CHAPTER-III
SEGMENTATION ALGORITHM USING FUZZY CLUSTERING

3.1 Fuzzy Clustering

Medical image segmentation demands an efficient and robust segmentation algorithm against noise. The conventional fuzzy c-means algorithm is an efficient clustering algorithm that is used in medical image segmentation. But FCM is highly vulnerable to noise since it uses only intensity values for clustering the images. This paper aims to develop an efficient fuzzy spatial c-means clustering algorithm which is robust to noise. The proposed clustering algorithm uses fuzzy spatial information to calculate membership value. To make the approach more robust to noise, the input image is denoised using an efficient denoising algorithm and then clustered using proposed FSCM [41] algorithm. A comparative study has been made between the conventional FCM and proposed FSCM. The proposed approach is found to be outperforming the conventional FCM.

In medical imaging, segmentation becomes extremely troublesome due to the complexity of images, and the absence of the models of the anatomy that fully capture the possible deformation in each structure. The medical images are often prone to severe noise, thus segmenting medical images are still a challenge for the field of signal processing. There are huge amount of works done for medical image segmentation with intent to improve the segmentation accuracy. Medical image segmentation techniques still need to be reconsidered,
and it is in the need of an efficient algorithm. The fuzzy c-means (FCM) algorithm is a well known clustering algorithm used for image segmentation. FCM does not use spatial information for image segmentation. So it is highly vulnerable to noise. The clustering technique which uses only intensity values for clustering can be extended to robust against noise by incorporating fuzzy spatial information. In this paper a novel fuzzy spatial c-means clustering for medical image segmentation is proposed. The input medical image is first denoised using an efficient denoising algorithm. The fuzzy c means parameters are initialized using histogram based fuzzy c means clustering to avoid local minima. The initial parameters obtained are used in clustering the image using proposed fuzzy spatial c means (FSCM) algorithm. FSCM uses fuzzy spatial information for clustering the images. The denoising and application of spatial information in clustering make the proposed algorithm to be robust against noise.

3.2 Related Works In Fuzzy System

There are huge amount of works related to enhancing the conventional FCM and other forms for image segmentation are found in the literature. Let us review some of them. Smaine Mazouzi and Mohamed Batouche [85] have presented an approach for improving range image segmentation, based on fuzzy regularization of the detected edges. Initially, a degraded version of the segmentation was produced by a new region growing- based algorithm. Next, the resulting segmentation was refined by a robust fuzzy classification of the pixels on the resulting edges which correspond to border of the extracted regions. Pixels on the boundary between two adjacent regions are labeled taking into account the two regions as fuzzy sets in the fuzzy classification stage, using an improved version of the Fuzzy C-Mean algorithm. The process was repeated for all region boundaries in the image.
A two-dimensional fuzzy C-means (2DFCM) algorithm was proposed by Jinhua Yu and Yuanyuan Wang [47] for the molecular image segmentation. The 2DFCM algorithm was composed of three stages. The first stage was the noise suppression by utilizing a method combining a Gaussian noise filter and anisotropic diffusion techniques. The second stage was the texture energy characterization using a Gabor wavelet method. The third stage was introducing spatial constraints provided by the denoising data and the textural information into the two-dimensional fuzzy clustering. The incorporation of intensity and textural information allow the 2DFCM algorithm to produce satisfactory segmentation results for images corrupted by noise (outliers) and intensity variations.

Hadi Sadoghi Yazdi and Jalal A. Nasiri [36] have presented a fuzzy image segmentation algorithm. In their algorithm, human knowledge was used in clustering features for fuzzy image segmentation. In fuzzy clustering, the membership values of extracted features for each pixel at each cluster change proportional to zonal mean of membership values and gradient mean of adjacent pixels. The direction of membership variations are specified using human interaction. Their segmentation approach was applied for segmentation of texture and documentation images and the results have shown that the human interaction eventuates to clarification of texture and reduction of noise in segmented images.

G.Sudhavani and Dr.K.Sathyaprasad [88] have described the application of a modified fuzzy C-means clustering algorithm to the lip segmentation problem. The modified fuzzy C-means algorithm [5] was able to take the initial membership function from the spatially connected neighboring pixels. Successful segmentation of lip images was possible
with their method. Comparative study of their modified fuzzy C-means was done with the traditional fuzzy C-means algorithm by using Pratt's Figure of Merit. (2009)

B. Sowmya and B. Sheelarani [87] have explained the task of segmenting any given color image using soft computing techniques. The most basic attribute for segmentation was image luminance amplitude for a monochrome image and color components for a color image. Since there are more than 16 million colors available in any given image and it was difficult to analyze the image on all of its colors, the likely colors are grouped together by image segmentation. For that purpose soft computing techniques have been used. The soft computing techniques used are Fuzzy C- Means algorithm (FCM,) Possibilistic C - Means algorithm (PCM) and competitive neural network. A self estimation algorithm was developed for determining the number of clusters.

Agus Zainal Arifin and Akira Asano [4] have proposed a method of image thresholding by using cluster organization from the histogram of an image. A similarity measure proposed by them was based on inter-class variance of the clusters to be merged and the intra-class variance of the new merged cluster. Experiments on practical images have illustrated the effectiveness of their method. (2006)

A high speed parallel fuzzy C means algorithm for brain tumor image segmentation is presented by S. Murugavalli and V. Rajamani [68]. Their algorithm has the advantages of both the sequential FCM and parallel FCM for the clustering process in the segmentation techniques and the algorithm was very fast when the image size was large and also it requires less execution time. They have also achieved less processing speed and minimizing the need for accessing secondary storage compared to the previous results. The reduction in the
computation time was primarily due to the selection of actual cluster centre and the accessing minimum secondary storage. (2006)

T. Bala Ganesan and R. Sukanesh [10] have dealt with Brain Magnetic Resonance Image Segmentation. Any medical image of human being consists of distinct regions and these regions could be represented by wavelet coefficients. Classification of these features was performed using Fuzzy Clustering method (FCM Fuzzy C-Means Algorithm). Edge detection technique was used to detect the edges of the given images. Silhouette method was used to find the strength of clusters. Finally, the different regions of the images are demarcated and color coded. (2008)

H. C. Sateesh Kumar et al. [80] have proposed Automatic Image Segmentation using Wavelets (AISWT) to make segmentation fast and simpler. The approximation band of image Discrete Wavelet Transform was considered for segmentation which contains significant information of the input image. The Histogram based algorithm was used to obtain the number of regions and the initial parameters like mean, variance and mixing factor. The final parameters are obtained by using the Expectation and Maximization algorithm. The segmentation of the approximation coefficients was determined by Maximum Likelihood function.

Histogram specification was proposed by Gabriel Thomas [33] as a way to improve image segmentation. Specification of the final histogram was done relatively easy and all it takes is the definition of a low pass filter and the amplification and attenuation of the peaks and valleys respectively or the standard deviation of the assumed Gaussian modes in the final specification. Examples showing better segmentation were presented. The attractive side of
their approach was the easy implementation that was needed to obtain considerable better results during the segmentation process.

3.3 Preprocessing

The main characteristics of medical images are noise, blurred edges which make complexities in segmentation. The preprocessing step removes the noise in the image using sparse 3D transform-domain collaborative filtering [53].

3.3.1 Sparse 3D Transform-Domain Collaborative Filtering

The input noisy image is processed by successively extracting reference blocks from it using a sliding window. Block matching (BM) is the next step which is the process of stacking of the image blocks together that are similar to the reference block to form a 3D array (group). Grouping is the collection of similar D dimensional fragments of a given signal into a D+1 dimensional data structure which is called group. The block matching becomes inefficient due to the noise in the image, so first a basic estimate is determined by hard-thresholding. The obtained basic estimate is used to calculate the coefficients for weiner filtering so that the accuracy improves. The measurement of the block-distance is done after a coarse prefiltering. This prefiltering is realized by applying a normalized 2D linear transform (DCT) on both blocks and then hard-thresholding the obtained coefficients. The block-distance \(d(Z_{x_R}, Z_x)\) is given by,

\[
d(Z_{x_R}, Z_x) = \frac{\left\| \gamma'(T_{2D}^{ht}(Z_{x_R})) - \gamma'(T_{2D}^{ht}(Z_x)) \right\|_2^2}{(N_1^{ht})^2}
\]  

(3-1)
where \( Y \) is the hard-thresholding operator with threshold \( \lambda \), \( N^\text{ht} \) is the block-size and \( T^\text{ht}_{2D} \) denotes the normalized 2D linear transform. \( Z \) is located at coordinate \( x, N \in X \) in noisy image \( z \) and \( \hat{Z}_x \) is the reference block located at the current coordinate \( x \in X \).

Using the \( d \)-distance (1), the result of BM is a set \( S^\text{ht}_{x,R} \) that contains the coordinates of the blocks that are similar to \( \hat{Z}_x \).

\[
S^\text{ht}_{x,R} = \left\{ x \in X : d(\hat{Z}_x, Z_x) \leq T^\text{match}_{\text{ht}} \right\}
\]

where the fixed \( T^\text{match}_{\text{ht}} \) is the maximum \( d \)-distance for which two blocks are considered similar.

Hard-thresholding is applied for the blocks or groups in their 3D transform domain. After the effective noise attenuation by hard-thresholding, inverse transform is applied which yields a 3D array of block-wise basic estimates. Thus the collaborative filtering of \( Z^\text{ht}_{x,a} \) is realized.

\[
\hat{Y}^\text{ht}_{S^\text{ht}_{x,R}} = T^\text{ht}_{3D}^{-1} \left( \gamma \left( T^\text{ht}_{3D} \left( Z^\text{ht}_{S^\text{ht}_{x,R}} \right) \right) \right)
\]

Where \( \gamma \) is a hard-threshold operator. The array \( \hat{Y}^\text{ht}_{S^\text{ht}_{x,a}} \) comprises of \( S^\text{ht}_{x,a} \) stacked block-wise estimates, \( \forall x \in S^\text{ht}_{x,a} \), \( T^\text{ht}_{3D} \) denotes normalized 3D transform.
In $Y_{xR}$ the subscript $x$ denotes the location of this block-estimate and the subscript XR indicates the reference block.

By using the basic estimate $y$ of the true image, denoising can be improved by performing grouping within this basic estimate and collaborative empirical Wiener filtering.

Hence, the coordinates of the matched blocks are the elements of the set $S_{xR}^{wie}$.

$$S_{xR}^{wie} = \left\{ x \in X : \frac{\| \hat{Y}_{xR}^{basic} - \hat{Y}_x^{basic} \|}{\left( N_{wie}^1 \right)^2} \right\}$$

(3-4)

The set $S_{xR}^{wie}$ is used to form two groups, one by stacking together the basic estimate blocks $\hat{Y}_{x \in S_{xR}^{wie}}^{basic}$ and another by stacking together the noisy blocks $Z_{x \in S_{xR}^{wie}}$.

The empirical Wiener shrinkage coefficients are determined from the energy of the 3D transform coefficients of the basic estimate group as

$$W_{S_{xR}^{wie}}^{wie} = \left[ \begin{array}{c} T_{3D}^{wie} (\hat{Y}_{S_{xR}^{wie}}^{basic}) \\ T_{3D}^{wie} (\hat{Y}_{S_{xR}^{wie}}^{basic}) \end{array} \right]^2 + \sigma^2$$

(3-5)

Then the collaborative Wiener filtering of $Z_{xR}^{wie}$ is realized as the element-by-element multiplication of the 3D transform $T_{3D}^{wie} (Z_{xR}^{wie})$ coefficients of the noisy data with the Wiener
shrinkage coefficients \( W_{S_x} \). Subsequently, the inverse transform \( T_{3D}^{-1} \) produces the group of estimates,

\[
\hat{Y}_{S_{x,R}}^{wie} = T_{3D}^{-1} \left( W_{S_{x,R}}^{wie} T_{3D}^{wie} (Z_{S_{x,R}}^{wie}) \right)
\]  

(3-6)

This group comprises of the block-wise basic estimates \( \hat{Y}_{S_{x,R}}^{wie} \) located at the matched locations \( x \in S_{x,R}^{wie} \). To compute the basic and the final estimates of the true image, aggregation of the corresponding block-wise estimates \( \hat{Y}_{x,R}^{wie, x_R} \) and \( \hat{Y}_{x,R}^{ht, x_R} \), \( \forall x_R \in X \) is done. Aggregation is performed by a weighted averaging at those pixel positions where there are overlapping block-wise estimates. Aggregation weight is given by,

\[
W_{x,R}^{ht} = \begin{cases} 
\frac{1}{\sigma_x^2 N_{x,R}^{har}} & \text{if } N_{x,R}^{har} \geq 1 \\
1 & \text{otherwise}
\end{cases}
\]  

(3-7)

If the additive noise in the groups \( Z_{S_x}^{wie} \) and \( Z_{S_x}^{we} \) is independent, the total sample variance in the corresponding groups of estimates (6) and (9) is respectively equal to \( \sigma_x^2 N_{x,R}^{har} \) and \( \sigma_x^2 \)

\[
\left\| W_{S_{x,R}}^{wie} \right\|_2^2, \text{ where } N_{x,R}^{har} \text{ is the number of retained (nonzero) coefficients after hard-thresholding}
\]

and \( W_{S_x} \) are the Wiener filter coefficients.
Finally the global basic estimate $y^{basic}$ is computed by a weighted average of the block-wise $y^{ht,sx}$ estimates using the weights $w^{ht,sx}$,

$$y^{basic}_{x_R}(x) = \frac{\sum_{x_R \in X} \sum_{x_m \in S^{ht}_{x_R}} w^{ht}_{x_R} y^{ht,sx}_{x_R}(x)}{\sum_{x_R \in X} \sum_{x_m \in S^{ht}_{x_R}} w^{ht}_{x_R} x^{ht}_{x_R}(x)}, \forall x \in X$$  \hspace{1cm} (3-8)

where $X_{sx} : X \rightarrow \{0,1\}$ is the characteristic function of the square support of a block located at $x_{sx} \in X$, and the block-wise estimates $y^{ht,sx}$ are zero-padded outside of their support. The global final estimate $y^{final}$ is computed by $y^{basic}_{sx}(x)$, where $y^{basic}_{sx}(x), y^{ht,sx}_{sx}, s^{wie}_{sx}$ and $w^{ht}_{sx}$ are replaced by $y^{final}, y^{basic}_{sx}, s^{wie}_{x_R}$ and $w^{wie}_{x_R}$. Thus $y^{final}$ contains the denoised image which is the input for the fuzzy spatial c-means clustering algorithm.

### 3.4. Proposed Fuzzy Spatial C-Means Clustering (FSCM):

#### 3.4.1 Conventional FCM:

Clustering is the process of finding groups in unlabeled dataset based on a similarity measure between the data patterns (elements) [50]. A cluster contains similar patterns placed together. The fuzzy clustering technique generates fuzzy partitions of the data instead of hard partitions. Therefore, data patterns may belong to several clusters, having different membership values with different clusters. The membership value of a data pattern to a cluster denotes similarity between the given data pattern to the cluster. Given a set of $n$ data
patterns, $X = x_1, \ldots, x_k, \ldots, x_n$, the fuzzy clustering technique minimizes the objective function, $O(U,C)$:

$$O_{fcm}(U, C) = \sum_{k=1}^{n} \sum_{i=1}^{v} (u_{ik})^m d^2(x_k, c_i)$$  \hspace{1cm} (3-9)$$

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, $v$ is the number of clusters. The minimization of objective function $J(U, C)$ can be brought by an iterative process in which updating of degree of membership $u_{ik}$ and the cluster centers are done for each iteration.

$$u_{ik} = \frac{1}{\sum_{j=1}^{v} (\frac{d_{ik}}{d_{ij}})^{m-1}}$$  \hspace{1cm} (3-10)$$

$$c_j = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m}$$  \hspace{1cm} (3-11)$$

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

Thus the conventional clustering technique clusters an image data only with the intensity values but it does not use the spatial information of the given image.

3.4.2 Initialization:

The theory of Markov random field says that pixels in the image mostly belong to the same cluster as their neighbors. The incorporation of spatial information in the clustering process
makes the algorithm robust to noise and blurred edges. But when using spatial information in
the clustering optimization function may converge in local minima, so to avoid this problem
the fuzzy spatial c means algorithm is initialized with the Histogram based fuzzy c-means
algorithm. The optimization function for histogram based fuzzy clustering is given by,

\[ O_{hscm}(U,C) = \sum_{i=1}^{C} \sum_{l=1}^{L} (u_{il})^m H(l) \ d^2(l,c_i) \]  

(3-12)

where \( H \) is the histogram of the image of L-gray levels. Gray level of all the pixels in the
image lies in the new discrete set \( G = \{0,1,\ldots,L-1\} \). The computation of membership degrees
of \( H(l) \) pixels is reduced to that of only one pixel with \( l \) as grey level value. The member ship
function \( u_{il} \) and center for histogram based fuzzy c-means clustering can be calculated as.

\[ u_{il} = \frac{1}{\sum_{j=1}^{V} \left( \frac{d_{ij}}{d_{jl}} \right)^{m-1}} \]  

(3-13)

\[ c_i = \frac{\sum_{l=1}^{L} (u_{il})^m H(l) l}{\sum_{l=1}^{L} (u_{il})^m} \]  

(3-14)

where \( d_{ij} \) is the distance between the center \( i \) and the gray level \( l \)

3.4.3 Proposed IFSCM:

The histogram based FCM algorithm converges quickly since it clusters the histogram instead
of the whole image. The center and membership values of all the pixels are given as input to
the fuzzy spatial c-means algorithm. The main goal of the FSCM [50] is to use the spatial information to decide the class of a pixel in the image.

The objective function of the proposed FSCM is given by

$$O_{FCM}(U, C) = \sum_{k=1}^{n} \sum_{j=1}^{m} (u_{ik}^s)^m d^2(x_k, c_i)$$  \hspace{1cm} (3-15)

The spatial membership function $u_{ik}^s$ of the proposed FSCM is calculated as

$$u_{ik}^s = \frac{P_{ik}}{\sum_{k=1}^{m} \left( \frac{d_{ik}}{d_{ij}} \right)^{m-1} \left( \frac{NN_i(k)}{N_k} \sum_{j=1}^{N_i} \left( \frac{d_{ij}}{d_{ij}} \right)^{m-1} \right)}$$  \hspace{1cm} (3-16)

where $P_{ik}$ is the apriori probability that $k^{th}$ pixel belongs to $i^{th}$ cluster and calculated as

$$P_{ik} = \frac{NN_i(k)}{N_k}$$  \hspace{1cm} (3-17)

where $NN_i(k)$ is the number of pixels in the neighborhood of $k^{th}$ pixel that 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 $i^{th}$ Thus the center $c_i^s$ of each cluster is calculated as

$$c_i^s = \frac{\sum_{k=1}^{n} (u_{ik}^s)^m x_k}{\sum_{k=1}^{n} (u_{ik}^s)^m}$$  \hspace{1cm} (3-18)

Two kinds of spatial information are incorporated in the membership function of conventional FCM.

1. Apriori probability
2. Fuzzy spatial information

**Apriori probability:**

This parameter assigns a noise pixel to one of the clusters to which its neighborhood pixels belong. The noise pixel is included in the cluster whose members are majority in the pixels neighborhood.

**Fuzzy spatial information:**

In the equation (3-12) the second term in the denominator is the average of fuzzy membership of the neighborhood pixel to a cluster. Thus a pixel gets higher membership value when their neighborhood pixels have high membership value with the corresponding cluster.

### 3.5. Results and Discussion

The proposed FSCM algorithm converges very quickly because it gets initial parameters form already converged histogram based FCM. The proposed approach is applied on three kinds of images real world images, synthetic brain MRI image, original brain MRI image. In all the images additive Gaussian white noise is added with noise percentage level 0%, 5%, 15%, and 25% and corresponding results are shown. The quality of segmentation of the proposed algorithm can be calculated by segmentation accuracy $A_s$ given as.

$$A_s = \frac{N_c}{T_p} \times 100$$  (3-19)

$N_c$ is the number of correctly classified pixels, and $T_p$ is the total number pixels in the given image.
Figure 12: Segmentation accuracy of FCM, FSCM and FSCMD with denoising in segmenting synthetic brain MRI images with different noise level percentage.
Figure 13 Segmentation results of synthetic brain MRI image with 15% noise. (a) Noisy image. (b) Conventional FCM (c) Proposed approach without denoising. (d) Proposed approach with denoising. (e) Base true.
Figure 14 Segmentation results of original brain MRI image. (a) Original brain MRI image with tumor. (b) Conventional FCM (c) Proposed approach without denoising (d) Proposed approach with denoising.

The standard test image cameraman is used in the experiments with real-world image. From the segmentation results of cameraman image, it is clear that the proposed approach with denoising produces improved results for higher noise levels. The original image and the results for different noise levels 5%, 15% and 25% are shown in Figure 4, 5 and 6 respectively. The proposed algorithm with denoising produced better results even under the noise level 25% in which the conventional FCM produced poor results.
Figure 15 Segmentation results of cameraman with 5% noise (a) Original cameraman image (b) Noisy image. (c) Conventional FCM (d) Proposed approach without denoising (e) Proposed approach with denoising
A Robust Segmentation Approach for Noisy Medical Images Using Fuzzy Clustering With Spatial Probability.

Figure 1.6 Segmentation results of cameraman with 25% noise (a) Noisy image (b) Conventional FCM (c) Proposed approach without denoising (d) Proposed approach with denoising.
3.6 Discussion and Conclusion

In this work, an efficient and robust fuzzy spatial c-means clustering algorithm for medical image segmentation is developed. The proposed method denoises the input image using sparse 3D transform-domain collaborative filtering. The denoised image is used for segmentation, histogram based FCM is used for initializing the parameters of proposed FSCM. The novel FSCM uses the initial parameters and refines the clustering by taking into account of fuzzy spatial information. The proposed algorithm is found to be robust against noise. Experimental results show that the proposed algorithm outperforms the conventional FCM.