A New Modifies Spatial FPCM that Incorporates the Spatial Information into the Membership Function to Improve the Segmentation Results

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Abstract

FCM is one of a conventional clustering method and has been generally applied for medical image segmentation. On the other hand, conventional FCM at all times suffers from noise in the images. Even though the unique FCM algorithm yields good results for segmenting noise free images, it fails to segment images corrupted by noise, outliers and other imaging artifact. The most important shortcoming of standard FCM and FPCM algorithms are that the objective function does not think about the spatial dependence therefore it deal with image as the same as separate points. In order to decrease the noise effect during image segmentation, the proposed method incorporates spatial information into the FPCM cluster algorithm. The proposed algorithm is applied to both artificial synthesized image and real image. Segmentation results demonstrate that the presented algorithm performs more robust to noise than the standard FCM and FPCM algorithm.

Keywords: *Image processing, MR images segmentation, Fuzzy C-Means, Fuzzy Possibilistic C-Means, spatial information, Clustering.*

1. Introduction

Image segmentation plays a major role in the field of biomedical applications. The segmentation technique is widely used by the radiologists to segment the input medical image into meaningful regions [1]. The specific application of this technique is to detect the tumor region by segmenting the abnormal MR input image. The size of the tumor region can be tracked using these techniques which aid the radiologists in treatment planning [2]. The primitive techniques are based on manual segmentation which is a time consuming process besides being susceptible to human errors. Several automated techniques have been developed which removes the drawbacks of manual segmentation.

Clustering is one of the widely used image segmentation techniques which classify patterns in such a way that samples of the same group are more similar to one another than samples belonging to different groups [3]. Hard clustering methods assume that each data vector belongs to one class, however in practice clusters may overlap, and data vectors belong partially to several clusters [4]. This scenario can be modeled properly using fuzzy set theory (Zadeh 1965), in which the membership degree, u_{ij} of a pattern x_j to the i-th cluster is a value in the interval [0, 1]. Bezdek (1982) explicitly formulated this approach oriented to clustering by introducing the Fuzzy-C-Mean (FCM) clustering algorithm [5]. Unfortunately, this method is sensitive to noise and outliers in the data. To reduce this undesirable effect, a number of approaches have been proposed, but the most remarkable has been the possibilistic approach first introduced by Krishnapuram and Keller (1993), with their Possibilistic C-Means (PCM) algorithm [6]. In this algorithm the membership is interpreted as the compatibilities of the datum to the class prototypes (typicalities) which correspond to the intuitive concept of degree of belonging or compatibility. These typicality-based memberships automatically reduce the effect of noise and outliers, and improve the solution. Nevertheless, the main drawback with this approach consists on the quality of the initializations. In the case of poor initializations, it is possible that the PCM will converge to a “worthless” partition where part or all the clusters are identical (coincident) while other clusters go undetected. To avoid the undesirable tendency to produce coincident clusters, a mixed c-Means approach was proposed (Pal et al. 1997) called Fuzzy- Possibilistic C-Means (FPCM). This algorithm suggests an iterative alternating optimization approach to find local minima of both objective functions [7]. Upon closer examination of the basic architecture of the FPCM, two conclusions arise.

FCM and FPCM advantages include a straightforward implementation, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data. A major disadvantage of their use in imaging applications, however, are that FCM and FPCM does not incorporate information about spatial context, causing it to be sensitive to noise and other imaging artifacts. The pixels on an image are highly correlated, i.e. the pixels in the immediate neighborhood possess nearly the same feature data. Therefore, the spatial relationship of neighboring pixels is an important characteristic that can be of great aid in imaging segmentation. The spatial function is the weighted summation of the membership function in the neighborhood of each pixel under consideration. However, the standard FCM and FPCM does not take into account spatial information, which makes their very sensitive to noise. In a standard FCM and FPCM technique, a noisy pixel and an outlier data is wrongly classified because of its abnormal feature data.

This paper introduces a modified segmentation algorithm for possibilistic fuzzy c-means clustering by incorporating spatial information around each pixel. The proposed algorithm greatly attenuates the effect of noise and outlier data and biases the algorithm toward homogeneous clustering.

The organization of the paper is as follows. In section 2, traditional fuzzy c-means algorithm and Possibilistic c-means algorithm and possibilistic fuzzy c-means algorithm and spatial fuzzy c-means are introduced. In section 3, we obtain the Possibilistic fuzzy c - means cluster segmentation algorithm based on modified membership and modified cluster center based on Spatial Information. The experimental comparisons are presented in section 4. Finally, in section 5, we conclude and address the future work.

2. Algorithms

A. Traditional Fuzzy C-Means

The segmentation of imaging data involves partitioning the image space into different cluster regions with similar intensity image values. The most medical images always present overlapping gray-scale intensities for different tissues. Therefore, fuzzy clustering methods are particularly suitable for the segmentation of medical images. There are several FCM clustering applications in the MRI segmentation of the brain. The Fuzzy c-means (FCM) can be seen as the fuzzified version of the k-means algorithm. It is a method of clustering which allows one piece of data to belong to two or more clusters. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function JFCM:

$$J_{FCM} = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}{}^{m} \left| x_j - v_i \right|^2 \qquad (1)$$

Where X = {x_1, x_2,..., x_n} $\subseteq R^p$ is the data set in the p-dimensional vector space, p is the number of data items, c is the number of clusters with 2 ≤ c ≤ n-1. V = {v_1, v_2,..., v_c} is the c centers or prototypes of the clusters, v_i is the p-dimension center of the cluster i. U = {μ_{ij}} represents a fuzzy partition matrix with $u_{ij} = u_i(x_j)$ is the degree of membership of x_j in the ith cluster, x_j is the jth of p-dimensional measured data. The fuzzy partition matrix satisfies:

$$\begin{aligned} &0 \langle \sum_{j=1}^{n} u_{ij} \langle n \quad , \forall\ i \in \{1, \ldots\ldots, c\} \\ &\sum_{j=1}^{c} u_{ij} = 1 \quad , \forall\ j \in \{1, \ldots\ldots, n\} \qquad (2) \\ &0 \le U_{ij} \le 1 \quad , \forall i, j \end{aligned}$$

The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification; it is a fixed number greater than one. The objective function JFCM can be minimized under the Constraint of U. specifically, taking of JFCM with respect to uij and vi and zeroing then respectively, tow necessary but not sufficient conditions for JFCM to be at its local extreme will be as the following:

$$U_{ij} = \sum_{k=1}^{c} \left(\frac{\| x_j - v_i \|}{\| x_j - v_k \|} \right)^{\frac{-2}{m-1}} \qquad (3)$$

$$for\ i = 1,2,\ldots..c \quad and \quad for\ j = 1,2,\ldots\ldots,n$$

$$V_i = \frac{\sum_{j=1}^{n} (u_{ij})^m x_j}{\sum_{j=1}^{n} (u_{ij})^m} \quad for\ i = 1,2,\ldots..c \qquad (4)$$

Although FCM is a very useful clustering method, its memberships do not always correspond well to the degree of belonging of the data, and may be inaccurate in a noisy environment, because the real data unavoidably involves some noises [8].

B. Fuzzy possibilistic c-means algorithm

In the FPCM: Memberships and typicalities are important for the correct feature of data substructure in clustering problem. Thus, an objective function in the FPCM depending on both memberships and typicalities can be shown as:

$$J_{FPCM} = \sum_{j=1}^{N} \sum_{i=1}^{c} (u_{ij}{}^{m} + t_{ij}{}^{\eta}) \left| x_j - v_i \right|^2 \qquad (5)$$

With the following constraints:

$$\sum_{i=1}^{c} u_{ij} = 1 \quad \forall\, j \in \{1,......,n\} \tag{6}$$

$$\sum_{j=1}^{n} t_{ij} = 1 \quad \forall\, i \in \{1,......,c\} \tag{7}$$

Where U is membership matrix, t is possibilistic matrix, and V is the resultant cluster centers, c and n are cluster number and data point number respectively. A solution of the objective function can be obtained via an iterative process where the degrees of membership, typicality and the cluster centers are update via:

$$U_{ij} = \sum_{k=1}^{c} \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{\frac{-2}{m-1}} \tag{8}$$

$$for\ i = 1,2,.....c \quad and \quad for\ j = 1,2,......,n$$

$$t_{ij} = \sum_{k=1}^{n} \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|}\right)^{\frac{-2}{\eta-1}} \tag{9}$$

$$for\ i = 1,2,.....c \quad and \quad for\ j = 1,2,......,n$$

$$V_i = \frac{\sum_{j=1}^{n} (u_{ij}{}^{m} + t_{ij}^{\eta})\ x_j}{\sum_{j=1}^{n} (u_{ij}{}^{m} + t_{ij}^{\eta})} \quad for\ i = 1,2,.....c \tag{10}$$

FPCM produces memberships and possibilities simultaneously, along with the usual point prototypes or cluster centers for each cluster. FPCM is a hybridization of possibilistic c-means (PCM) and fuzzy c-means (FCM) that often avoids various problems of PCM, FCM and FPCM. FPCM solves the noise sensitivity defect of FCM, overcomes the coincident clusters problem of PCM. But the noise data have an influence on the estimation of centroids.

C. Spatial Fuzzy C-Means (SFCM)

One of the important characteristics of an image is that neighboring pixels have similar feature values, and the probability that they belong to the same cluster is great. The spatial information is important in clustering, but it is not utilized in a standard FCM algorithm [9]. To exploit the spatial information, a spatial function is defined as:

$$S_{ij} = \sum\nolimits_{k \in NB(x_j)} U_{ik} \tag{11}$$

The spatial function is the weighted summation of the membership function in the neighborhood of each pixel under consideration. Just like the membership function, the spatial function sij represents the probability that pixel xj belongs to ith clustering. The spatial function is the largest if all of its neighborhood pixels belong to ith clustering, and is the smallest if none of its neighborhood pixels belong to ith clustering. The spatial function is incorporated into membership function as follows:

$$U^*_{ij} = \frac{U_{ij}^p * S_{ij}^q}{\sum_{k=1}^{c} U_{kj}^p * S_{kj}^q} \tag{12}$$

$$for \quad i = 1,2,....,c \quad and \quad j = 1,2,.....,n$$

Where p and q are parameters to control the relative importance of both functions. In a homogenous region, the spatial functions simply fortify the original membership, and the clustering result remains unchanged. However, for a noisy pixel, this formula reduces 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. There are two steps at each clustering iteration. The first step is to calculate the membership function in the spectral domain and the second step is to map the membership information of each pixel to the spatial domain and then compute the spatial function from that.

3. A modified fuzzy possibilistic c-means algorithm with spatial information

We can compare the membership of central pixel with the one of neighbor pixels in a window to analysis whether the central pixel is classified rightly or not. This spatial relationship is important in clustering; therefore a new spatial function is defined as:

$$S_{ij}^{\;*} = \sum\nolimits_{k \in H(x_j)} U_{ik} \beta_{k1} + \frac{\sum_{k \in H(x_j)} U_{ik} \beta_{k2}}{\sum_{t=1}^{c} \sum_{k \in H(x_j)} U_{tk}} \tag{13}$$

Where H (xj) represents a square window centered on pixel xj in the spatial domain. Introduced new spatial function has two parts. The first part is controlled by β_{k1} coefficient caused that misclassified pixels from noisy regions can be easily corrected. The second part is controlled by β_{k2} coefficient caused membership function quantitative according to distance between pixels.

$$\beta_{k1} = \frac{1}{1 + \exp(\theta_1 \| j - k \|)} \tag{14}$$

$$\beta_{k2} = \frac{1}{1 + \exp(\theta_2 \| x_j - x_k \|)} \tag{15}$$

The spatial function is incorporated into membership function and possibilistic matrix as follows:

$$U^{*}_{ij} = \frac{U_{ij}^{p} * s^{*q}_{ij}}{\sum_{k=1}^{c} U_{kj}^{p} * s^{*q}_{ij}} \tag{16}$$

$$for \quad i = 1,2,....,c \qquad and \quad j = 1,2,.....,n$$

$$t^{*}_{ij} = \frac{t_{ij}^{p} * s^{*q}_{ij}}{\sum_{k=1}^{c} t_{kj}^{p} * s^{*q}_{ij}} \tag{17}$$

$$for \quad i = 1,2,....,c \qquad and \quad j = 1,2,.....,n$$

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

Modified FPCM approach is given below:

Step 1: Select the data set.

Step 2: Fix m >1 and $2 \le c \le n-1$ and $3 \le \eta \le 5$ and give c initial cluster centers V_i.

Step 3: Compute Uij with V_i by Eq. (8).

Step 4: Compute β_{k1} and β_{k2} by Eq. (14) and (15).

Step 5: Compute S^{*}_{ij} by Eq. (13).

Step 6: Update the membership matrices by Eq. (16) and the possibilistic matrix by Eq. (17)

Step 7: Update the centroids using (10).

Step 8: if $\|V_{new} - V_{old}\| \le \varepsilon$ Stop the iteration otherwise, go to step 4

4. Experimental Result

The proposed Modified Fuzzy Possibilistic C-Means and FCM algorithm are implemented using MATLAB and tested on both artificial synthesized image and real image to explore the segmentation accuracy of the proposed approach. The proposed algorithms are evaluated in a condition with noise interference since the MR images are usually noisy. MR image which are interfered with different noise are shown in figures 1, 2. Figure 1(a) shows the main artificial synthesized image. Figures 1(b), (c) and (d) show the artificial synthesized images corrupted by the Salt- Pepper noise with noise density d=0.2, Gaussian noise (m=0, v=0.05) and Speckle noise (m=0, v=0.1), respectively. Figure 2(a) shows the main real image. Figures 2(b), (c) and (d) show the real images corrupted by the Salt- Pepper noise with noise density d=0.2, Gaussian noise (m=0, v=0.05) and Speckle noise (m=0, v=0.2), respectively.

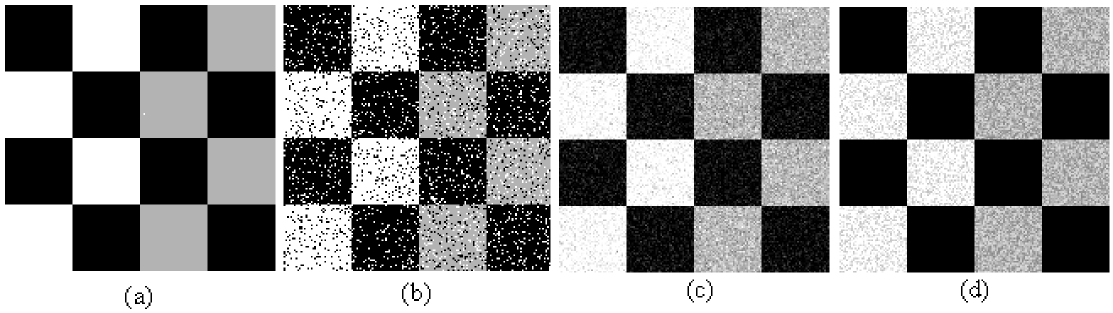


Figure1: artificial synthesized images: (a) original image, (b) image degraded by Salt-Pepper noise, (c) image degraded by Gaussian noise, (d) image degraded by Speckle noise

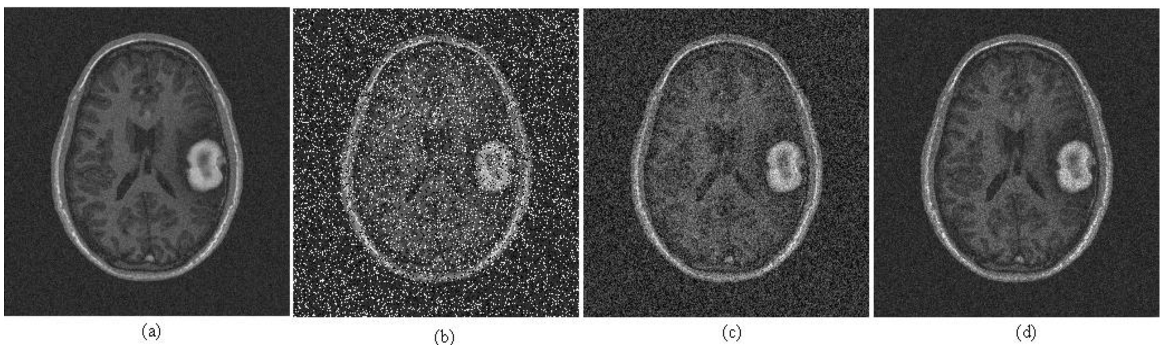


Figure2: MRI image: (a) original image, (b) image degraded by Salt-Pepper noise, (c) image degraded by Gaussian noise, (d) image degraded by Speckle noise

A. Cluster validity functions

In order to obtain a quantitative comparison, two types of cluster validity functions, fuzzy partition and feature structure, are often used to evaluate the performance of clustering in different clustering methods. The representative functions for the fuzzy partition are partition coefficient V_{pc}[10] and partition entropy V_{pe}[11]. They are defined as follows:

$$V_{pc}(U) = \frac{1}{n}\left(\sum_{K=1}^{n}\sum_{i=1}^{c} u_{ik}^{2}\right) \qquad (18)$$

And

$$V_{pe}(U) = -\frac{1}{n}\left(\sum_{K=1}^{n}\sum_{i=1}^{c} u_{ik}\log u_{ik}\right) \qquad (19)$$

The idea of these validity functions is that the partition with fuzziness means better performance. As a result, the best clustering is achieved when the value Vpc is maximal or Vpe is minimal.

B. Experimental results on synthetic image

In this section, the results of the proposed algorithm are presented. It is compared with the standard FCM and FPCM algorithm. Table 1 tabulates the Vpc and Vpe and number of iteration of the three algorithms on three different noise degraded images shown in Figs. 1 (a-c), respectively.

Table1. COMPRESSION OF THE CLUSTERING RESULTS ON TREE KIND NOISE DEGRADED SYNTHETC IMAGE USING FCM, FPCM and SFPCM ALGORITHMS.

Noise Type	Algorithm	Vpc	Vpe	Number iteration
No noise	FCM	0/9999	0/0047	10
No noise	FPCM	0/9999	0/0047	10
No noise	sFPCM	0/9999	0/0047	10
Salt-pepper	FCM	0/9996	0/0051	12
Salt-pepper	FPCM	0/9996	0/0051	12
Salt-pepper	sFPCM	0/9996	0/0048	12
Gaussian	FCM	0/9204	0/0678	17
Gaussian	FPCM	0/9217	0/0668	17
Gaussian	sFPCM	0/9711	0/0225	11
speckle	FCM	0/9123	0/0672	28
speckle	FPCM	0/9123	0/0672	28
speckle	sFPCM	0/9511	0/0363	16

From Table 1, obviously, SFPCM achieves better performance than FCM and FPCM, which demonstrates the modified FPCM algorithm (SFPCM) a visually significant improvement of robustness to noise over the FCM and FPCM algorithm.

Figs. 3(a-c) display the clustering results of the synthetic image using the FCM, FPCM and SFPCM algorithm respectively; correspondingly, the clustering results on Salt-Pepper degraded synthetic image using the FCM, FPCM and SFPCM algorithm were shown in Figs. 4(a-c) respectively, the clustering results on Gaussian degraded synthetic image using the FCM, FPCM and SFPCM algorithm were shown in Figs. 5(a-c) respectively and the clustering results on speckle degraded synthetic image using the FCM, FPCM and SFPCM algorithm were shown in Figs. 6(a-c) respectively.

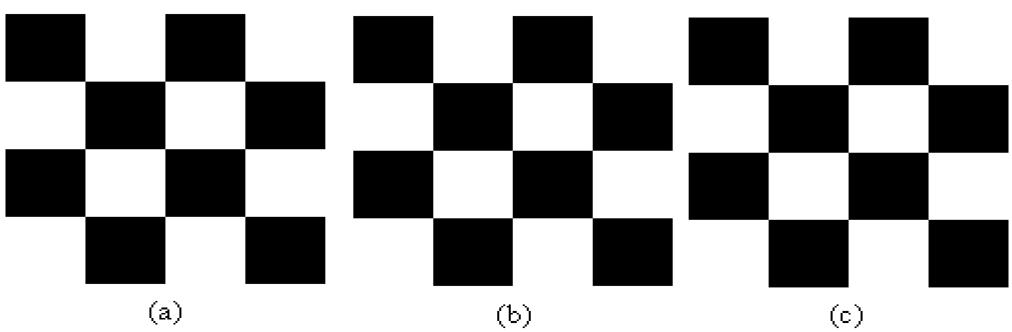


Figure3: Comparison of segmentation results on synthetic image which is no noise. (a) FCM result (b) PFCM result (c) SFPCM result

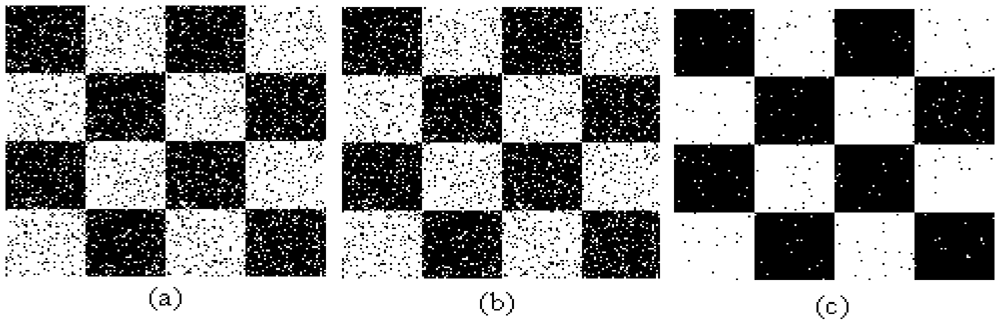


Figure4: Comparison of segmentation results on synthetic image which is corrupted by 2% Salt- Pepper noise. (a) FCM result (b) PFCM result (c) SFPCM result.

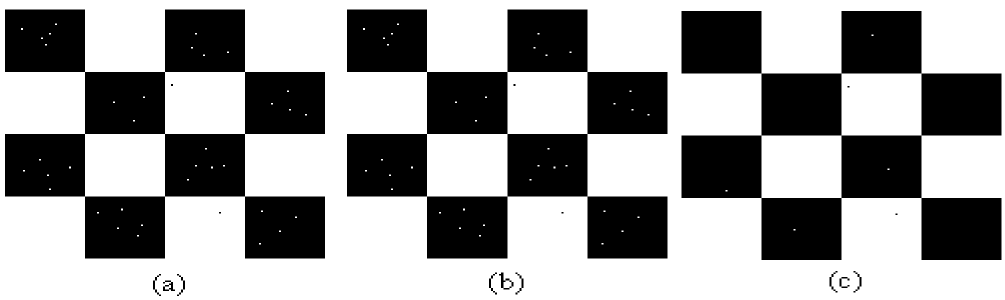


Figure5: Comparison of segmentation results on synthetic image which is corrupted by 2% Salt- Pepper noise. (a) FCM result (b) PFCM result (c) SFPCM result

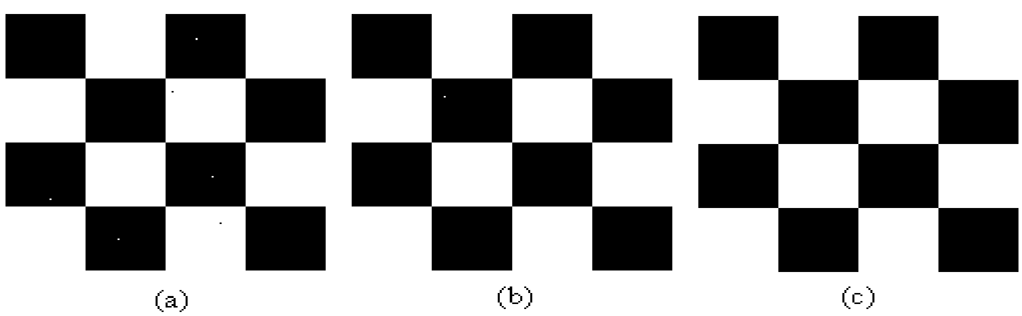


Figure6: Comparison of segmentation results on synthetic image which is corrupted by speckle noise (m=0, v=0.2) noise.(a) FCM result (b) FPCM result (c) SFPCM result

C. Experimental result on real image

In this section, the results of the proposed algorithm on real image are presented. It is compared with the standard FCM and FPCM algorithm. Table 2 tabulates the Vpc and Vpe and number of iteration of the three algorithms on three different noise degraded images shown in Figs.2 (a-c), respectively.

Table2. COMPRESSION OF THE CLUSTERING RESULTS ON TREE KIND NOISE DEGRADED REAL IMAGE USING FCM, FPCM and SFPCM ALGORITHMS.

Noise Type	Algorithm	Vpc	Vpe	Number iteration
No noise	FCM	0/8558	0/1165	51
No noise	FPCM	0/8558	0/1165	51
No noise	sFPCM	0/9431	0/0425	29
Salt-pepper	FCM	0/8373	0/1226	27
Salt-pepper	FPCM	0/8373	0/1165	27
Salt-pepper	sFPCM	0/9374	0/0464	33
Gaussian	FCM	0/7669	0/1812	59
Gaussian	FPCM	0/7685	0/1801	58
Gaussian	sFPCM	0/8296	0/1286	30
speckle	FCM	0/8126	0/1467	103
speckle	FPCM	0/8126	0/1467	103
speckle	sFPCM	0/9283	0/0545	54

Table 2 shows that our proposed algorithm improves significantly the performances of clustering on Salt-Pepper degraded image and Gaussian degraded image and speckle degraded image compare to the standard FCM and FPCM algorithm.

Figs. 7(a-c) display the clustering results of the real MRI image using the FCM, FPCM and SFPCM algorithm respectively; correspondingly, the clustering results on Salt-Pepper degraded real MRI image using the FCM, FPCM and SFPCM algorithm were shown in Figs. 8(a-c) respectively, the clustering results on Gaussian degraded real MRI image using the FCM, FPCM and SFPCM algorithm were shown in Figs. 9(a-c) respectively and the clustering results on speckle degraded real MRI image using the FCM, FPCM and SFPCM algorithm were shown in Figs. 10(a-c) respectively.

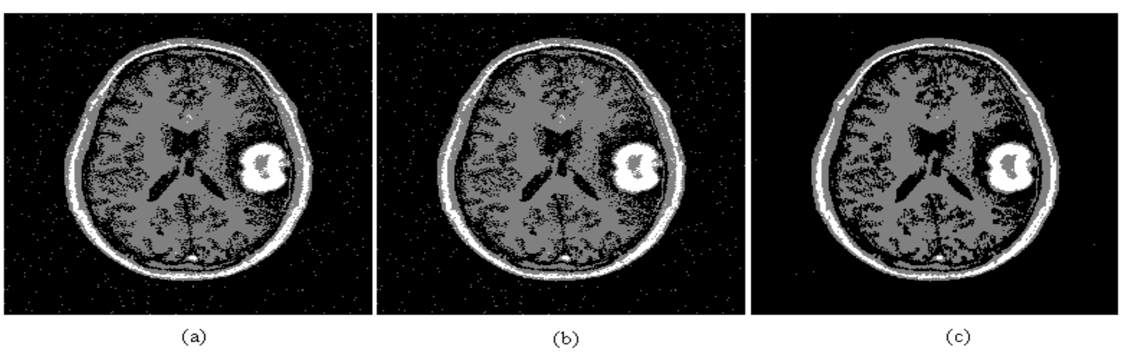
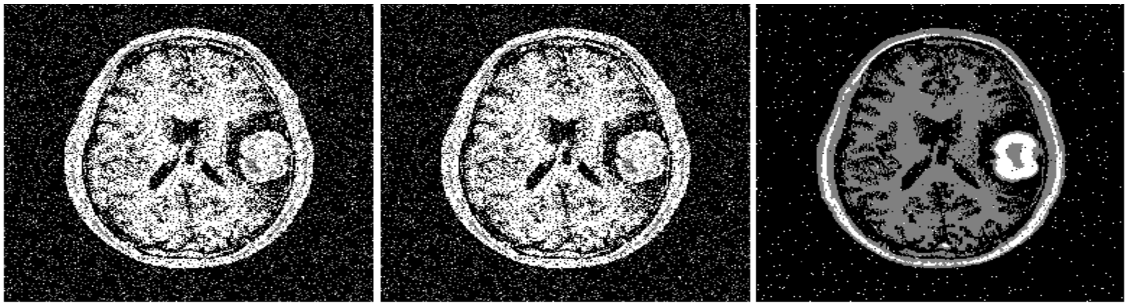
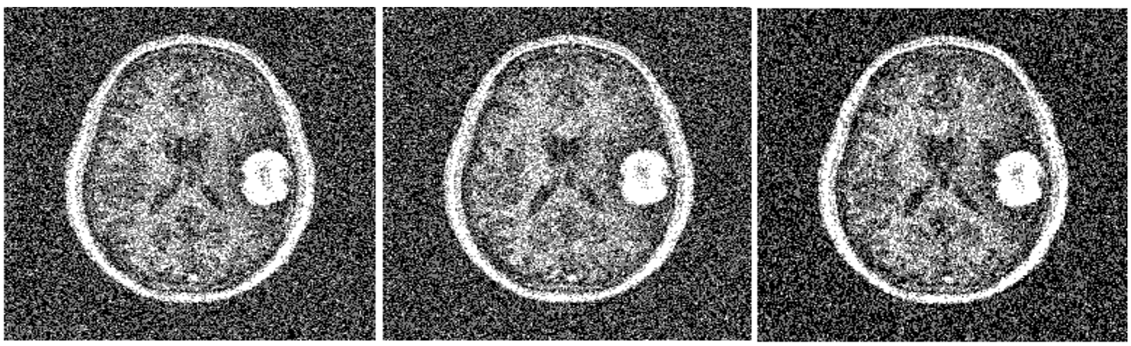


Figure7: Comparison of segmentation results on MRI image which is no noise. (a) FCM result (b) PFCM result (c) SFPCM result



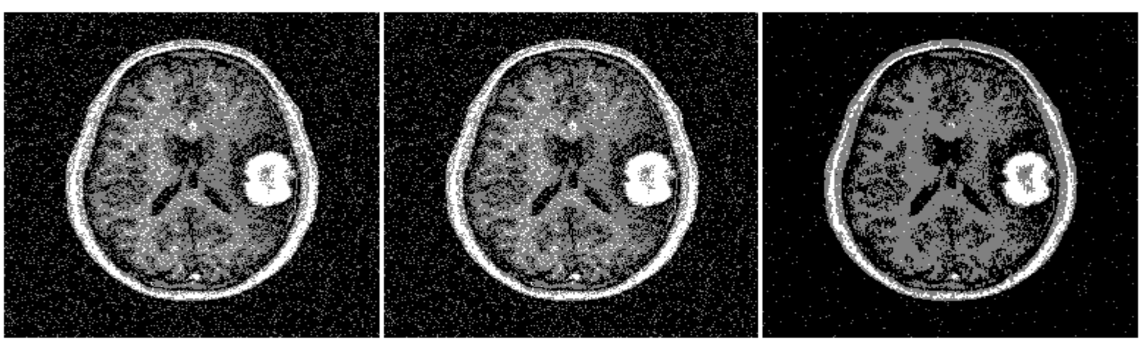
(a) (b) (c)

Figure8: Comparison of segmentation results on MRI image which is corrupted by 2% Salt- Pepper noise. (a) FCM result (b) PFCM result (c) SFPCM result



(a) (b) (c)

Figure9: Comparison of segmentation results on MRI image which is corrupted by Gaussian noise (m=0, v=0.05) noise. (a) FCM result (b) FPCM result (c) SFPCM result



(a) (b) (c)

Figure10: Comparison of segmentation results on MRI image which is corrupted by speckle noise (m=0, v=0.2) noise.(a) FCM result (b) FPCM result (c) SFPCM result

5. Conclusions

In this paper, we proposed a new modify spatial FPCM that incorporates the spatial information into the membership function to improve the segmentation results. In the new spatial function we used two contribution factors. The first one was according to distances between central pixel with neighbor pixels. The second factor was calculated according to value difference of central pixel with neighbor pixels. Using of these contribution factors caused that spatial function is made of according to distance and value pixels. The new method was tested on MRI images and evaluated by using various cluster validity functions. Preliminary results showed that the effect of noise in segmentation was considerably less with the new algorithm than with the conventional FCM and FPCM.

References

[1] B. Buyuksarac and M. Ozkan. "Image segmentation in mri using true ti and true Pd values."In Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE, volume 3, pages 2661 –2664, 2001.

[2] Norbert Rohrl, Jose Iglesias-Rozas and Galia Weidl, "Computer Assisted Classification of Brain Tumors", Springer Berlin Heidelberg, pp. 55-60, 2008.

[3] Wen, P, Zheng, L and Zhou, J, "Spatial credibilistic clustering algorithm in noise image segmentation", IEEE International Conference on Industrial Engineering and Engineering Management, pp: 543 -547, 2007.

[4] J.M. Gorriz, J. Ramirez, E.W. Lang, C.G. Puntonet, "Hard c-means clustering for voice activity detection," Speech Commun, vol. 48, 2006, pp. 1638-1649.

[5] J. C. Bezdek, "Pattern Recognition with Fuzzy Objective Function Algorithms", New York, Plenum, 1981.

[6] R. Krishnapuram, J. M. Keller, A Possibilistic approach to clustering, IEEE Transactions on fuzzy systems, Vol. 1, No. 2, May 1993.

[7] N. R. Pal, K. Pal and J. C. Bezdek, "A mixed c-means clustering model", Proceedings of the Sixth IEEE International Conference on Fuzzy Systems, Vol. 1, pp. 11-21, Jul. 1997.

[8] W.J. Chen, M.L. Giger, U. Bick, "A fuzzy c means (FCM)-based approach for computerized segmentation of breast lesions in dynamic contrast enhanced MRI images," Acad. Radiol, vol. 13, 2006, pp. 63-72.

[9] Hadi Seyedarabi, Hamed Shamsi, Ebrahim Borzabadi, Musa Shamsi, "A Modified Fuzzy C-Means Clustering with Spatial Information for Image Segmentation" International Conference on Information and Computer Applications (ICICA 2011) pp. 121-125.

[10] Bezdek JC, "Cluster validity with fuzzy sets," Journal of Cybernetics, vol. 3, 1974, pp. 58-73.

[11] Bezdek JC, "Mathematical models for systematic and taxonomy, "In: proceedings of eight international conferences on numerical taxonomy, July. 2004, pp. 143-166.

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