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Hybrid Segmentation Approach using FCM and Dominant Intensity Grouping with Region Growing on Medical Image

S.Zulaikha Beevi*
Assistant Professor, Department of IT,
National College of Engineering, Tirunelveli Dt,
Tamilnadu, India.
zulaikha23@gmail.com

M.Mohammed Sathik
Associate Professor, Department of CS,
Sathakathullah Appa College,,Tirunelveli Dt,
Tamilnadu,India
mmdsadiq@gmail.com.

K.Senthamarai Kannan
Prof/Head, Department of Statistics,
Manonmaniam Sundaranar University,
Tirunelveli Dt,Tamilnadu,India.
senkannan2002@gmail.com

J.H Jaseema Yasmin,
Assistant Professor, Department of CSE
National College of Engineering, Tirunelveli Dt,
Tamilnadu,India
jaseema72@gmail.com

Abstract - Image segmentation is a critical part of clinical diagnostic tools. Medical image segmentation demands an efficient and robust segmentation algorithm against noise. Therefore, accurate segmentation of medical images is highly challenging; however, accurate segmentation of these images is very important in correct diagnosis by clinical tools. 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 a novel and efficient fuzzy spatial c-means clustering algorithm which is robust to noise. The proposed segmentation is based on improved spatial fuzzy c mean with dominant grey level of image. In this method, the color image is converted to grey level image and to make the approach more robust to noise. The input image is deniosed using an efficient denoising algorithm to decrease noise. Afterwards, the fuzzy spatial information is used to calculate membership value. Clusters with error more than a threshold are divided to two sub clusters. This process continues until there remain no such, erroneous, clusters. The dominant connected component of each cluster is obtained -- if existed. In obtained dominant connected components, the n biggest connected components are selected. N is specified based upon considered number of clusters. Averages of grey levels of n selected components, in grey level image, are considered as dominant grey levels. Dominant grey levels are used as cluster center. Eventually, the image is clustered using specified cluster center. Using the dominant cluster center, the image is segmented using region growing. Experimental results are demonstrated to show effectiveness of new method.

Keywords: FCM, Dominant grey level, Medical image, segmentation.

I. INTRODUCTION

Due to advances much attempted thus achieved in computer technologies, the number of application for digital image processing is increasing specially through recent years [12]. Lots of researches have been done in field of image segmentation and different methods suggested for image segmentation but nevertheless most of them were and are flawless to some extent. Medical Image segmentation has very important rule in many computer-aided diagnostic tools. These tools could save clinicians tremendous amount of time [6]. The main part of these tools is to design an efficient segmentation algorithm. Medical images mostly contain unknown noise, in homogeneity and complicated structure. Therefore segmentation of medical images is a challenging and complex task. Medical image segmentation has been an active research area for a long time. There are many segmentation algorithms but there is not a generic algorithm for totally successful segmentation of medical images. These algorithms mostly are considering thresholds known as threholding, region growing, clustering, and active controls. Thresholding methods are restrictive and should be combined by other method [13] and segmentation using region growing and active control needs locate multiple seed for each region [13]. Expectation maximization (EM) and fuzzy c-mean (FCM) are the most popular fuzzy clustering algorithms. EM algorithm was used for segmentation of brain MR [14, 16]. EM algorithm models intensity distribution as normal distribution of image, which is untrue and relatively unaccountable, especially for noisy images [14]. Fuzzy Clustering is the most popular unsupervised learning. FCM just consider intensity of image; in noisy images, intensity is not trustful. Therefore, the obtained result via this algorithm may not be acceptable in noisy images. Many algorithms, however, introduced to make FCM robust against noise but most of them still are not robust [9, 1, 17, 7, 5, 15]. The idea of a noise cluster is introduced in [7] to cluster noise element of image in different cluster. Multi scale is used in [1] to enforce spatial constraints. Post process the membership function to reduce the effect of noise introduced in [15]. The possibilistic c-mean which do a possibilistic partition is introduced in [10]. RFCM, an improved FCM, introduced in [11] which use a modified object function for incorporating spatial context. A modification on FCM introduced in [2] which adds a term for object function to influence labeling of a pixel by its immediate neighborhood . In the rest of this paper FCM, decreasing noise of Image, dominant color extraction and clustering, which are used in this paper, will be explained. Experimental results are demonstrated to show effectiveness of new method.

II.METHODOLOGY

The color image is converted to gray level image and stationary wavelet is applied to decrease noise. The image is clustered using ordinary FCM, afterwards, which prepares the stage in which clustering error for each cluster would be calculated. Within the very next stage, clusters with error more than a threshold are divided to two sub clusters. This process continues until there remain no such, erroneous, clusters. The dominant connected component of each cluster is obtained -- if existed -- after which detained ones can be found in dominant grey level extraction section. In obtained dominant connected components, the *n* biggest connected components are selected. *N* is specified based upon considered number of clusters. Averages of grey levels of n selected components, in grey level image, are considered as Dominant grey levels. Dominant grey levels are used as cluster centers. Eventually, the image is clustered using specified cluster centers. Steps of our method are as follows:

1. The color image is converted to grey level image and is applied to decrease noise.
2. Image is clustered using improved spatial FCM. Then clustering error for each cluster is calculated.
3. Clusters with error more than a threshold are divided to two sub clusters.
4. The previous process continues until there remain no such, erroneous, clusters.
5. The dominant connected component of each cluster is obtained if existed. (section II.C)
6. In obtained dominant connected components, the *n* biggest connected components are selected. *N* is specified based on considered number of clusters.
7. Averages of grey levels of n selected components are considered as Dominant grey levels.
8. Dominant grey levels are used as cluster centers.
9. Input image is clustered using specified cluster centers.

A. The Conventional FCM

Clustering is the process of finding groups in unlabeled dataset based on a similarity measure between the data patterns (elements) [12]. 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):

$$O_{fcm}(U,C) = \sum_{k=1}^{n}\sum_{i=1}^{v}\left(u_{ik}\right)^m d^2(x_k, c_i) \quad (1)$$

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.

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

$$c_i = \frac{\sum_{k=1}^{n}\left(u_{ik}\right)^{m} x_k}{\sum_{k=1}^{n}\left(u_{ik}\right)^{m}} \quad (3)$$

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 dose not use the spatial information of the given image.

B. Image Denoising

For conventional FCM, w e use Stationary wavelet Transform (SWT) for decreasing noise in image. For this, we used r.r.coifman el al [6] work. Their algorithm is as follow: Image is transformed to wavelet coefficients. Soft or hard thresholding is applied to detail coefficients. Therefore, coefficients smaller than threshold are eliminated. At last, inverse Stationary wavelet transform is applied to approximation and detail coefficients.

C . Dominant Intensity Grouping- Extraction

After clustering process, binary image of each cluster is obtained and connected components of each binary image are obtained as well. To eliminate insignificant connected components (for example a thin circle in brain image), morphological filters are applied to binary images for thinning connected component. Moreover, we use a threshold to eliminate tiny connected components. All the tiny connected components are removed, the biggest connected component of each binary image is obtained. The n biggest connected components are selected. N is specified based on considered number of clusters. N binary image contain n selected connected components are obtained. N grey level images are obtained with multiplication the n binary images and original grey level image. Averages of features of n grey level images are considered as Dominant intensity.

III. PROPOSED METHODOLOGY

A. 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,

$$\mathrm{O_{hfcm}}(\mathrm{U},\mathrm{C}) = \sum_{l=1}^{L}\sum_{i=1}^{v}(u_{il})^{\mathrm{m}}\ \mathrm{H}(l)\ \mathrm{d}^2(l,\mathrm{c_i}) \quad (4)$$

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,…,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.

$$u_{il} = \frac{1}{\sum_{J=1}^{V}\left(\frac{d_{li}}{d_{lj}}\right)^{\frac{1}{m-1}}} \quad (5)$$

$$c_i = \frac{\sum_{l=1}^{L}(u_{il})^{\mathrm{m}}\ H(l)\,l}{\sum_{l=1}^{L}(u_{il})^{\mathrm{m}}} \quad (6)$$

B Histogram Initialization

The histogram based FCM algorithm converges quickly since it clusters the histogram instead of the whole image. The center and member ship values of all the pixels are given as input to the fuzzy spatial c-means algorithm. The main goal of the ISFCM 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

$$\mathrm{O_{fcm}}(\mathrm{U},\mathrm{C}) = \sum_{k=1}^{n}\sum_{i=1}^{v}\left(u_{ik}^{s}\right)^{\mathrm{m}}\mathrm{d}^2(\mathrm{x_k},\mathrm{c_i}) \quad (7)$$

$$u_{ik}^{s} = \frac{P_{ik}}{\left(\sum_{J=1}^{V}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{1}{m-1}}\right)\left(N_k\sum_{z=1}^{N_k}\left(\sum_{J=1}^{V}\left(\frac{d_{iz}}{d_{jz}}\right)^{\frac{1}{m-1}}\right)\right)} \quad (8)$$

The spatial membership function u_{ik}^{s} of the proposed ISFCM is calculated using the equation (8).

Where P_{ik} is the apriori probability that kth pixel belongs to ith cluster and calculated as

$$P_{ik} = \frac{NN_i(k)}{N_k} \quad (9)$$

Where $NN_i(k)$ is the number of pixels in the neighborhood of kth 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 ith cluster and zth neighborhood of ith Thus the center c_i^s of each cluster is calculated as

$$c_i^s = \frac{\sum_{k=1}^{n}\left(u_{ik}^{s}\right)^m x_k}{\sum_{k=1}^{n}\left(u_{ik}^{s}\right)^m} \quad (10)$$

C Dominant Intensity Grouping – Extraction

After clustering process, binary image of each cluster is obtained and connected components of each binary image are obtained as well. To eliminate insignificant connected components (for example a thin circle in brain image), Morphological filters are applied to binary images for thinning connected component. Moreover, we use a threshold to eliminate tiny connected components. The biggest connected component of each binary image is obtained after which they obtained connected components; the *n* biggest connected components are selected. *N* is specified based on considered number of clusters. *N* binary image contain n selected connected components are obtained. *N* grey level images are obtained with multiplication the n binary images and original grey level image. Averages of features of n grey level images are considered as Dominant grey levels.

D Multistep Morphological Filter

After clustering, the connected components of each binary image are obtained. In this study, we consider an efficient and fast segmentation algorithm to compute high frequency components in the focused regions, whereas less sensitive to noise in the defocused regions. Then we employ a morphological approach so that even focused smooth areas can be merged into the surrounding areas with dominant intensity. To eliminate insignificant connected components, morphological filters are applied again for thinning connected component. Grayscale erosion is used to smooth small light regions. It is defined as the minimum of the difference of a local region of an image and a grayscale mask. The shape of the input mask (known as the structuring element, or SE) is generally chosen to emphasize or de-emphasize elements in the image. The general effects of performing erosion on a grayscale image are: If all the values in the structuring element are positive, the output image tends to be darker than the input. Light elements within the image are reduced or eliminated, depending on how their shapes relate to the structuring element used. The degree of these effects depends greatly on the shape and values within the structuring element and by the details within the image itself. Gray scale morphological closing of an image is defined as the erosion of the dilation of the image. In this proposed approach, we applied morphological operation to four levels and we eliminated insignificant connected components, so that the final segmentation performs well. The final decision of the focused regions is conducted by region growing and thresholding. The result is the reduction of small negative regions within the image.

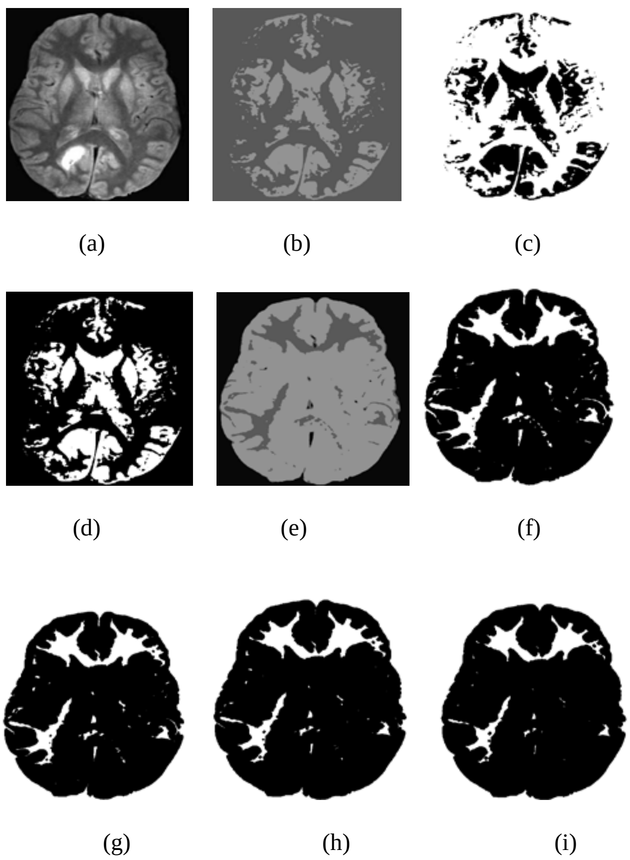
E . Region Growing and Adaptive Thresholding

The simplification of morphological filter is followed by region growing segmentation. Suppose that we start with a single pixel *p* and wish to expand from that seed pixel to fill a coherent region. Let's define a similarity measure *S*(*i*, *j*) such that it produces a high result if pixels *i* and *j* are similar and a low one otherwise. First, consider a pixel *q* adjacent to pixel *p*.

We can add pixel q to pixel p's region if $S(p, q) > T$ for some threshold T. We can then proceed to the other neighbors of p and do likewise. Suppose that $S(p, q) > T$ and we added pixel q to pixel p's region. We can now similarly consider the neighbors of q and add them likewise if they are similar enough. If we continue this recursively, we have an algorithm analogous to a flood fill but which works not on binary data but on similar grayscale data. One obvious similarity measure is to compare individual pixel intensities. This can be sensitive to noise, though. We can reduce our sensitivity to noise by comparing neighborhood characteristics between pixels. For example, we could compare the average intensities over a neighborhood around each pixel. Notice, though, that this is simply the same as applying an averaging kernel through convolution and then doing single-pixel comparison.

IV. RESULT AND DISCUSSION

The proposed algorithm converges very quickly because it gets initial parameters from already converged histogram based FCM. The proposed approach is applied on synthetic MRI image and original brain MRI image. In all the images additive Gaussian white noise is added with noise percentage level 0%, 5%. As it is obvious our algorithm performs better in this experiment and ordinary FCM fails to segment image properly. Ordinary FCM can't separate different parts of brain and assigns brain to two significant clusters instead of three clusters. Ordinary FCM assigns two parts of brain with close colors to one cluster. The reason for which ordinary FCM fails to separate two parts of brain is closeness of those two parts and the existence of a non dominant cluster in image that is not visible to the user's eyes. Furthermore we use multilevel morphological operators to eliminate in dominant regions. Therefore we have no tiny circle as a cluster.



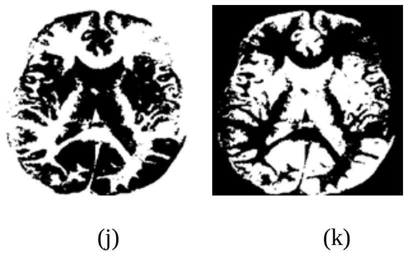


Figure 1. Experimental results of applying ordinary FCM vs. ISFCM without noise. (a). Original image (b) FCM Clustering (c). segmented image with black matter (d) segmented image with white matter (e) ISFCM clustering (f) Level 1 morphological filter (g) Level 2 morphological filter (h) Level 3 morphological filter (i) Level 4 morphological filter (j) segmented image with proposed algorithm with black matter (k) segmented image with proposed algorithm with white matter

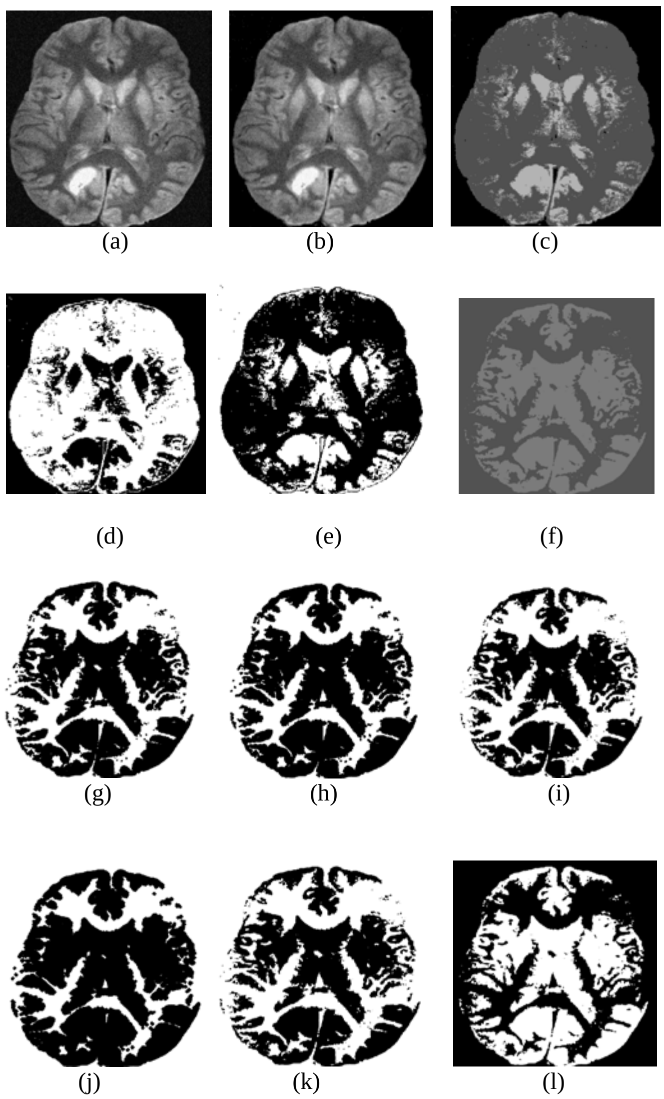


Figure 2. Experimental results of applying ordinary FCM vs. ISFCM on noisy image (a). Noisy image (3% added white gaussian noise) (b) wavelet denoised image (c).FCM clustering (d). Segmented image with white matter (e). Segmented image with black matter (f).ISFCM clustering (g) Level 1 morphological filter (h) Level 2 filter (i) Level 3 filter (j) Level 4 filter (k) Segmented image with white matter (l) Segmented image with black matter

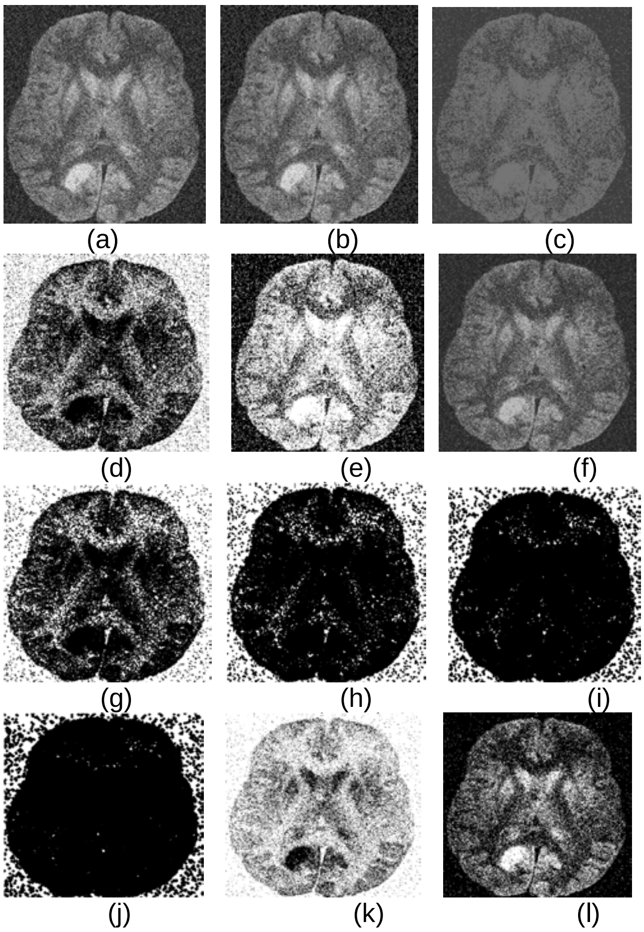


Figure 3. Experimental results of applying ordinary FCM vs. ISFCM on noisy image (a). Noisy image (15% added white gaussian noise) (b) wavelet denoised image (c).FCM clustering (d). Segmented image with white matter (e). Segmented image with black matter (f).ISFCM clustering (g) Level 1 morphological filter (h) Level 2 filter (i) Level 3 filter (j) Level 4 filter (k) Segmented image with white matter (l) Segmented image with black matter

Table I. The segmentation accuracy of conventional FCM, 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
Proposed approach with Denoising	94.7572	94.6435	94.1857	94.2538

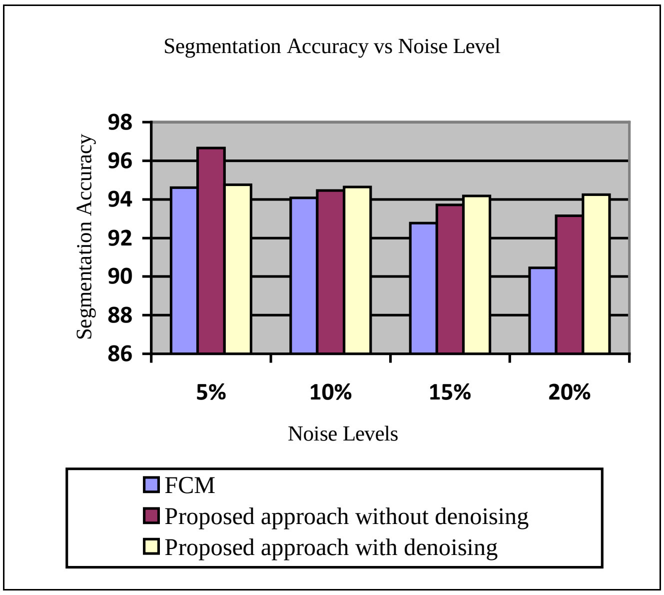


Figure 4. Segmentation accuracy of conventional FCM, proposed approach without denoising and proposed approach with denoising in segmenting synthetic brain MRI images with different noise levels.

Table II. The PSNR values of segmented image of conventional FCM, proposed approach without denoising and proposed approach with denoising for different noise levels

Segmentation Fidelity (PSNR Values) *at threshold 40*					
Approaches	***Noise Level (%)***				
	3	***5***	***7***	***10***	***15***
FCM	25.69	22.17	19.76	17.81	16.32
Proposed approach without Denoising	27.52	23.12	22.62	19.8	22.18
Proposed approach with Denoising	28.28	25.46	24.49	24.51	25.01

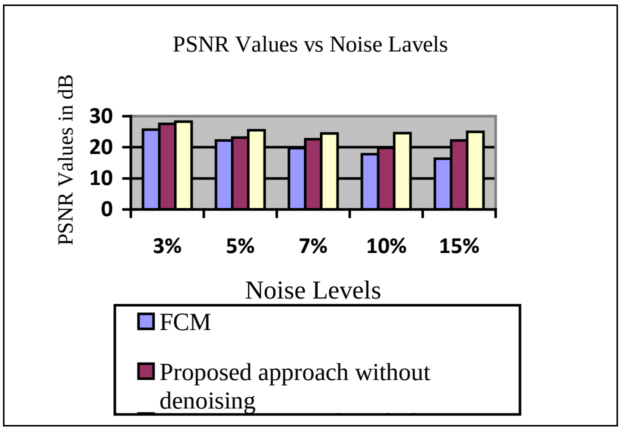


Figure 5. The PSNR values of segmented image of conventional FCM, proposed approach without denoising and proposed approach with denoising for different noise levels

V. CONCLUSION

Image segmentation is very important key in success of clinical tools. Medical images usually have unknown noise. Therefore, accurate segmentation of these images is difficult. Researchers proposed lots of methods for image segmentation. In this paper, we have presented a robust and efficient approach for the effectual segmentation of noisy medical images we proposed a new method for image segmentation based on region processing and improved spatial FCM. First, dominant connected components of image are obtained. Then average of gray level of pixels in each dominant connected component is considered as dominant gray level. Then image is clustered by considering dominant gray levels as centre for clustering. Experiment results show robustness of new method over conventional FCM.

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