A Robust Segmentation Approach for Noisy Medical Images Using Fuzzy Clustering With Spatial Probability

Zulaikha Beevi[1] and Mohamed Sathik[2]
[1]Department of IT, National College of Engineering, India
[2]Department of Computer Science, Sadakathullah Appa College, India

Abstract: *Image segmentation plays a major role in medical imaging applications. During last decades, developing robust and efficient algorithms for medical image segmentation has been a demanding area of growing research interest. The renowned unsupervised clustering method, Fuzzy C-Means (FCM) algorithm is extensively used in medical image segmentation. Despite its pervasive use, conventional FCM is highly sensitive to noise because it segments images on the basis of intensity values. In this paper, for the segmentation of noisy medical images, an effective approach is presented. The proposed approach utilizes histogram based Fuzzy C-Means clustering algorithm for the segmentation of medical images. To improve the robustness against noise, the spatial probability of the neighboring pixels is integrated in the objective function of FCM. The noisy medical images are denoised, with the help of an effective denoising algorithm, prior to segmentation, to increase further the approach's robustness. A comparative analysis is done between the conventional FCM and the proposed approach. The results obtained from the experimentation show that the proposed approach attains reliable segmentation accuracy despite of noise levels. From the experimental results, it is also clear that the proposed approach is more efficient and robust against noise when compared to that of the FCM.*

Keywords: *Image segmentation, medical images, Magnetic Resonance Imaging (MRI), clustering, FCM, histogram, membership function, spatial probability, denoising, Principal Component Analysis (PCA), Local Pixel Grouping (LPG).*

Received December 21, 2009; accepted May 20, 2010

1. Introduction

Image segmentation plays an important role in image analysis and computer vision and it is considered as one of the major obstruction in the development of image processing technology [44]. In general, image segmentation is a process of partitioning an image into non-overlapped, consistent regions that are homogeneous with respect to some characteristics like intensity, color, tone or texture, and more [9]. Image segmentation has been widely used in areas such as robot vision, geographical imaging, object recognition and medical imaging [5, 33, 40]. A remarkable amount of thorough research has been reported in the literature, regarding the development of enormous number of techniques for image segmentation [14, 30, 33]. From these references, it is clear that several categories of image segmentation methodologies are available. Among the available categories, clustering based approaches have been extensively studied and widely utilized for image segmentation [21].

In recent decades, the need for computers in assisting the processing and analysis of medical images has become inevitable with the mounting size and number of medical images [33]. Image segmentation, as a task of delineating anatomical structures and other areas of interest, plays a vital role in enormous number of biomedical imaging applications like the quantification of tissue volumes [22], diagnosis [36], localization of pathology [48], study of anatomical structure [41], treatment planning [20], partial volume correction of functional imaging data [27], and computer integrated surgery [2, 13]. In many medical image analysis and quantization methods, the initial and essential step is the segmentation of medical images, which is a significant and challenging problem. During recent decades, the automatic segmentation of medical images has gained immense importance among several researchers. The task of medical image segmentation has become extremely troublesome due to the complexity of images and also the absence of the models of the anatomy that fully captures the possible deformation in each structure. The accurate segmentation of medical images is one of the most important tasks in diverse medical applications.

In the recent literature, a plentiful of general approaches has been proposed on medical image segmentation [33]. The medical image segmentation methods available in the literature can be divided into eight categories. They are namely:

1. Thresholding approaches.
2. Clustering approaches.

3. Classifiers.
4. Region growing approaches.
5. Artificial Neural Networks (ANNs).
6. Deformable models.
7. Markov Random Field (MRF) models.
8. Atlas-Guided approaches [33].

Among these methods, clustering based approaches have received a great deal of attention in medical imaging research community. Several clustering strategies have been used by researchers, such as crisp clustering scheme and fuzzy clustering scheme, each of which has its own special characteristics [44]. The issues like limited spatial resolution, poor contrast, overlapping intensities, noise and intensity inhomogeneities differences, makes crisp clustering scheme a complex task for images in many real situations. On the other hand, as a soft segmentation method, fuzzy clustering scheme is extensively studied and successfully applied in many image segmentation methods [29, 37, 38].

The segmentation methods based on fuzzy clustering have considerable advantages over crisp clustering based methods, owing to the fact that they could retain much more information from the original image [5, 34]. Fuzzy C-Means (FCM) clustering algorithm [4] is the most popular fuzzy clustering method, which is widely used in many image segmentation methods due to its robust characteristics for ambiguity and it can also retain much more information than crisp clustering methods. For noise-free images and images with low levels of noise, the conventional FCM can produce better results. But, the conventional FCM faces two disadvantages while used in segmentation of noise-corrupted images [45]. First disadvantage is that the FCM doesn't integrate the information regarding the spatial context that makes it more sensitive to the noise and other imaging artifacts. The second drawback is that the cluster assignment is absolutely on the basis of the distribution of the pixel intensity which makes it sensitive to intensity variations due to the illumination or the object geometry [23].

To ascend the robustness of conventional FCM against noise, various algorithms have been presented in the literature. These methods can be categorized into two different groups:

1. Imposing spatial constraints to clustering algorithms [1, 6, 23, 38].
2. Introducing other features or dissimilarity index which is insensitive to intensity variations in the objective function of FCM [6, 23].

In recent times, enhancing the performance of FCM based image segmentation methods by the incorporation of spatial information into the objective function, has gained enormous importance. Several approaches have been presented by researchers, which incorporates the local spatial information into the conventional FCM [21, 22, 36, 48] to achieve effective segmentation. Majority of the researches in the medical image segmentation literature uses MR images [40] owing to the advantages of Magnetic Resonance Imaging (MRI) over other diagnostic imaging and there are several methods available for MR image segmentation [5, 8, 18, 32, 40]. In spite of the availability of many segmentation approaches for MR images, people are still looking forward in developing very interesting algorithms, which can quickly and correctly segment an image. A robust and efficient approach for the segmentation of medical images corrupted by noise is presented in our earlier work [49], using the Sparse 3d Transform-Domain Collaborative Filtering denoising algorithm.

In this paper, we have presented a robust and effective approach for the segmentation of noisy medical images. In the presented approach, the fuzzy clustering concepts are utilized in effectively segmenting the medical images. The renowned unsupervised fuzzy clustering algorithm FCM is employed in the proposed approach to achieve effectual segmentation. To make the proposed approach robust against noise, the spatial probability of neighboring pixels is integrated into the conventional FCM. By using an efficient denoising algorithm, the input noisy medical image is first denoised so as to improve its robustness further. The integration of spatial information into the conventional FCM takes longer time to converge as well as there are lots of possibilities to converge in the local minima. As a result, in the presented approach, to evade local minima, the parameters of the FCM algorithm are initialized using histogram. Comparing to the conventional FCM, the histogram based FCM converges very swiftly. The employed denoising algorithm and the integrated spatial information have increased the robustness of the proposed approach against noise. The experimental results demonstrate the robustness and efficiency of the proposed segmentation approach. In addition, a comparative analysis is made between the conventional FCM, our earlier work [49] and the proposed segmentation approach.

The rest of the paper is organized as follows. The description of the denoising algorithm employed in the proposed approach is provided in section 2. The robust and effective approach proposed for the segmentation of noisy medical images is detailed in section 3. The experimental results and discussions are presented in section 4. Finally, the conclusions are summed up in section 5.

2. Description of the Employed Denoising Algorithm

Usually, the medical images obtained from sensors are bound to contain noise and blurred edges. The process of segmentation is made more intricate, owing to the presence of these artifacts in medical images. Consequently, denoising images prior to segmentation perhaps produce better segmentation accuracy. Recently, Lei Zhang *et al.* [46] presented an efficient denoising algorithm, which is used in the proposed approach. Initially, the input noisy medical images are denoised using the above-mentioned denoising algorithm. A brief description of the denoising strategy employed in the proposed approach is provided in the following:

- *LPG-PCA Based Denoising Algorithm*

Since noise is an inevitable one in image acquisition, denoising plays an important role in increasing the quality of the image. Noise removal has been widely studied as a primary low-level image processing procedure and copious amount of denoising schemes have been proposed. In our approach, we employed an efficient Principal Component Analysis (PCA) based denoising algorithm with Local Pixel Grouping (LPG). In order to preserve the image local structures in a better way, a pixel and its nearest neighbors are represented as a vector variable in which training samples are chosen from the local window with a help of block matching based LPG. The LPG methodology assures that merely the sample blocks with equal contents are utilized in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to reduce the noise. The LPG-PCA denoising process is repeated once, to increase the denoising performance further and the noise level is adjusted adaptively in the second stage. The LPG-PCA based denoising algorithm is described as follows:

In the $m \times n$ dataset matrix X_υ, every component $x_k^\upsilon, k = 1,2,\cdots,m$, of the vector variable x_υ contains n samples. The row vector holding the n samples of x_k^υ is represented by X_k^υ. Therefore, the dataset X_υ can be represented as $X_\upsilon = [(X_1^\upsilon)^T \cdots (X_m^\upsilon)^T]^T$. Correspondingly, we have $X = [X_1^T \cdots X_m^T]^T$, where X_k is the row vector having the n samples of x_k, and $X_\upsilon = X + V$, where $V = [V_1^T \cdots V_m^T]^T$ is the dataset of noise variable υ and V_k is the row sample vector of υ_k. Subsequently, we centralize dataset X_υ. The mean value of X_k^υ is $\mu_k = (1/n)\sum_{i=1}^{n} X_k^\upsilon(i)$, and X_k^υ is centralized by $\overline{X}_k^\upsilon = X_k^\upsilon - \mu_k$. As the noise υ_k is zero-mean, X_k can also be centralized by $\overline{X}_k = X_k - \mu_k$. Consequently, the centralized datasets of X_υ and X are attained as $\overline{X}_\upsilon = [(\overline{X}_1^\upsilon)^T \cdots (\overline{X}_m^\upsilon)^T]^T$ and $\overline{X} = [\overline{X}_1^T \cdots \overline{X}_m^T]^T$, and we have $\overline{X}_\upsilon = \overline{X} + V$.

Refer to PCA [46], by calculating the covariance matrix of $\overline{X}$, indicated by $\Omega_{\bar{x}}$, the PCA transformation matrix $P_{\bar{x}}$ can be attained. Yet, the accessible dataset $\overline{X}_\upsilon$ is noise corrupted, so $\Omega_{\bar{x}}$ cannot be directly calculated. With the linear model $\overline{X}_\upsilon = \overline{X} + V$, we contain:

$$\Omega_{\bar{x}_\upsilon} = \frac{1}{n}\overline{X}_\upsilon \overline{X}_\upsilon^T = \frac{1}{n}(\overline{X}\overline{X}^T + \overline{X}V^T + V\overline{X}^T + VV^T) \quad (1)$$

as $\overline{X}$ and V are uncorrelated, items $\overline{X}V^T$ and $V\overline{X}^T$ will be nearly zero matrices and therefore:

$$\Omega_{\bar{x}_\upsilon} \approx \frac{1}{n}(\overline{X}\overline{X}^T + VV^T) = \Omega_{\bar{x}} + \Omega_\upsilon \quad (2)$$

Where $\Omega_{\bar{x}} = (1/n)\overline{X}\overline{X}^T$ *and* $\Omega_\upsilon = (1/n)VV^T$. The component $\Omega_\upsilon(i,j)$ is the correlation among υ_i and υ_j. As υ_i and υ_j are uncorrelated for $i \neq j$, we recognize that Ω_υ is a $m \times m$ diagonal matrix in which all the diagonal components being σ^2. Otherwise, Ω_υ can be written as $\sigma^2 I$, in which I is the identity matrix. Subsequently, it can be effortlessly demonstrated that the PCA transformation matrix $P_{\bar{x}}$ related with $\Omega_{\bar{x}}$ is identical as the PCA transformation matrix related with $\Omega_{\bar{x}_\upsilon}$. On the basis of $\Omega = \Phi\Lambda\Phi^T$, we can decompose $\Omega_{\bar{x}}$ as:

$$\Omega_{\bar{x}} = \Phi_{\bar{x}}\Lambda_{\bar{x}}\Phi_{\bar{x}}^T \quad (3)$$

Where $\Phi_{\bar{x}}$ is the $m \times m$ orthonormal eigenvector matrix and $\Lambda_{\bar{x}}$ is the diagonal eigenvalue matrix. As $\Phi_{\bar{x}}$ is an orthonormal matrix, the Ω_υ can be written as:

$$\Omega_\upsilon = (\sigma^2 I)\Phi_{\bar{x}}\Phi_{\bar{x}}^T = \Phi_{\bar{x}}(\sigma^2 I)\Phi_{\bar{x}}^T = \Phi_{\bar{x}}\Omega_\upsilon\Phi_{\bar{x}}^T \quad (4)$$

Therefore we have:

$$\begin{aligned}\Omega_{\bar{x}_\upsilon} &= \Omega_{\bar{x}} + \Omega_\upsilon = \Phi_{\bar{x}}\Lambda_{\bar{x}}\Phi_{\bar{x}}^T + \Phi_{\bar{x}}(\sigma^2 I)\Phi_{\bar{x}}^T \\ &= \Phi_{\bar{x}}(\Lambda_{\bar{x}} + \sigma^2 I)\Phi_{\bar{x}}^T = \Phi_{\bar{x}}\Lambda_{\bar{x}_\upsilon}\Phi_{\bar{x}}^T\end{aligned} \quad (5)$$

Where $\Lambda_{\bar{x}_\upsilon} = \Lambda_{\bar{x}} + \sigma^2 I$. Equation 5 implies that $\Omega_{\bar{x}_\upsilon}$ and $\Omega_{\bar{x}}$ contains the similar eigenvector matrix $\Phi_{\bar{x}}$. Accordingly, in practical implementation we can directly calculate $\Phi_{\bar{x}}$ by decomposing $\Omega_{\bar{x}_\upsilon}$, instead of $\Omega_{\bar{x}}$, and next the orthonormal PCA transformation matrix for $\bar{X}$ is set as:

$$P_{\bar{x}} = \Phi \frac{T}{x} \tag{6}$$

Applying $P_{\bar{x}}$ to data set, we have $\bar{X}_{\upsilon}$:

$$\bar{Y}_{\upsilon} = P_{\bar{x}}\bar{X}_{\upsilon} = P_{\bar{x}}\bar{X} + P_{\bar{x}}V = \bar{Y} + V_Y \tag{7}$$

Where $\bar{Y} = P_{\bar{x}}\bar{X}$ is the decorrelated dataset for $\bar{X}$ and $V_Y = P_{\bar{x}}V$ is the transformed noise dataset for V. As $\bar{Y}$ and noise V_Y are uncorrelated, we can simply derive that the covariance matrix of $\bar{Y}_{\upsilon}$ is:

$$\Omega_{\bar{y}_{\upsilon}} = \frac{1}{n}\bar{Y}_{\upsilon}\bar{Y}_{\upsilon}^{T} = \Omega_{\bar{y}} + \Omega_{\upsilon_y} \tag{8}$$

Where $\Omega_{\bar{y}} = \Lambda_{\bar{x}}$ is the covariance matrix of decorrelated dataset $\bar{Y}$ and $\Omega_{\upsilon_y} = P_{\bar{x}}\Omega_{\upsilon}P\frac{T}{X}$ is the covariance matrix of noise dataset V_Y.

In the PCA transformed domain $\bar{Y}_{\upsilon}$, the majority energy of noiseless dataset $\bar{Y}$ concentrates on the several most essential components, whilst the energy of noise V_Y distributes much more evenly. The noise in $\bar{Y}_{\upsilon}$ can be suppressed by utilizing the Linear Minimum Mean Square-Error estimation (LMMSE) technique. As $\bar{Y}_{\upsilon}$ is centralized, the LMMSE of $\bar{Y}_k$, i.e., the k^{th} row of $\bar{Y}$, is attained as:

$$\hat{\bar{\bar{Y}}}_k = w_k . \bar{\bar{Y}}_{\upsilon}^{k} \tag{9}$$

Where, the shrinkage coefficient $w_k = \Omega_{\bar{y}}(k,k) / \Omega_{\upsilon_y}(k,k)$ and $\bar{\bar{Y}}_{\upsilon}^{k}$ is the k^{th} row of $\bar{Y}_{\upsilon}$. In flat zones, $\Omega_{\bar{y}}(k,k)$ is very smaller than $\Omega_{\upsilon_y}(k,k)$ therefore w_k is close to 0. Therefore, majority of the noise will be suppressed in $\hat{\bar{\bar{Y}}}_k$ by LMMSE operator $\hat{\bar{\bar{Y}}}_k = w_k . \bar{\bar{Y}}_{\upsilon}^{k}$. In implementation, $\Omega_{\bar{y}_{\upsilon}}$ is calculated initially from the available noisy dataset $\bar{Y}_{\upsilon}$ and $\Omega_{\bar{y}}(k,k)$ is estimated by $\Omega_{\bar{y}}(k,k) = \Omega_{\bar{y}_{\upsilon}}(k,k) - \Omega_{\upsilon_y}(k,k)$. In flat zones, it is often that $\Omega_{\bar{y}_{\upsilon}}(k,k) - \Omega_{\upsilon_y}(k,k) \le 0$, and next we set $\Omega_{\bar{y}}(k,k) = 0$. In this case w_k will be precisely 0 and all the noise in $\bar{\bar{Y}}_{\upsilon}^{k}$ will be removed.

The matrix of all $\hat{\bar{\bar{Y}}}_k$ is represented by $\hat{\bar{Y}}$. By transforming $\hat{\bar{Y}}$ back to the time domain, we acquire the denoised result of $\bar{X}_{\upsilon}$ as:

$$\hat{\bar{X}} = P\frac{T}{x} . \hat{\bar{Y}} \tag{10}$$

In equation 10, we utilized the fact that $P_{\bar{x}}^{-1} = P_{\bar{x}}^{T}$. Adding up the mean values μ_k back to $\hat{\bar{X}}$ provides the denoised dataset $\hat{X}$. The estimation of the central block $\bar{x}_0$, represented as $\hat{\bar{x}}_0$, can then be extracted from $\hat{X}$ and finally the denoised result of the underlying central pixel can be extracted from $\hat{\bar{x}}_0$. Employing the above process to every pixel, results in the full denoised image of I_{υ}.

3. Effective Approach for Noisy Medical Image Segmentation Using Spatial FCM

The robust and effective approach proposed for the segmentation of noisy medical images is detailed in this section. Moreover, a brief explanation about the conventional FCM and its initialization using histogram is presented.

3.1. Fuzzy C-Means Clustering (FCM)

The well-known Fuzzy C-Means (FCM) clustering algorithm was originally introduced by Dunn [11] and later it is enhanced by Bezdek [4]. The FCM algorithm is mainly an iterative clustering method, which results an optimal c partition by minimizing the weighted within group sum of squared error objective function $O(U,C)$ [31]. Normally, the FCM algorithm requires the number of clusters as an input. The fuzzy clustering techniques usually produce fuzzy partitions of the data instead of hard partitions. As a result, data patterns may be a member of several clusters with different membership values in each cluster [26]. A data pattern's membership value to a cluster symbolizes the similarity between the given data pattern to the cluster. For a given set of n data patterns, $X = x_1, \cdots, x_k, \cdots, x_n$,, the fuzzy clustering technique minimizes the objective function, $O(U,C)$ [15]:

$$O(U,C) = \sum_{k=1}^{n}\sum_{i=1}^{v}(u_{ik})^{m} d^{2}(x_k, c_i) \tag{11}$$

Where x_k is the k^{th} D-dimensional data vector, c_i is the center of cluster i, u_{ik} is the degree of membership of x_k in the i^{th} cluster, m is the weighting exponent, $d(x_k, c_i)$ is the distance between data x_k and cluster center c_i, n is the number of data patterns and v is the number of clusters [15]. The objective function $O(U,C)$ is minimized by means of an iterative process through which the degree of membership, u_{ik}, and the cluster centers, c_i, are updated, as below:

$$u_{ik} = \frac{1}{\sum_{J=1}^{V}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \tag{12}$$

$$c_i = \frac{\sum_{k=1}^{n}(u_{ik})^{m} x_k}{\sum_{k=1}^{n}(u_{ik})^{m}} \tag{13}$$

Where, $\forall i\ u_{ik}$ satisfies: $u_{ik} \in [0,1]$, $\forall k \sum_{i=1}^{v} u_{ik} = 1$ and $0 < \sum_{k=1}^{n} u_{ik} < n$.

3.2. Initialization

The conventional FCM algorithm computes the centroids and membership function pixel-by-pixel, when employed for image segmentation. This made the convergence of the algorithm a time-consuming one, which in turn makes it more impractical for image segmentation. Moreover, FCM is a local search optimization algorithm, and because of this it is very sensitive to the initial centroid. Therefore, the algorithm will obtain the local optimum solution easily [39], if the initial centroid is selected randomly. In order to shun the blindness of random evaluation and also to make the initial centroid approach the globally optimum solution, the gray level histogram of the image is utilized in the FCM algorithm that minimizes the number of iteration steps and improves the speed of segmentation. The objective function $O(U,C)$ of the histogram based FCM is as follows:

$$O(U, C) = \sum_{l=1}^{L}\sum_{i=1}^{v}(u_{il})^{m}\, H(l)\, d^{2}(l, c_i) \tag{14}$$

Where, H is the histogram of the image of L-gray levels. The calculation of membership degrees of $H(l)$ pixels is reduced to a single pixel with l as grey level value. The membership function u_{il} and center c_i for histogram based FCM can be computed using:

$$u_{il} = \frac{1}{\sum_{J=1}^{V}\left(\frac{d_{li}}{d_{lj}}\right)^{\frac{2}{m-1}}} \tag{15}$$

$$c_i = \frac{\sum_{l=1}^{L}(u_{il})^{m} H(l)\, l}{\sum_{l=1}^{L}(u_{il})^{m}} \tag{16}$$

Where, d_{li} is the distance between the cluster center i and the gray level l.

3.3. Proposed Methodology

As histogram based FCM algorithm operates merely on the histogram of an image, it is faster than the conventional FCM that processes the entire data [16]. Despite the fact that, conventional FCM algorithm works well on the majority of noise-free images, it has a major drawback, (i.e.,) it is highly sensitive to noise and many other imaging artifacts. The histogram-based FCM can be made more robust against noise and blurred edges by incorporating the spatial information into it. The objective function $O(U,C)$ of the proposed segmentation approach is given by:

$$O(U,C) = \sum_{k=1}^{n}\sum_{i=1}^{v}\left(u_{ik}^{s}\right)^{m} d^{2}(x_k, c_i) \tag{17}$$

The spatial membership function u_{ik}^{s} of the proposed segmentation approach is computed using the below equation:

$$u_{ik}^{s} = \frac{P_{ik}}{\left(\sum_{J=1}^{V}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}\right)\left(N_k \sum_{z=1}^{N_k}\left(\sum_{J=1}^{V}\left(\frac{d_{iz}}{d_{jz}}\right)^{\frac{2}{m-1}}\right)\right)} \tag{18}$$

Where, P_{ik} is the apriori probability that k^{th} pixel belongs to i^{th} cluster and is computed as:

$$P_{ik} = \frac{NN_i(k)}{N_k} \tag{19}$$

Where $NN_i(k)$ is the number of pixels in the neighborhood of k^{th} pixel which belongs to cluster i after defuzzification, N_k is the total number of pixels in the neighborhood, d_{iz} is the distance between i^{th} cluster and z^{th} neighborhood of i^{th} cluster. The center c_i^{s} of every cluster is manipulated as:

$$c_i^{s} = \frac{\sum_{k=1}^{n}\left(u_{ik}^{s}\right)^{m} x_k}{\sum_{k=1}^{n}\left(u_{ik}^{s}\right)^{m}} \tag{20}$$

In the proposed segmentation approach, two kinds of spatial information are included in the membership function of FCM algorithm. They are given as follows:

- *Apriori Probability*: In order to assign a noise pixel to a cluster that contains a majority of the noise pixel's neighborhood as its members, this parameter is incorporated in the membership function.
- *Fuzzy Spatial Information*: The second term in the denominator of equation (18) is the average of fuzzy membership of the neighborhood pixels to a cluster. So, a pixel gets maximum membership value to a cluster when its neighborhood pixels have high membership value to that cluster.

4. Experimental Results and Discussion

The experimental results of the proposed segmentation approach are presented in this section. With the aid of Matlab (MATLAB 7.8), the proposed segmentation approach is implemented. The parameter attained from the histogram of the image is used in the initialization of the objective function of the proposed segmentation approach and thus it converged very quickly. The following three categories of images namely, synthetic brain MRI images, original brain MRI images and real world images are utilized in the experimentation. The segmentation accuracy A_S is computed using the following equation to evaluate the quality of the segmentation results:

$$A_S = \frac{N_C}{T_P} \times 100 \tag{21}$$

Where, N_C denotes the number of correctly segmented pixels, and T_P represents the total number of pixels in the specified image. Additive White Gaussian Noise (AWGN) of different levels (5%, 10%, 15%, and 20%) is added to the image in order to assess the robustness of the proposed segmentation approach against the noise. The segmentation accuracy of conventional FCM, our earlier work with denoising [49], proposed approach without denoising and proposed approach with denoising for different noise levels is depicted in Figure 1 and the values are given in Table 1.

Table 1. The segmentation accuracy of conventional FCM, our earlier work with denoising [48], proposed approach without denoising and proposed approach with denoising for different noise levels.

Segmentation Accuracy				
Approaches	**Noise Level (%)**			
	5	**10**	**15**	**20**
Fcm	94.6095	94.0754	92.7734	90.4663
Proposed Approach Without Denoising	94.6605	94.4505	93.7195	93.1519
Our Earlier Work With Denoising [48]	94.7675	94.6604	94.2069	94.2856
Proposed Approach With Denoising	94.7572	94.6435	94.1857	94.2538

From Figure 1, the segmentation accuracy remains stable for proposed approach with denoising, even at a higher noise level (20%). The proposed approach without denoising preserved its consistency up to 15% noise level, whereas the accuracy of traditional FCM decreases considerably for noise level greater than 10%.

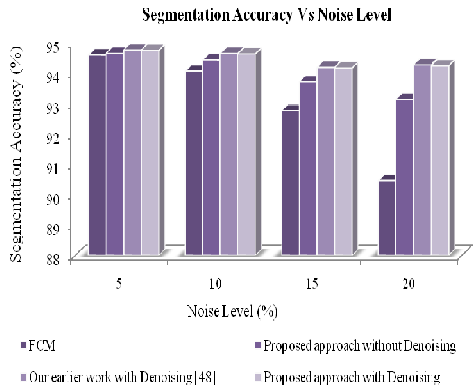
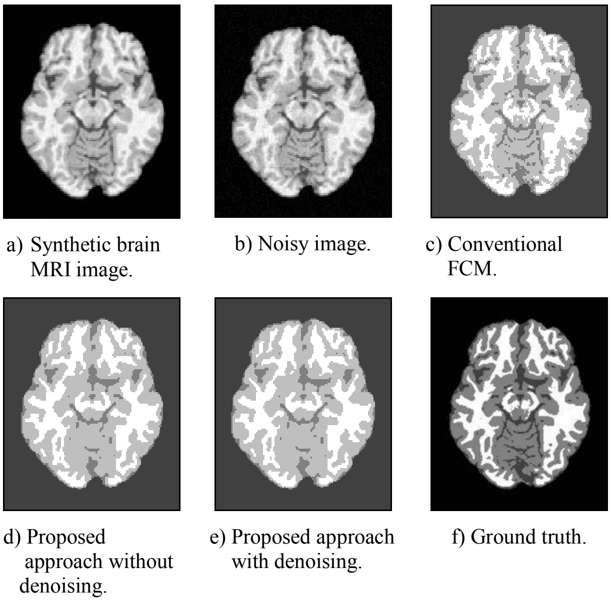


Figure 1. Segmentation accuracy of conventional FCM, our earlier work with denoising [48], proposed approach without denoising and proposed approach with denoising in segmenting synthetic brain MRI images with different noise levels.

The segmentation results of conventional FCM, proposed approach without denoising and proposed approach with denoising for synthetic brain MRI images are portrayed in Figure 2. Correspondingly, in Figure 3 the results for an original brain MRI image are shown.

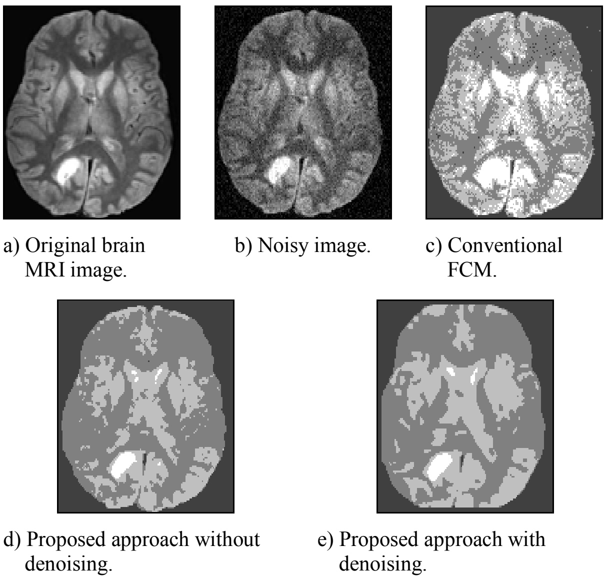
For experimentation with real-world images, the standard test image cameraman is used. The segmentation results of cameraman image demonstrated that the proposed approach with denoising produces improved results for higher noise levels. The original image and the outputs for various noise levels 5%, 15% and 20% are portrayed in Figures 4, 5 and 6, respectively. Even under the noise level 25%, the proposed approach with denoising produced improved results whereas the conventional FCM produced poor results.



a) Synthetic brain MRI image. b) Noisy image. c) Conventional FCM.

d) Proposed approach without denoising. e) Proposed approach with denoising. f) Ground truth.

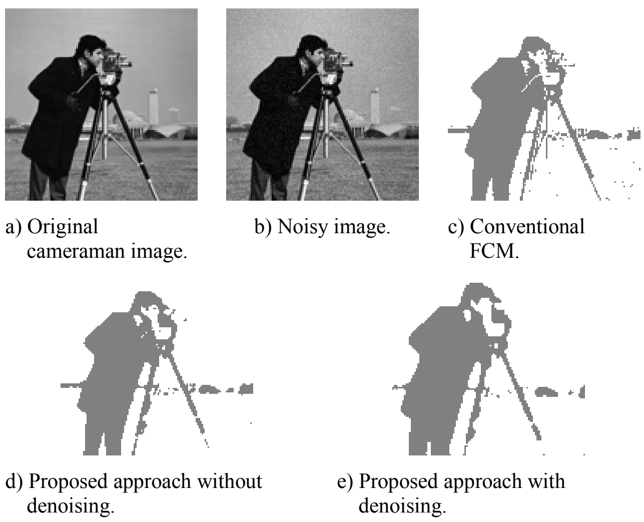
Figure 2. Segmentation results of synthetic brain MRI image with 5% noise.



a) Original brain MRI image. b) Noisy image. c) Conventional FCM.

d) Proposed approach without denoising. e) Proposed approach with denoising.

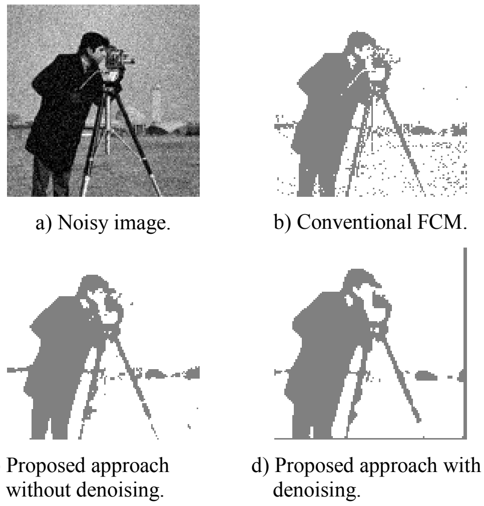
Figure 3. Segmentation results of original brain MRI image with 15% noise.



a) Original cameraman image. b) Noisy image. c) Conventional FCM.

d) Proposed approach without denoising. e) Proposed approach with denoising.

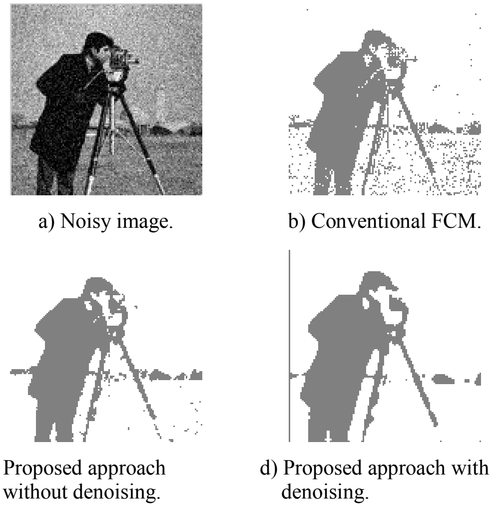
Figure 4. Segmentation results of cameraman with 5% noise.



a) Noisy image. b) Conventional FCM.

c) Proposed approach without denoising. d) Proposed approach with denoising.

Figure 5. Segmentation results of cameraman with 15% noise.



a) Noisy image. b) Conventional FCM.

c) Proposed approach without denoising. d) Proposed approach with denoising.

Figure 6. Segmentation results of cameraman with 20% noise.

5. Conclusions

In this paper, we have presented a robust and effective approach for the segmentation of medical images corrupted by noise. For the segmentation of noisy medical images, the proposed approach utilized a histogram based Fuzzy C-Means clustering with spatial probability. The robustness of the presented approach is ascended by the incorporation of spatial probability into the objective function of FCM. The robustness of the proposed approach is further improved by the denoising of noisy images prior to segmentation with the help of LPG-PCA based denoising algorithm. For different noise levels, the presented approach has been found robust. The efficiency and robustness of the proposed approach in segmenting noisy medical (MRI) as well as real images has been demonstrated using the experimentation with synthetic and real images.

References

[1] Ahmed M., Yamany S., Mohamed N., Farag A., and Moriarty T., "A Modified Fuzzy C-Means Algorithm for Bias Field Estimation and

Segmentation of MRI Data," *Computer Journal of IEEE Transactions on Medical Imaging*, vol. 21, no. 3, pp.193-199, 2002.

[2] Ayache N., Cinquin P., Cohen I., Cohen L., Leitner F., and Monga O., "Segmentation of Complex Three Dimensional Medical Objects: A Challenge and a Requirement for Computer-Assisted Surgery Planning and Performance," in Taylor R., Lavallee S., Burdea G., and Mosges R., (Eds), Computer-Integrated Surgery: Technology and Clinical Applications, MIT Press, pp. 59-74, 1996.

[3] Balafar M., Ramli R., Saripan M., Mahmud R., Mashohor S., and Balafar M., "New Multi-Scale Medical Image Segmentation Based on Fuzzy C-Mean (FCM)," *in Proceedings of IEEE Conference on Innovative Technologies in Intelligent Systems and Industrial Applications*, Cyberjaya, pp. 66-70, 2008.

[4] Bezdek J., *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, New York, 1981.

[5] Bezdek J., Hall L., and Clarke L., "Review of MR Image Segmentation Techniques Using Pattern Recognition," *Computer Journal of Medical Physics*, vol. 20, no. 4, pp.1033-1048, 1993.

[6] Chen S. and Zhang D., "Robust Image Segmentation Using FCM with Spatial Constraints Based on New Kernel-Induced Distance Measure," *Computer Journal of IEEE Transactions on Systems, Man, and Cybernetics*, vol. 34, no. 4, pp.1907–1916, 2004.

[7] Chuang K., Tzeng H., Chen S., Wua J., and Chen T., "Fuzzy C-Means Clustering with Spatial Information for Image Segmentation," *Computer Journal of Medical Imaging and Graphics*, vol. 30, no. 1, pp. 9-15, 2006.

[8] Dawant B., Zijidenbos A., and Margolin R., "Correction of Intensity Variations in MR Image for Computer-Aided Tissue Classification," *IEEE Transactions on Medical Imaging*, vol. 12, no. 4, pp. 770-781, 1993.

[9] Dong G. and Xie M., "Color Clustering and Learning for Image Segmentation Based on Neural Networks," *Compute IEEE Transactions on Neural Networks*, vol. 16, no. 4, pp. 925-936, 2005.

[10] Du R. and Lee H., "A Modified-FCM Segmentation Algorithm for Brain MR Images," *in Proceedings of ACM International Conference on Hybrid Information Technology*, Hubei, pp. 25-27, 2009.

[11] Dunn J., "A Fuzzy Relative of the ISODATA Process and Its Use in Detecting Compact Well Separated Clusters," *Journal of Cybernetics*, vol. 3, no. 3, pp. 32-57, 1974.

[12] Fan J., Zhen W., and Xie W., "Suppressed Fuzzy C-Means Clustering Algorithm," *Pattern Recognition Letters*, vol. 24, no. 9-10, pp. 1607-1612, 2003.

[13] Grimson W., Ettinger G., Kapur T., Leventon M., Wells W., and Kikinis R., "Utilizing Segmented MRI Data in Image Guided Surgery," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 11, no. 8, pp. 1367-1397, 1998.

[14] Haralick R. and Shaprio L., "Image Segmentation Techniques," *Computer Vision, Graphics and Image Processing*, vol. 29, no. 1, pp. 100-132, 1985.

[15] Hsieh C., Kuo C., Chao C., and Lu P., "Image Segmentation Based on Fuzzy Clustering Algorithm," *IAPR Workshop on Machine Vision Applications*, Japan, pp. 460-463, 1994.

[16] Huang Z., Xie Y., Liu D., and Hou L., "Using Fuzzy C-means Cluster for Histogram-Based Color Image Segmentation," *in Proceedings of the 2009 International Conference on Information Technology and Computer Science*, Ukraine, pp. 597-600, 2009.

[17] Hung W., Yang M., and Chen D., "Parameter Selection for Suppressed Fuzzy C-Means with an Application to MRI Segmentation," *Pattern Recognition Letters*, vol. 27, no. 5, pp. 424-438, 2006.

[18] Johnson B., Atkins M., Mackiewich B., and Andson M., "Segmentation of Multiple Sclerosis Lesions in Intensity Corrected Multispectral MRI," *IEEE Transactions on Medical Imaging*, vol. 15, no. 2, pp. 154-169, 1996.

[19] Kannan S., Ramathilagam S., and Sathya A., "Robust Fuzzy C-Means in Classifying Breast Tissue Regions," *in Proceedings of ARTCOM International Conference on Advances in Recent Technologies in Communication and Computing*, Kerala, pp. 543-545, 2009.

[20] Khoo V., Dearnaley D., Finnigan D., Padhani A., Tanner S., and Leach M., "Magnetic Resonance Imaging (MRI): Considerations and Applications in Radiotherapy Treatment Planning," *Radiotherapy and Oncology*, vol. 42, no. 1, pp. 1-15, 1997.

[21] Lai C. and Chang C., "A Hierarchical Evolutionary Algorithm for Automatic Medical Image Segmentation," *An International Journal Expert Systems with Applications*, vol. 36, no. 1, pp. 248-259, 2009.

[22] Larie S. and Abukmeil S., "Brain Abnormality in Schizophrenia: A Systematic and Quantitative Review of Volumetric Magnetic Resonance Imaging Studies," *The British Journal of Psychiatry*, vol. 172, no. 2, pp. 110-120, 1998.

[23] Liew A., Yan H., Law N., "Image Segmentation Based on Adaptive Cluster Prototype

Estimation," *IEEE Transactions on Fuzzy Systems*, vol. 13, no. 4, pp. 444-453, 2005.

[24] Li M., Huang T., and Zhu G., "Improved Fast Fuzzy C-Means Algorithm for Medical MR Images Segmentation," *in Proceedings of the WGEC Second International Conference on Genetic and Evolutionary Computing*, Hubei, pp. 285-288, 2008.

[25] Lung H. and Kim J., "A Generalized Spatial Fuzzy C-Means Algorithm for Medical Image Segmentation," *in Proceedings of the 18th International Conference on Fuzzy Systems*, Jeju-Island, pp. 409-414, 2009.

[26] Mendes M. and Sacks L., "Assessment of the Performance of Fuzzy Cluster Analysis in the Classification of RFC Documents," *in Proceedings of the 2000 London Communications Symposium*, London, pp. 1-5, 2000.

[27] Muller-Gartner H., Links J., Prince J., Bryan R., McVeigh E., Leal J., Davatzikos C. and Frost J., "Measurement of Radiotracer Concentration in Brain Gray Matter using Positron Emission Tomography: MRI-Based Correction for Partial Volume Effects," *Compute Journal of Cerebral Blood Flow and Metabolism*, vol. 12, no. 4, pp. 571-583, 1992.

[28] Murugavalli S. and Rajamani V., "A High Speed Parallel Fuzzy C-Mean Algorithm for Brain Tumor Segmentation," *ICGST International Journal on Bioinformatics and Medical Engineering,* vol. 6, no. 1, pp. 29-34, 2006.

[29] Noordam J., Van den Broek W., and Buydens L., "Geometrically Guided Fuzzy C-Means Clustering for Multivariate Image Segmentation," *in Proceedings of International Conference on Pattern Recognition,* USA, pp. 462-465, 2000.

[30] Pal N. and Pal S., "A Review on Image Segmentation Techniques," *Pattern Recognition*, vol. 26, no. 9, pp. 1277–1294, 1993.

[31] Pal N., Pal K., Keller J., and Bezdek J., "A Possibilistic Fuzzy C-Means Clustering Algorithm," *IEEE Transactions on Fuzzy Systems*, vol. 13, no. 4, pp. 517-530, 2005.

[32] Pham D. and Prince J., "An Adaptive Fuzzy C-Means Algorithm for Image Segmentation in the Presence of Intensity Inhomogeneities," *Pattern Recognition Letters*, vol. 20, no. 1, pp. 57-68, 1999.

[33] Pham D., Xu C., and Prince J., "A Survey of Current Methods in Medical Image Segmentation," *Annual Review of Biomedical Engineering*, vol. 2, no. 3, pp. 315-337, 2000.

[34] Salman N., "Image Segmentation Based on Watershed and Edge Detection Techniques," *The International Arab Journal of Information Technology*, vol. 3, no. 2, pp. 104-110, 2006.

[35] Sudhavani G. and Sathyaprasad K., "Segmentation of Lip Images by Modified Fuzzy C-Means Clustering Algorithm," *International Journal of Computer Science and Network Security IJCSNS*, vol. 9, no. 4, pp. 187-191, 2009.

[36] Taylor P., "Invited Review: Computer Aids for Decision-Making in Diagnostic Radiology - A Literature Review," *The British Journal of Radiology*, vol. 68, no. 813, pp. 945-957, 1995.

[37] Tolias Y. and Panas S., "On Applying Spatial Constraints in Fuzzy Image Clustering Using a Fuzzy Rule Based System," *IEEE Signal Processing Letters,* vol. 5, no. 10, pp. 245-247, 1998.

[38] Tolias Y. and Panas S., "Image Segmentation by a Fuzzy Clustering Algorithm using Adaptive Spatially Constrained Membership Functions," *IEEE Transactions on Systems, Man, Cybernetics,* vol. 28, no. 3, pp. 359-369, 1998.

[39] Wang Z. and Lu R., "A New Algorithm for Image Segmentation Based on Fast Fuzzy C-Means Clustering," *in Proceedings of the 2008 International Conference on Computer Science and Software Engineering*, USA, pp. 14-17, 2008.

[40] Wells W., LGrimson W., Kikinis R., and Arrdrige S., "Adaptive Segmentation of MRI Data," *IEEE Transactions on Medical Imaging*, vol. 15, no. 4, pp. 429-442, 1996.

[41] Worth A., Makris N., Caviness V., and Kennedy D., "Neuroanatomical Segmentation in MRI: Technological Objectives," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 11, no. 8, pp. 1161-1187, 1997.

[42] Wu K. and Yang M., "Alternative C-Means Clustering Algorithms," *Pattern Recognition*, vol. 35, no. 10, pp. 2267-2278, 2002.

[43] Yang M. and Wu K., "A Similarity-Based Robust Clustering Method," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 4, pp. 434-448, 2004.

[44] Yang Y., Zheng C., and Lin P., "Fuzzy C-Means Clustering Algorithm with a Novel Penalty Term for Image Segmentation," *Opto-Electronics Review*, vol. 13, no. 4, pp. 309-315, 2005.

[45] Yu J. and Wang Y., "Molecular Image Segmentation Based on Improved Fuzzy Clustering," *Journal of Biomedical Imaging*, vol. 2007, no. 1687, pp. 1-9, 2008.

[46] Zhang L., Dong W., Zhang D., and Shi G., "Two-Stage Image Denoising by Principal Component Analysis with Local Pixel Grouping," *Pattern Recognition*, vol. 43, pp. 1531-1549, 2010.

[47] Zhou H., Schaefer G., Sadka A., and Celebi E., "Anisotropic Mean Shift Based Fuzzy C-Means Segmentation of Skin Lesions," *in Proceedings*

of the 5th International Conference on Soft Computing as Transdisciplinary Science and Technology, USA, pp. 438-443, 2008.

[48] Zijdenbos A. and Dawant B., "Brain Segmentation and White Matter Lesion Detection in MR Images," *Critical Reviews in Biomedical Engineering*, vol. 22, no. 5-6, pp. 401-465, 1994.

[49] Zulaikha S. and Mohamed M., "An Effective Approach for Segmentation of MRI Images: Combining Spatial Information with Fuzzy C-Means Clustering," *European Journal of Scientific Research*, vol. 41, no. 3, pp. 437-451, 2010.

Zulaikha Beevi received her BE, degree from the Department of Civil and Transportation Engineering, Institute of Road and Transport Technology, TamilNadu, India and her M.Tech from the Department of Center for Information Technology and Engineering, Manonmaniam Sundaranar University, TamilNadu, India in 1992 and 2005, respectively. Currently, she is pursuing her PhD, working with Prof. M. Mohamed Sathik and Prof. K. Senthamarai Kannan. She is working as an assistant professor in National College of Engineering, Tirunelveli, TamilNadu, India.

Mohamed Sathik received his BSc, and MSc degrees from the Department of Mathematics, and his M.Phill. from the Department of Computer Science, and his M.Tech in computer science and IT, MS, from the Department of Counseling and Psycho Therapy, and his MBA degree from reputed institutions. He has two years working experience as a coordinator for M.Phil Computer Science Program, Directorate of Distance and Continuing Education, M.S. University. He served as an additional coordinator in Indra Gandhi National Open University for four years. He headed the University Study Center for MCA Week End Course, Manonmaniam Sundaranar University for 9 years. He has been with the department of Computer Science, Sadakathullah Appa College for 23 years. Currently, he is working as a reader for the same department. He works in the field of image processing, specializing particularly in medical imaging. Dr. Mohamed Sathik guided 30 M.Phil Computer Science Scholors and guiding 14 Ph.D Computer Science Scholor from M.S. University, Tirunelveli, Barathiyar University, Coimbatore and Periyar Maniammai University, Tanjavur. He presented 12 papers in international conferences in image processing and presented 10 papers in national conferences. He published 3 papers in international journals and 5 papers in proceedings with ISBN.