonstrate its efficiency.

d) Tissue segmentation accuracy: The tissue segmentation accuracy (TSA) [15] is defined as follows:

$$TSA = \frac{2N_{CTK}}{N_{CITK} + N_{GTK}} \tag{18}$$

where N_{CTK} denotes the number of pixels that are correctly (inside the mask of ground truth) assigned to tissue k by a given method, N_{CITK} is the total number of pixels (inside and outside the mask of ground truth) assigned to tissue k and N_{GTK} is the number of pixels belonging to tissue k in the discrete anatomical model (the ground truth mask).

Fig. 2, Fig. 3 and Fig. 4 also show the *TSA* values of CSF, GM and WM, respectively by the above three different algorithms for 51 T1-weighted MRI brain images with 9% noise and 40% IIH. The evaluation results also clearly show the superiority of the SpFCM method over the FCM and sFCM methods.

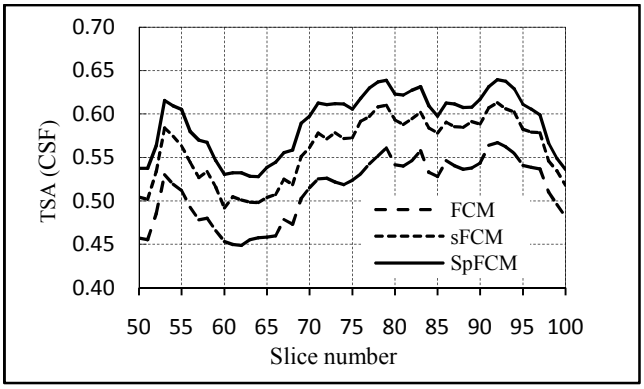

Fig. 2. Tissue Segmenation Accuracy (*TSA*) values of the CSF of 51 T1-weighted MRI brain images with 9% noise and 40% IIH.

Fig. 3. Tissue Segmenation Accuracy (*TSA*) values of the GM of 51 T1-weighted MRI brain images with 9% noise and 40% IIH.

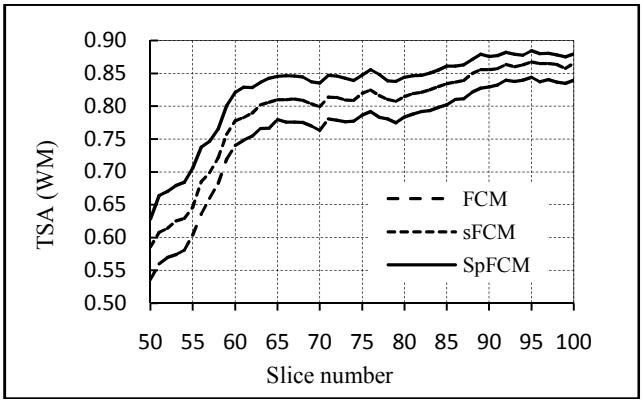

Fig. 4. Tissue Segmenation Accuracy (*TSA*) values of WM of 51 T1-weighted MRI brain images with 9% noise and 40% IIH.

B. Real-patient MRI Images

As the ground truth of segmentation for real-patient MRI images is not usually available, it is impossible to use the similarity index and tissue segmentation accuracy to evaluate the segmentation results of a method. The performance of the proposed SpFCM method on real-patient MRI data is evaluated quantitatively in terms of partition coefficient and partition entropy.

1) Quantitative evaluation: Table II shows the average partition coefficient (V_{pc}) and average partition entropy (V_{pe}) values of 5 real-patient MRI images for the FCM, sFCM and the proposed SpFCM methods. The evaluation results show that the proposed SpFCM method provides superior results for the real-patient MRI images also.

TABLE II. AVERAGE VALIDITY FUNCTIONS FOR REAL-PATIENT MRI IMAGES

Segmented image	**Segmented technique**	**Validity Functions**	
		V_{pc}	V_{pe}
Real-patient MRI images	FCM	0.809085	0.365638
	sFCM	0.891727	0.187955
	SpFCM	0.926185	0.122923

V. CONCLUSION

In this paper, a spatial fuzzy C-means (SpFCM) clustering algorithm is proposed with applications to MRI image segmentation. A probability function is employed in a membership function corresponding to each pixel to generate local membership values by utilizing local spatial information within a square window centered at that pixel. This probability function shows the degree of belongingness of neighbouring pixels to a cluster with respect to the centered pixel. Finally, a weighted joint membership function is defined by utilizing the local and global membership functions to generate final membership values and cluster centers. The algorithm is tested both in qualitatively and quantitatively on simulated and real-patient MRI brain images. The main advantage of the SpFCM algorithm is that it can produce superior segmentation results from the MRI images which have high levels of noise and intensity inhomogeneity. The experimental results indicate that the proposed SpFCM algorithm effectively outperforms the FCM and sFCM algorithms for MRI image segmentation in terms of suppressing noise, cluster validity functions and tissue segmentation accuracy.

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