Enhancement of Magnetic Resonance Images Using Soft Computing Based Segmentation

Arshad Javed, Wang Yin Chai, Abdulhameed Rakan Alenezi, and Narayan Kulathuramaiyer

***Abstract*—Segmentation is the process of extracting points, lines or regions, which are then used as inputs for complementary tasks such as registration, measurement, movement analysis, visualization , etc in MRI. The noise in MR images degrades the image quality and also affect on the segmentation process which can lead to wrong diagnosis. The main aim of this study is to suggest a system to enhance the quality of the human brain MRI. In the proposed system, median filter is used for image enhancement of brain MRI and fuzzy *c*-means for segmentation purpose. The proposed method is completely automatic that is there is no user involvement in the proposed system. The system is tested on different kinds of brain MR images and proved robust against noise as well as segments the images fast with improvements.**

***Index Terms*—Dunn's index, fuzzy *c*-means (FCM), image segmentation, median filter.**

I. Introduction

Segmentation subdivides a digital image into non-overlapping regions or objects having the similar features. In other terms, Image segmentation splits an image into significant portions with respect to some particular problem.

Magnetic Resonance Imaging (MRI) is a medical imaging method widely employed by the radiologist to diagnose the severity of the disease. Segmentation and Classification of images has become an important and effective tool for many technological applications like brain tumor segmentation from MR images, classify image a benign or malignant and many other post-processing techniques.

Segmentation is considered to be an essential step for many applications of the image processing. Up till now, no general segmentation method is proposed yet that is appropriate for all the image analysis application. Segmentation partition an image into groups that have homogenous information inside them and are heterogeneous of each other. These groups are known as segments. These segments further used for analysis and extracting useful information from the image. General segmentation techniques methods are categorized into major four following categories: Thresholding Approaches, Region Based Approaches, Markov Random Field and Artificial Neural Network (ANN) [1].

Tumor segmentation from MRI data is an important but time-consuming manual task performed by medical experts [2]. To Automate this process is difficult and challenging task due to high diversity in appearance of tumor tissue among different patients and, in numerous cases, resemblance with normal tissue.

In the past decade, many researchers proposed several automated segmentation methods with the combination of different techniques. These methods include, thresholding-region growing, edge detection-morphological and surface growing, seeded region growing algorithm based method, histogram-morphology based method, deformable surface modeling etc. All the segmentation methods are intensity dependent and may cause problem with phase map data. The one possible solution is fuzzy clustering. Brain has very complex structure in its nature. All tissues are connected with each other and MR images always present overlapping intensities for different tissues because of the noise and blur in acquisition [3]. Separation of these tissue classes and automatic segmentation is challenging due to the wide variety of tumor locations, sizes and shapes. In particular, boundaries between tissues are not clearly defined and memberships in the boundary regions are inherently fuzzy [4]. The conventional (hard) clustering methods restrict each point of the data set to exactly one cluster. Fuzzy sets give the idea of uncertainty of belonging described by a membership function. Therefore, fuzzy clustering methods turn out to be particularly suitable for the segmentation of MRI medical images [5].

There are many types of noises like *speckle*, *Gaussian*, *poison* and *salt & pepper* etc. But the most frequently occurring noise in the images is *salt & pepper*. Now-a-days the technologies are tremendously improving but the noise have been an exigent problem. The noise in images can occur due to faulty scanners, transmitting data from machine to computer or transforming the image from one format to another.

The key intention of this study is to develop an automatic system which enhances the image quality and performs the segmentation process in an efficient and automatic way.

The major contributions of the study are:

- Proposed Method is entirely unsupervised and fully automatic i.e. there is no user involvement in the system.
- It finds the optimal clusters by following some clusters validation criteria.

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- It is robust against noise.
- It performs fast.

The remaining paper is managed as:
Section II: Background study and formation of problems.
Section III: Detailed Methodology.
Section IV: Results and discussions.
Section V: Conclusion and future work.

II. Literature Review

Jian and Wang [16] proposed a method to find the numbers of clusters by analyzing k-means and genetic algorithm to select optimal clusters. This method shows some improved results but results are calculated by very small amount of data. This method is not applied on large and natural data to evaluate further results. Another method proposed by M. Masroor [7] for the brain MR image segmentation by the combination of *k-means* algorithm and *Perona Malik Anisotropic* filter. This method used Anisotropic diffusion filter and performed some morphological operations for the image enhancement. This method generated very good results but there no mechanism is adopted to select the optimal number of clusters. Chengzhong [8] proposed a method initial curve tracing by combining the *FCM* and *level set* method. In this method, *level set* method was modified. This modified method overcomes the problem of re-initialization of iteration to some extent. But no mechanism was adopted for the validation of clusters. The proposed method generates some improved results on some of the selected images which were taken only from internet and some noisy pixels were included in the candidate boundary. Min [9] proposed a method as Improved *Fast Fuzzy C-Means (FFCM)* Algorithm. *Otsu* and *Fast Fuzzy C-Means (FFCM)* Algorithms are combined in this method. For finding the optimal clusters *Otsu* algorithm is used and *FFCM* algorithm is utilized for calculating the partition matrix of the dataset. This method improved some speed performance over the standard *FCM* but there is no mechanism adopted for the validation of optimal clusters.

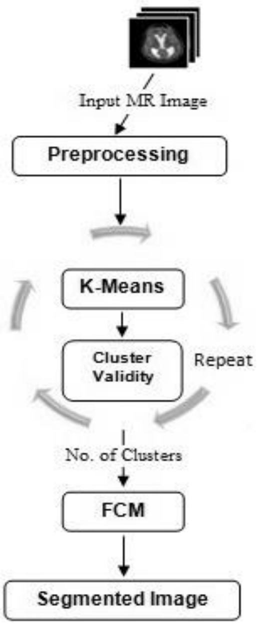


Fig. 1. Flowchart of proposed method.

One of the significant disadvantage of FCM technique is that, it does not perform well in noisy environment that effects on the performance of this and also on the segmentation performance. The other negative aspect of FCM is that it needs the optimal number of classes present in the image in advance manually.

III. Methodology

For achieving good segmentation results, it is essential that the image under consideration should be of noise free having good quality so that accurate analysis could be performed. If an image containing noise is given as input to the standard FCM then the standard FCM doesn't possess any internal mechanism to handle this problem. To overcome this problem, preprocessing step was first performed to enhance quality and reduce the noise of the medical image. After image enhancement FCM algorithm is applied for the segmentation. The detail about major components is described in the following subsections one by one.

A. Preprocessing

Median Filter: The *median* filter [10] is generally exploited to lessen image noise. This filter slightly works similar to the mean filter but this replaces only the median value while mean filter substitutes only mean value in the neighborhood of a pixel. However, this filter often performs well than the mean filter. This filter preserves the image's finer and useful detail. The median filter's performance is very helpful for removing the *salt & pepper* noise. This noise type is due to black and white pixels which occur randomly in the image. This filter considers neighborhood of each pixel in the image and replaces the pixel by median value. The criteria for calculating the median value is that it sorts the values in the surrounding neighborhood into numerical order then it substitutes median value with a pixel which is under consideration. This same procedure is performed at each pixel of the image. The great advantage of the median filter is that, the unaffected pixels remain unchanged in the image. The restoration of the image via median filter is given by:

$$y[m,n] = median\,\{x[i,j], (i,j) \in NB\} \qquad (1)$$

where *NB* represents a neighborhood centered around location $(m,\ n)$ in the image. A squared window having size 3×3 is utilized throughout this effort.

B. Segmentation

K-Means Clustering: K-Means clustering [7], [11], [12] also known as hard clustering. It is an unsupervised clustering method successfully applied in many fields like image segmentation, classification, pattern recognition, astronomy and classifier designs etc. This technique is used to groups the *n* data points into c classes. The algorithm randomly picks *k* points in the given vector space, these point serve as the initial clusters centers. After that each point is assigned to the clusters which have the closest distance with its center. Each cluster center c_j is revised by re-calculating the mean of its objects. The objects assignment process and re-computing centers for each cluster is repeated until the process converges. After some finite number of iterations the algorithm can be proven to converge. This algorithm is aimed at the minimization of an objective function which is given as:

$$J=\sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)}-c_j\right\|^2 \qquad (2)$$

where $\|x_i^{(j)}-c_j\|$ represents distance of a data point $x_i^{(j)}$ from the cluster center c_j. This distance is measured in terms of Euclidean.

Fuzzy C-Means Clustering (FCM): FCM [11], [13] is frequently applied in numerous areas like pattern recognition, classification, bioinformatics, image analysis and segmentation etc. In FCM clustering technique, a membership degree is assigned to each data point which specifies belongingness of a data point to a specific class. This membership value specifies a point to be in right cluster. A data point which lies on the boundary of a cluster may be assigned to a nearer cluster on the basis of smaller membership degree.

Minimization of an Objective function is the main aim of FCM algorithm. This objective function is:

$$W_m=\sum_{j=1}^{n}\sum_{i=1}^{c}U_{ij}^{m}\ \left\|x_{j-c_i}\right\|^2, \qquad 1\le m<\infty \qquad (3)$$

where U_{ij} represents the membership matrix, $\|\ldots\|$ represents the norm metric which is the Euclidian distance between a pixel x_j and cluster center c_i and m denotes the degree of fuzziness which checks the weight of fuzziness of resulting. FCM converges to a solution for representing the local minimum or Convergence can be perceived by evaluating the changes in the membership function or the cluster center at two successive iteration steps [14].

Comparison between K-Means and Fuzzy C-Means: FCM clustering algorithm tends to run slower than *k*-means algorithm, since it's actually performing more work. Each data point is evaluated with each cluster and more operations are required in each evaluation. *K*-Means just requires to do a distance calculation, while fuzzy c-means requires to do a full inverse-distance weighting.

Velmurugan and Santhanam [15] evaluated the performance of *k*-means and FCM clustering algorithms by considering the small and large datasets. In this method *k*-means and FCM techniques are applied on normal and uniform data and measured the time factors. In the both cases, *k*-means proved to be faster than fuzzy *c*-means and takes less time to distribute the data in clusters.

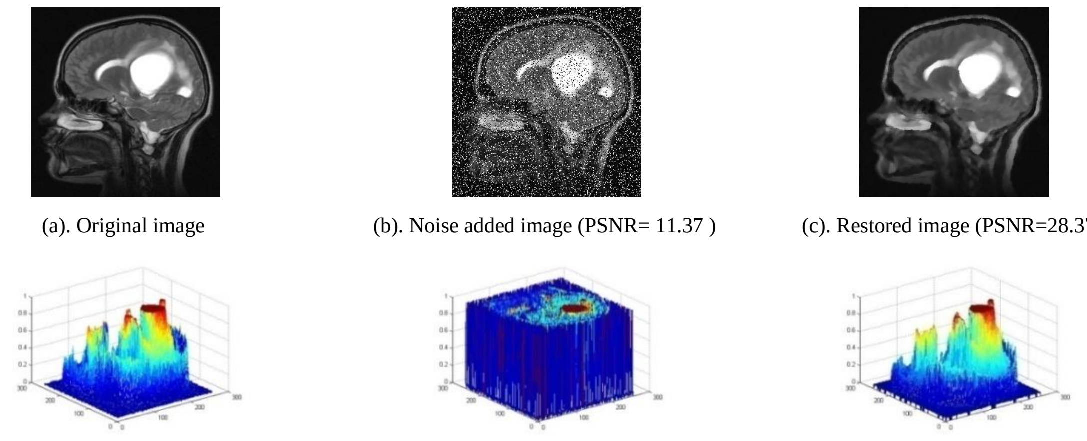
By considering the above facts, *k*-means was selected for selecting the optimal number of clusters because its fast. Fuzzy *c*-means was selected for segmentation purpose because its provide better solution for the objects which lies on the boundaries of regions. Fuzzy *c*-means assigns the membership degrees to each point. Also Fuzzy *c*-means gives the probability to a point to be in two or more clusters.

Cluster Validity Index: The process of measuring the results of a clustering technique in a quantitative manner is called Cluster Validity. By *k*-means algorithm, partition is acquired of the given data set in the form of clusters. Since *k*-means algorithm needs pre-defined number of clusters from user, so clustering results validation is required. Cluster validation criteria measures the fitness of the clusters formed i.e it measures the intra-cluster distances and inter-cluster distances.

Dunn's index (developed by J. C. Dunn in 1974) for validation of clusters [16] is a method which gives the idea of identifying the better partition sets of a dataset. In other terms, this method is used for measuring the intra-cluster and inter-cluster distances. In this method, the best partition of clusters is chosen on the basis of compactness and well separation. For any given partition of classes, Dunn's index *DI* is given as:

$$DI=\frac{\min\limits_{1\le i\le\le n_c}\left\{\min\limits_{1\le i\le\le n_c}\{dist(X_i,X_j)\}\right\}}{\max\limits_{1\le i\le\le n_c}\{diam(X_k)\}} \qquad (4)$$

where X_i , n_c , dist(X_i , X_j) and diam(X_k) represent the ith-cluster partition, cluster number, inter-cluster distance and intra-cluster distances respectively. The maximal value of *DI* means that given sample/ data is well-clustered.



(a). Original image (b). Noise added image (PSNR= 11.37) (c). Restored image (PSNR=28.37)

(d). Histogram of image 2(a) (e). Histogram of image 2(b) (f). Histogram of image 2(c)

Fig. 2. (a, b, c) Image ENHANCEMENT with median filter (d, e, f) Pixels distribution of tonal variation along *x*, *y*, *z*-axes.

TABLE I: RESULTS OF DE-NOISED/ ENHANCED IMAGES

Dataset	Noisy image		Restored Image
	Noise %age	PSNR (dB)	PSNR (dB)
Patient1, Slice-55	10%	+14.32	**+28.35**
Patient2, Slice-38	20%	+10.62	**+32.24**
Patient3, Slice-21	25%	+9.64	**+24.86**
Patient4, Slice-71	30%	+12.16	**+24.13**

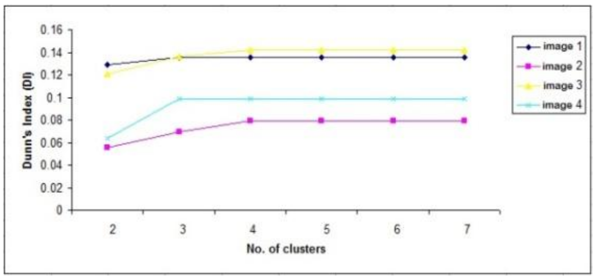
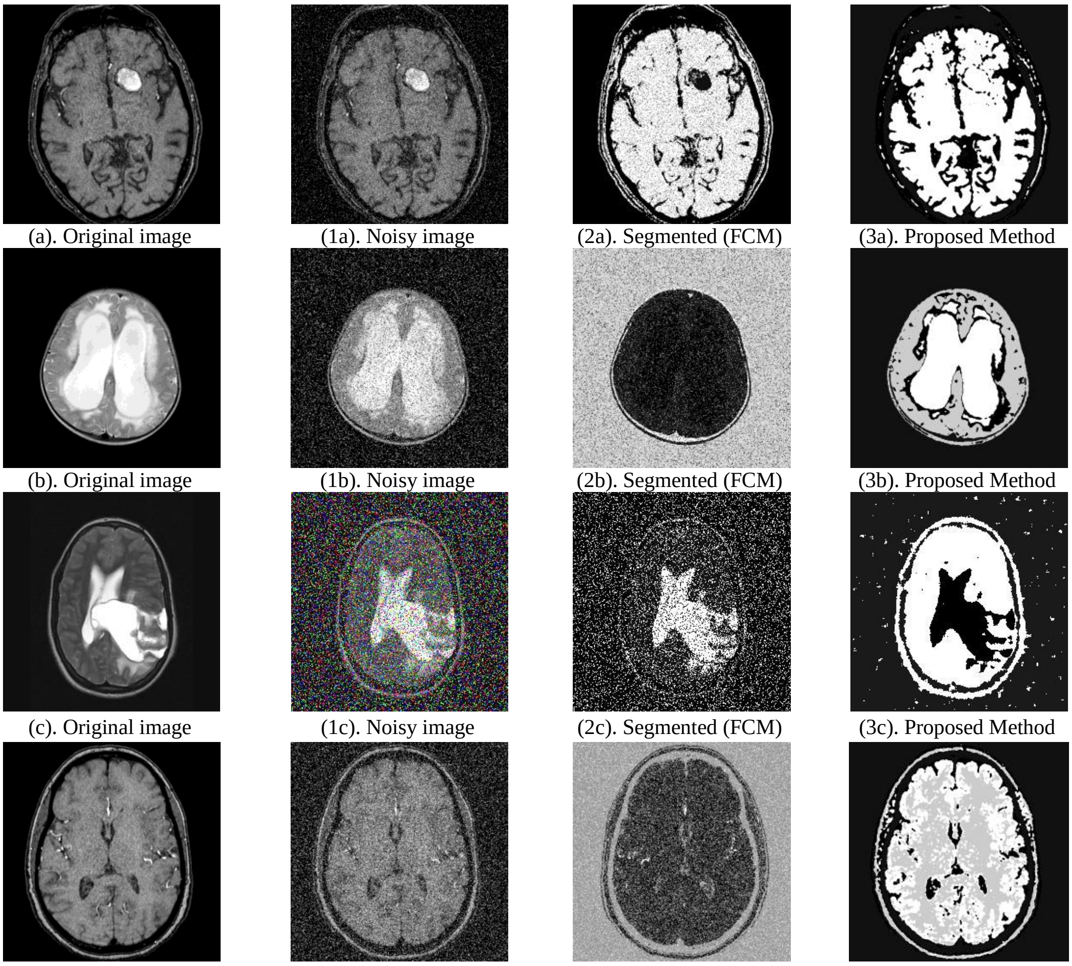


Fig. 3. Behavior of dunn's index.



(a). Original image (1a). Noisy image (2a). Segmented (FCM) (3a). Proposed Method

(b). Original image (1b). Noisy image (2b). Segmented (FCM) (3b). Proposed Method

(c). Original image (1c). Noisy image (2c). Segmented (FCM) (3c). Proposed Method

(d). Original image (1d). Noisy image (2d). Segmented (FCM) (3d). Proposed Method

Fig. 4. Visual results of segmentation (2a,2b,2c,2d) segmented by standard FCM (3a,3b,3c,3d) segmented by proposed method.

IV. RESULTS AND DISCUSSION

Though the proposed system have been tested over a wide variety of images with changing complexity, but only experimental results are shown on some of the selected images. The proposed method showed and confirmed the improved performance on large data as compared with the performance evaluated by Velmurugan and Santhanam [15] (evaluated performance on small data). The proposed method have also been tested on the noisy images which were taken some from internet and some from real data set of patients. First the salt & pepper noise was added in the images with varying noise quantity. Then the images were restored using the median filter and results are shown in the Fig. 2 with the help of histogram representation. The analysis results of image enhancement are shown in Table I. The results are compared with the help of peak signal to noise ratio (PSNR) which is the standard to measure the image quality. An image is considered to be the best if the PSNR of the image falls near 25-35 decibels. The Patient1, Slice-55 from the dataset in the Table I contains the noise as PSNR 14.32dB and after applying the median filter, noise is reduced from the image and PSNR becomes 28.35dB. Also Patient3, Slice-21 in Table I has the noise PSNR as 9.64dB and after reduction through median filter it becomes 24.86dB. The proposed method has showed the good results. Table II shows the values obtained from Dunn's cluster validity index during each repetition of *k*-means to select the optimal clusters. The maximal value of DI constitutes to the optimal choice for clusters. When *k*-means is run for Patient1, Slice-05 in Table II for number of clusters 3 (C=3), the DI value obtained is 0.1358 and all the onwards values becomes constant. It means that the number of clusters for img1 are maximum 3. The Fig. 3 shows the behavior of this Dunn's index on some of the selected images. It is easily observed from the behavior graph of DI that when no point moves to any cluster further, it becomes the constant and first maximal value is selected to select the best choice for optimal clusters. The performance and efficiency of whole proposed method is shown in Table III. The image is segmented with standard FCM algorithm with noise and without noise, the time of this segmentation process is calculated. For instance, the Patient1, Slice-05 in Table III from dataset is segmented first by standard FCM with the presence of noise which takes the time 1.1808 seconds. Then the same image is segmented by the proposed method, it takes the time 1.0390 seconds. It is easily observed that the standard FCM algorithm is not robust against noise and did not perform well in noisy environment. The presented system proved to be robust against noise. The standard FCM also takes more time to segment the noisy image as compared to proposed method. The proposed method segments the image fast and generates good results. The results of segmentation are shown in Fig. 4. In Fig. 4 (2a, 2b, 2c, 2d) the noisy images are segmented by standard FCM. In these segmented images, still noise exists and the regions boundaries are not clear. While the same images in Fig. 4(3a, 3b, 3c, 3d) are segmented by the proposed method. The regions boundaries of each segment in the images are sufficient clear. It can be easily observed that the proposed method proved to be robust against noise.

TABLE II: DUNN'S INDEX VALUES FOR APPROPRIATE CLUSTERS CALCULATED BY EQUATION 4

Dataset	Data Size (Pixels)	Dunn's Index Values by Clusters Wise						
		***C* = 2**	***C* = 3**	***C* = 4**	***C* = 5**	***C* = 6**	***C* = 7**	**Optimal Clusters**
Patient1, Slice-05	512 × 512	0.1291	**0.1358**	0.1358	0.1358	0.1358	0.1358	3
Patient2, Slice-19	448 × 448	0.0553	0.0693	**0.0789**	0.0789	0.0789	0.0789	4
Patient3, Slice-26	512 × 512	0.1205	0.1367	**0.1423**	0.1423	0.1423	0.1423	4
Patient4, Slice-55	256 × 256	0.0636	**0.0987**	0.0987	0.0987	0.0987	0.0987	3

TABLE III: PERFORMANCE OF PROPOSED METHOD/ RESULTS COMPARISONS

Dataset	Data Size (Pixels)	# of Clusters	Segmentation Time (sec)	
			Fuzzy *C*-Means	**Proposed Method**
Patient1, Slice-05	512 × 512	3	1.1808	**1.0390**
Patient2, Slice-19	448 × 448	4	2.8911	**2.0615**
Patient3, Slice-26	512 × 512	4	2.7263	**2.0190**
Patient4, Slice-55	256 × 256	3	0.5330	**0.2569**

V. CONCLUSION AND FUTURE WORK

In this paper, a brain MRI segmentation method is presented which performs the segmentation process with great performance in an automatic way. The proposed method reduces sufficient noise from images by *median filter*. As the noise in the images can cause the wrong diagnose, the proposed method proved to be robust against noise. The proposed system calculates the optimal number of clusters in an automatic and unsupervised way by following Dunn's cluster validity criteria. Furthermore, the proposed method utilize the spatial information of the image and enhances the image quality which is an important factor for performing the correct segmentation. The proposed method is applied on various images and observed that the noise effect in segmentation is significantly less. The great advantage of the presented system is, it is completely automatic and there is no involvement of any human expert in the system.

For CAD (Computer-Aided Diagnosis) System, this is just the first step and further, efforts are made for further enhancements. The further step we are looking for is to detect the tumor from brain MRI and validation of segmentation results with ground truth. At this current stage, the proposed technique is just an experimental stage.

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