Unsupervised learning algorithms for MRI Brain Tumor Segmentation

G.Sasibhusana Rao,
Dept. of ECE,
Andhra University College of Engineering(A),
Visakhapatnam, India
sasigps@gmail.com

B.Srinivas,
Dept. of ECE,
MVGR College of Engineering(A),
Vizianagaram, India,
srinivas.b@mvgrce.edu.in

Abstract—**The structure of the brain can be seen by the Magnetic Resonance (MR) image output. MR scanned image of the brain is utilized for the entire study in this paper. The MR image filter is more agreeable than some other outputs for analysis. It will not influence the human body since it does not hone any radiation. In digitization of MR scanned image, segmentation of brain tumor is one kind of challenging problems and it is critical to clinical diagnosis. So segmentation needs to be accurate, robust, and efficient to avoid impacts caused by various large and complex biases added to images. Clustering algorithms have been widely used for the segmentation. In this paper, the K-means (KM) clustering and Fuzzy C-means (FCM) clustering algorithms are used to locate the tumor and extract it. Comparative analysis in terms of Segmented area, Relative area, Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR) is performed between K-means clustering and FCM clustering algorithms. The obtained performance measures from the experiments indicate the superiority of the chosen FCM algorithm over the K-means algorithm. That is 0.93% of relative segmented tumor area for FCM shows that the area which was effected by the tumor in the original MR image is segmented as a tumor. The FCM Algorithm has less processing time of 8.639 seconds compared to 22.831 seconds for KM algorithm.**

Keywords: Unsupervised Learning Method; MRI Brain Segmentation; Fuzzy C means; K-means(KM) clustering algorithm; Magnetic Resonance Image (MRI).

I. INTRODUCTION

Medical images analysis decreases the doctor's workload. It determines the brain tumor class. In any case, segmentationof brain tumor isyet a critical issue because of differentsorts of tumors with various shapes, structure, and size. Many methods have been created for MR image segmentation [1], [5]. Out of which threshold based technique, region based technique, pixel classification, and model based methods are four major classes in segmentation. In threshold based methods [2], the objects' intensities are classified by comparing with one or many intensity thresholds. These thresholds may be global or local. These segmentation techniques cannot utilize all the data of MR image. Segmentation of region based methods predefines some similarity criterion. The pixels are examined and disjoint regions are formed. Some predefined technique is used to merge together the neighboring pixels with homogeneous properties [3],[4]. The limitation is of partial volume effect which restricts the segmentation accuracy of brain MRI. In the mathematical model based technique, prior knowledge of the shape, orientation, and the location is used to make a specific anatomic structure. It makes a consistent and connected model. These methodes are expensive [9] and difficult to initialize [10]. Pixel characterization techniques utilize supervised(directed) or unsupervised classifiers to group pixels in the image feature space. The supervised methods incorporate artificial neural networks and Bayes classifiers; unsupervised Methods incorporate K-means technique, Markov Random Fields (MRF) [6],[11] and Fuzzy Clustering technique [7], [9].

Study of cluster or segmentation technique [9], [10] based on clustering assembles a set of entities in a manner that entities in the identical cluster have a superior degree of alikeness to each compared to the other clusters. Clusters are defined as contiguous regions of more than one-dimensional space comprising comparative points of high density, alienated from other exemplary regions comprising moderate points of low density. In image breakdown, clustering is the order of arrangement of pixels conferring to more or less features like intensity. Under hard clustering, data elements fit into one cluster simply and the membership value of belongingness to a cluster is precisely one. Under soft clustering, elements of data fit into more prominent than the singlecluster and the membership value of belongingness to the cluster varies from 0 to 1.

II. ALGORITHMS

In this section, the two Clustering algorithms K-means and FCM are explained in detail.

A. K-means (KM) Clustering Algorithm

K-means [3] process at first defines the number of clusters k. Then the center of k-cluster is taken randomly. The distance between the individual pixels to centers of the individual cluster is measured by means of the Euclidean distance function. A single pixel is compared to all centers of the cluster using the formula for Euclidean distance. Then pixel is moved to the specific cluster having the least distance among all. Then the re-estimation of the centroid is done. Again each individual pixel is compared to all centroids. This procedure carries on until the center converges.

Algorithm for K-means:
Step i) Consider the number of cluster value as k.
Step ii) Pick the centers of k cluster randomly.
Step iii) Compute cluster's center or mean.
Step iv) Compute the distance between each pixel to each center of the cluster.
Step v) If the distance is close to the center then move to the particular cluster.
Step vi) Else, move to the subsequent cluster.
Step vii) Estimate the center again.

B. Fuzzy C-means (FCM) Clustering Algorithm

FCM algorithm [4],[12],[13] is one kind of clustering method, which was introduced by Dunn, was enhanced by Bezdek and was titivated further by M. Matteucci. During segmentation process, only local information is considered in the FCM clustering algorithm. The membership function is permitted to each information focuses (data points) directly related to each group focus (cluster center), on the distance between the group focus and information focuses. The membership function and group focuses are upgraded after each cycle.

n = Number of information focuses
v_q = Group focuses
m = Fuzziness index $m \in [1, \infty]$
K = Number of group focuses
μ_{pq} = Membership function of information focuses to group focuses
d_{pq} = The Euclidean distance between p^{th} information focuses and q^{th} group focuses.
The main FCM objective function is to minimize

$$G(u, v) = \sum_{p=1}^{n}\sum_{q=1}^{k}(\mu_{p,q})^m \|X_p - v_q\|^2$$

Where $\|X_p - v_q\|^2$ is the Euclidean distance between p^{th} information focuses and q^{th} group focuses.
Steps for FCM algorithm:
S = {s_1, s_2, s_3 ..., s_x} is the information focuses set and V_c = {v_1, v_2, v_3 ..., v_v} is the set of group focuses.
Step i) Arbitrarily select k group focuses.
Step ii) Function of Fuzzy membership μ_{pq} is calculated as

$$\mu_{pq} = \frac{1}{\sum_{r=1}^{k}\left(\frac{d_{pq}}{d_{pr}}\right)^{\frac{2}{m-1}}}$$

Step iii) Calculate Fuzzy centers $v_q = \frac{\sum_{p=1}^{n}(\mu_{pq})^m x_p}{\sum_{p=1}^{n}(\mu_{pq})^m}$

Step iv) Until the G minimum value is accomplished or $\|U_{r+1}-U_r\| < E$, Repeat 2 and 3 Steps where,
r = Iteration step
E = Termination criterion is in the range of [0, 1]
U = (μ_{pq}) + c is the matrix of fuzzy membership

III. METHODOLOGY

The software is developed to identify a tumor in the brain MR image. Firstly, a random brain MR image is taken, resized it to200X200 pixels and converted to a grayscale image. It is then segmented on the basis of KM and FCM clustering methods. In this method, 3 clusters centroid values are taken on basis of which the clustering takes place. In FCM, the centroid values lie between 0-255 since the grayscale values range from 0-255. In Fuzzy clustering, each point has a likelihood of belonging to each group, instead of totally belonging to only one group as it is the situation in the KM algorithm. Find the parameters like Segmented area, MSE, PSNR for both clustering algorithm and compare them.The complete procedure is shown in the following block diagram.

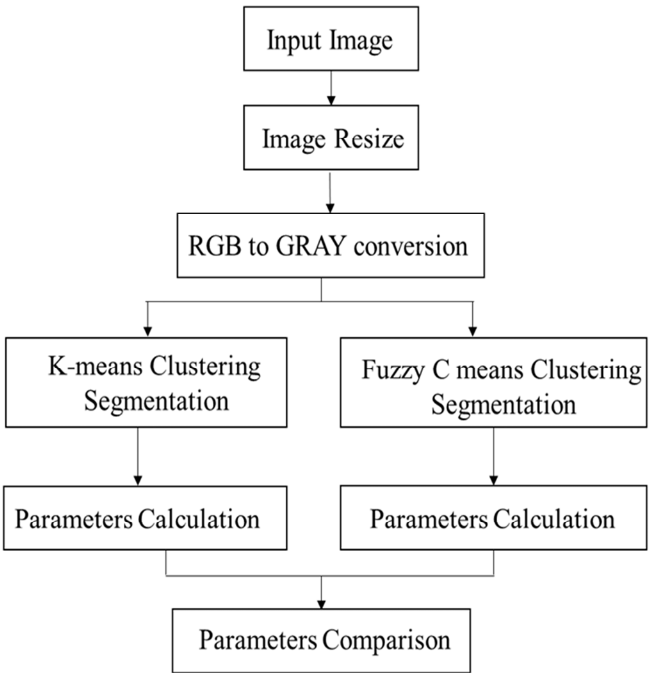

Fig. 1. Block diagram

IV. PERFORMANCE MEASURES

The following five performance measures are used in evaluating the performance of the proposed unsupervised clustering algorithms for segmentation of brain tumor.

MSE (mean squared error): The process of squaring the differentiated values are indicated by mean square error [1]. The average of the sum of the squares of the errors is called as MSE, is obtained by subtraction of the input and the segmented images. MSE is the cumulative squared error value between the input images R (a, b) and the segmented image S (a, b).

MSE = $\frac{1}{mn}\sum_{a=0}^{m-1}\sum_{b=0}^{n-1}[R(a,b) - s(a,b)]^2$

Where 'm' and 'n' denotes the number of rows and columns in the input image. To get better PSNR, the obtained value of MSE should be low for the segmented image.

PSNR (peak signal to noise ratio): Noise immunity of an image is indicated by peak signal to noise ratio [1]. More PSNR means that the MR brain image has very less interference due to noise. In the input MR brain image, the highest pixel value is denoted as a max_i. The MSE values represent the PSNR. The algorithm produces PSNR values, which is in the range of 40 and 100 dB, and so it is less sensitive to noise. PSNR shows resistance to the noise signals and also briefs the segmented image's quality.
Usually, PSNR can be expressed as

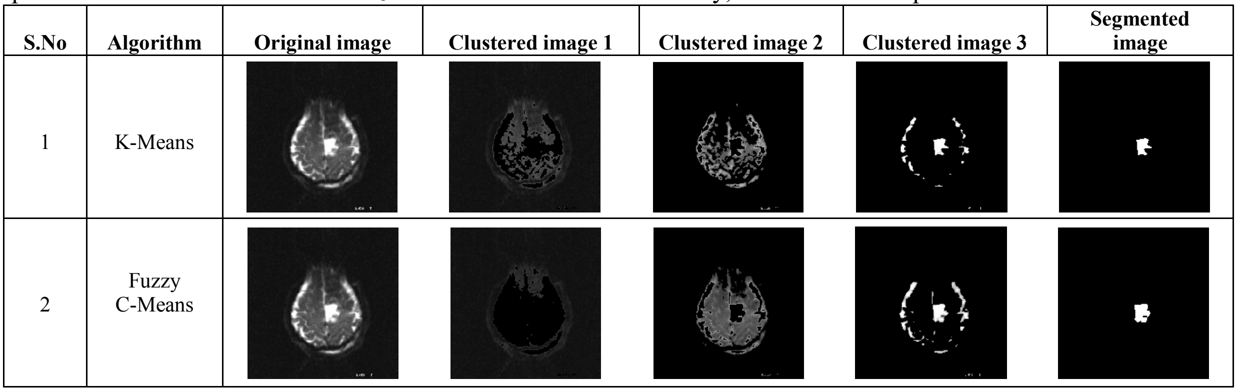

Fig. 2. Comparison of KM and FCM Clustering Algorithms for Segmentation

$$PSNR = 10\ log_{10}\left(\frac{MAX_i^2}{MSE}\right) = 20\ log_{10}\left(\frac{MAX_i}{\sqrt{MSE}}\right)$$

Processing or Execution Time (sec) [1] is expressed as the required time period for the system to complete the execution of the program.
*Segmented Are*a (pixel) of an image is defined as the number of ones in the segmented image.
Relative Tumor Area (pixel) [8] is defined as the ratio of segmented area to total area of the Input brain image. It is expressed as

$$Relative\ Tumor\ Area = \frac{segmented\ area}{total\ area\ of\ the\ Input\ Image} \times 100$$

V. EXPERIMENTAL RESULTS

The implementation of the proposed segmentation method for a brain tumor is done by using the software MatlabR2013a. The experiments are performed on Intel Core i5 CPU 2.5 GHz and the processor has a 8 GB RAM. For the purpose of segmentation, the dataset of MR images is taken from the open data source http://www.cancerimagearchive.net/display/ public/collections. The MR image considered for the experimentation has a default size of 200X200 pixels.

The results of MR image segmentation using KM and FCM algorithms are shown in Fig. 2 in a stepwise fashion. Fig. 2 consists of an original MR image, Clustered Image1, Clustered Image2, Clustered image3, and segmented image of the brain. An original MR image is converted to gray scale image from RGB image, where the clustered image is the image obtained, when centroids are chosen near to background, brain image, and tumor image pixel value of original image value.

The initial fuzzy partition matrix is first generated and calculation of the initial fuzzy cluster centers values are done. cc1=10.41, cc2=84.43, cc3=173.32 are taken as an initial cluster centroids. In each iteration, the cluster centers and the membership grade point are updated and the best location for the clusters is obtained by minimizing the objective function. This process is stopped when the highest number of iterations are attained or when the improvement in the objective function bitween two consecutive iterations is less than specified minimum improvement. The final cluster centers areccc1 =3.8650; ccc2 = 84.5062; ccc3 = 172.5919. The fifth image of Fig. 2 shows the required segmented image that is obtained by applying area opening operation on the clustered image3.

TABLE I. MSE, PSNR, PROCESSING TIME AND SEGMENTED AREA.

S.No	Algorithm	MSE	PSNR	P.TIME(sec)
1	K-means	0.0463	61.4723	22.831
2	Fuzzy C-means	0.0435	61.7434	8.639

From Table I, it can be the MSE value and processing time of FCM are less than that of KM. Better Peak signal to noise ratio is obtained for FCM.

TABLE II. RELATIVE AREA COMPARISON OF CLUSTERING ALGORITHMS

S.No	Algorithm	Total Input Image(pixels)	Segmented Area(pixels)	Relative tumor Area(pixels)
1	K-means	40000	303	0.76%
2	Fuzzy C-means	40000	372	0.93%

From Table II, the relative segmented tumor area of FCM is more than that of KM, because during segmentation process the sharp edges are missed in KM algorithm.

VI. CONCLUSIONS

In this paper, KM and FCM algorithms are applied for segmentation of MR image of the brain image. The segmentation results of the proposed algorithms for an MR brain image are obtained. The performance parameters of the MR brain tumor image such asMSE, processing time (sec), PSNR value (dB), segmented area, and relative segmented area using the proposed methodologies are calculated and are shown in Table 1 and 2. From these results, it is concluded that the FCM has better performance characteristics like 0.93% of relative segmented tumor area and less processing time of 8.639 seconds and KM has a less relative segmented area of 0.76% and processing time of 22.831 seconds. Hence the cluster center can be initialized to a better proper value for better segmentation.

REFERENCES

[1] Vishnuvarthanan, G., M. P. Rajasekaran, P. Subbaraj, Anitha V. "An unsupervised learning method with a clustering approach for tumor identification and tissue segmentation in magnetic resonance brain images." *Applied Soft Computing* 38 (2016): 190-212.

[2] Raghtate, Ganesh S., Suresh S. Shankar. "Modified Fuzzy C Means with Optimized Ant Colony Algorithm for Image Segmentation." In *Computational Intell. and Comm. Networks (CICN), 2015 Int. Conf. on*, pp. 1283-1288. IEEE, 2015.

[3] Madhukumar, S., and N. Santhiyakumari. "Evaluation of k-Means and fuzzy C-means segmentation on MR images of brain." *The Egyptian Journal of Radiology and Nuclear Medicine* 46, no. 2 (2015): 475-479.

[4] Arora, Nitesh, Rajoo Pandey. "Noise adaptive FCM algorithm for segmentation of MRI brain images using local and non-local spatial information." In *Intell. Sys. Design and Applications (ISDA), 2015 15th Int. Conf. on*, pp. 610-617. IEEE, 2015.

[5] Telrandhe, Swapnil R., Amit Pimpalkar, AnkitaKendhe. "Detection of brain tumor from MRI images by using segmentation & SVM." In *Futuristic Trends in Res. and Innovation for Social Welfare (Startup Conclave), World Conf. on*, pp. 1-6. IEEE, 2016.

[6] Ashraf, Ahmed B., Sara C. Gavenonis, Dania Daye, Carolyn Mies, Mark A. Rosen, and Despina Kontos. "A multichannel Markov random field framework for tumor segmentation with an application to classification of gene expression-based breast cancer recurrence risk." *IEEE transactions on medical imaging* 32, no. 4 (2013): 637-648.

[7] Thara, K. S., K. Jasmine. "Brain tumour detection in MRI images using PNN and GRNN." In *Wireless Comm., Signal Processing and Networking, Int. Conf. on*, pp. 1504-1510. IEEE, 2016.

[8] Jose, Alan, S. Ravi, M. Sambath. "Brain tumor segmentation using k-means clustering and fuzzy c-means algorithms and its area calculation." *International Journal of Innovative Research in Computer and Comm. Engg.* 2, no. 3 (2014): 3496-3501.

[9] Gopal, N. N., M. Karnan. "Diagnose brain tumor through MRI using image processing clustering algorithms such as Fuzzy C Means along with intelligent optimization techniques." In *Computational Intell. and Computing Res., 2010 IEEE Int. Conf. on*, pp. 1-4. IEEE, 2010.

[10] Benson, C. C., V. Deepa, V. L. Lajish, Kumar Rajamani. "Brain tumor segmentation from MR brain images using improved fuzzy c-means clustering and watershed algorithm." In *Advances in Computing, Comm., and Informatics, 2016 Int. Conf. on*, pp. 187-192. IEEE, 2016.

[11] Abdulbaqi, Hayder Saad, Mohd Zubir Mat, Ahmad Fairuz Omar, Iskandar Shahrim Bin Mustafa, Loay Kadom Abood. "Detecting brain tumor in magnetic resonance images using hidden markov random fields and threshold techniques." In *Res. and Development, 2014 IEEE Student Conf. on*, pp. 1-5. IEEE, 2014.

[12] Das, Amita, and Sukanta Kumar Sabut. "Kernelized fuzzy C-means clustering with adaptive thresholding for segmenting liver tumors." *Procedia Comp. Sci.* 92 (2016): 389-395.

[13] Abdel-Maksoud, Eman, Mohammed Elmogy, and Rashid Al-Awadi. "Brain tumor segmentation based on a hybrid clustering technique." *Egyptian Informatics Journal* 16, no. 1 (2015): 71-81.