

Brain Tumour Segmentation Using Clustering Algorithms

Varsha A. Kshirsagar¹, J. R. Panchal²

¹Student, Department of Electronics & Telecommunication, SCOE,Pune

²Professor, Department of Electronics & Telecommunication, SCOE,Pune

Abstract: The image segmentation is performed to detect, extract and characterize the anatomical structure. Here, we apply two widely used algorithm for tumour detection (i) K-means clustering (ii) Fuzzy C Means clustering The segmentation algorithms are compared to estimate the efficiency by evaluating the execution time and accuracy of the algorithm. The result shows that the execution time is less in K-Means compared to Fuzzy C Means clustering technique, because the number of iterations of K-Means is less than Fuzzy C Means clustering . Further, the tumour area is calculated for accurate result

Keywords: Image segmentation, K-Means clustering, Fuzzy C-means clustering techniques, Segmentation algorithms

1. Introduction

The recent survey [4] has concluded that brain tumour comes next to lung cancer around the world .Early detection and treatment can increase the rate of survival. Magnetic Resonance Imaging(MRI)depends on computer technology to generate and display digital images Segmentation is an important process in most medical image analysis[12],[14]. It is very difficult to conduct surgery without using image processing techniques. Structures like tumour, brain tissue cannot be identified without image segmentation [3]. Clustering to Magnetic Resonance (MR) brain tumours maintains efficiency. Clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy

Here, an object density-based image segmentation [7],[10] is used, which incorporates intensity-based, edge-based and texture-based segmentation techniques. The method consist of three main stages: pre processing, object segmentation and final segmentation. Image enhancement, noise reduction and layer-of-interest extraction are some of the task of pre processing

The paper presents the efficient use of clustering algorithm to detect the tumour cells from MR images which may present the characteristic of severity of the tumour such that required evaluation and treatment can be facilitated. In this paper, we present a segmentation method which helps in identifying the affected region and also able to calculate the affected area.

2. Method Used for Segmentation of Brain Tumor

Our method relies on the intensities of individual pixels, based on which it would be easier to segregate the affected areas. An intensity image i.e greyscale image[1] can be considered as a data matrix[15], whose values represent the intensities within some range and each element of the matrix corresponds to one image pixel. A brain Image consists of four regions i.e. gray matter (GM), white matter (WM), cerebrospinal fluid (CSF) and background These regions can be considered as four different classes. Therefore, an input

image needs to be divided into these four classes .These four classes are called the clusters with pixels of different intensities[11] .Here we use two clustering method for efficient segmentation 1.(A) K-Means Clustering (B)Fuzzy C Means Clustering. We compare both the algorithm and calculate the efficiency of both the method based on performance and execution time.2.(C) Calculation of Area of Tumour.

2.1 K-Means Clustering

K-means is a widely used clustering algorithm to partition data into k clusters. Clustering is the process for grouping data points with similar feature vectors into a single cluster and for grouping data points with dissimilar feature vectors into different clusters. Let the feature vectors derived from l clustered data be $X = \{x_i | i=1,2,\dots, l\}$. The generalized algorithm initiates k cluster centroids $C = \{c_j | j=1,2,\dots,k\}$ by randomly selecting k feature vectors are grouped into k clusters using a selected distance measure such as Euclidean distance so that,[2] .

$$d = \sqrt{|x_i - c_j|}$$

The next step is to recompute the cluster centroids based on their group members and then regroup the feature vector according to the new cluster centroids. The clustering procedure stops only when all cluster centroids tend to converge

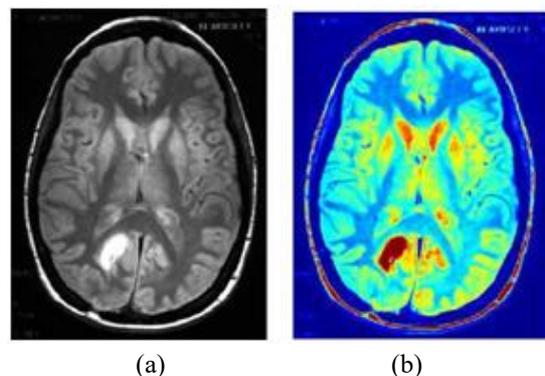


Figure 1: (a) Original image and(b) Image after pseudo color translation

Basically, feature space selection[6] is a key issue in K-means clustering segmentation. The fig(a) is the original MR Image ,fig(b) represents the image after pseudo color translation .The original MR brain image is rendered as a gray-level image that is insufficient to support fine features. To obtain more useful feature and enhance the visual density, the pseudo-color transformation is applied that maps the grey-level pixel to color-level pixel which gradually maps gray-level values 0 to 255 into blue-to-green-to-red color

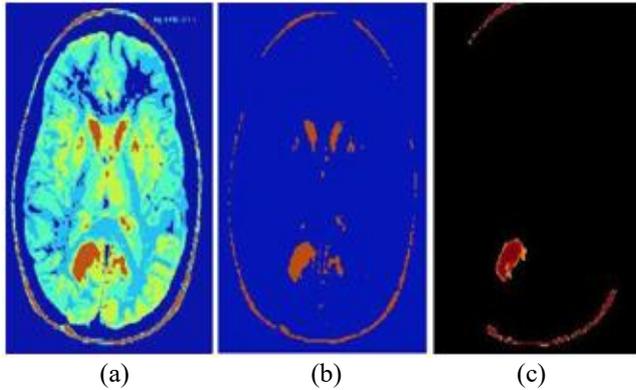


Figure 2: (a) K-means clustered image (b) Image after Cluster Selection (c) Segmented Tumour image

The fig 2 shows the result after K-means Clustering in $L^*a^*b^*$ color space. Image obtained are as follows Cluster selection, region elimination and the segmented tumour image respectively

To retrieve important features and to benefit the clustering process, the RGB color space is further converted to a CIELab color model ($L^*a^*b^*$) [2]. The $L^*a^*b^*$ space consists of a luminosity layer L^* , a chromaticity-layer a^* , which indicates where color falls along the red-green axis, and a chromaticity-layer b^* , which indicates where the color falls along the blue-yellow axis.[8]

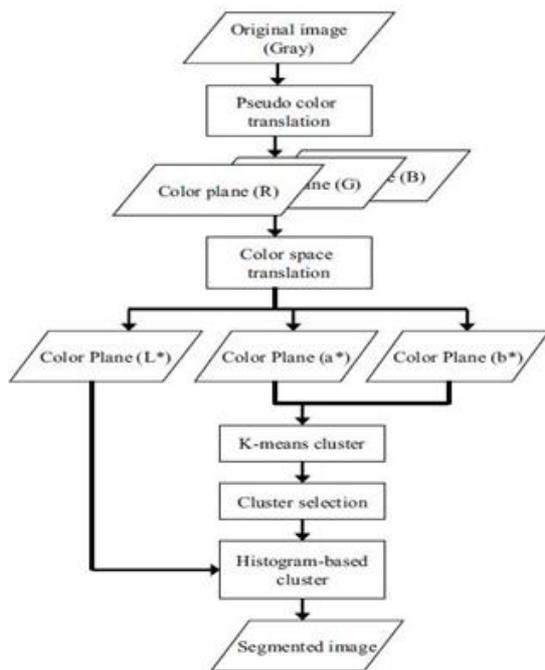


Figure 3: Flow chart of K-Means Clustering with Color-level Mapping

The translating formula calculates the tri-stimulus coefficients first as

$$\begin{aligned} W &= 0.4303R + 0.3416G + 0.1784B, \\ Y &= 0.2219R + 0.7068G + 0.0713B, \\ Z &= 0.0202R + 0.1296G + 0.9393B \end{aligned}$$

The CIELab color model[13], is calculated as:

$$\begin{aligned} L^* &= 116(h(Y/YS))-16, \\ a^* &= 500(h(W/WS))- \\ &h(Y/YS) \quad b^* = 200(h(Y/YS)- \\ &h(Z/ZS)), \end{aligned}$$

Where YS , WS , and ZS are the standard stimulus coefficients.

(B) Fuzzy C Means Clustering

The FCM algorithm[5],[9],attempts to partition a finite collection of pixels into a collection of "C" fuzzy clusters with respect to some given criterion. Depending on the data and the application, different types of similarity measures may be used to identify classes. This algorithm is based on minimization of following objective function:

$$J = \sum_{i=1}^N \sum_{j=1}^C \mu_{ij}^m |x_i - c_j|^2$$

Where, J is the objective function N is the number of pixels in the image, C is the number of clusters, μ is the membership table -- a table of $N \times C$ entries which contains the membership values of each data point and each cluster, m is a fuzziness factor (a value larger than 1), x_i is the i th pixel in N, c_j is j th cluster in C and $|x_i - c_j|$ is the Euclidean distance between x_i and c_j . [10]

Algorithm: FCM

The input to the algorithm is the N pixels on the image and m, the fuzziness value. The fuzziness value of 2 is used in this system.[5],[3].

Step 1: Initialize μ with random values between zero and one;but with the sum of all fuzzy membership table elements for a particular pixel being equal to 1 -- in other words, the sum of the memberships of a pixel for all clusters must be one.

Step 2: Calculate an initial value for J using

Step 3: Calculate the centroids of the clusters c_j using,

$$c_j = \frac{\sum_{i=1}^N \mu_{ij}^m x_i}{\sum_{i=1}^N \mu_{ij}^m}$$

Step 4: Calculate the fuzzy membership table using

$$\mu_{ik} = \frac{1}{\sum_{k=1}^c \left(\frac{|x_i - c_j|}{|x_i - c_k|} \right)^{\frac{2}{m-1}}}$$

Step 5: Recalculate J.

Step 6: Go to step 3 until a stopping condition is reached

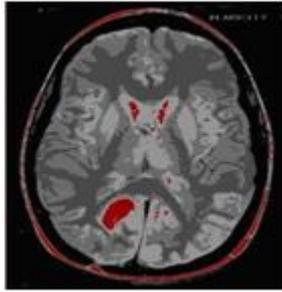


Figure 4: (a) FCM clustered image

The input is a MRI brain tumour image after Pseudo Color Translation as shown in Figure 1. Figure 4 shows the image after Clustering using Fuzzy C-Means Clustering [1] Algorithm. The clustering is in $L^*a^*b^*$ color space[3]

2(c) Calculate the area of the tumour

It is very essential to find the area of the tumour for better accurate results .The area is determined by selecting the tumour region and calculating the pixel values and adding the values. This method will provide a good result with less effort.

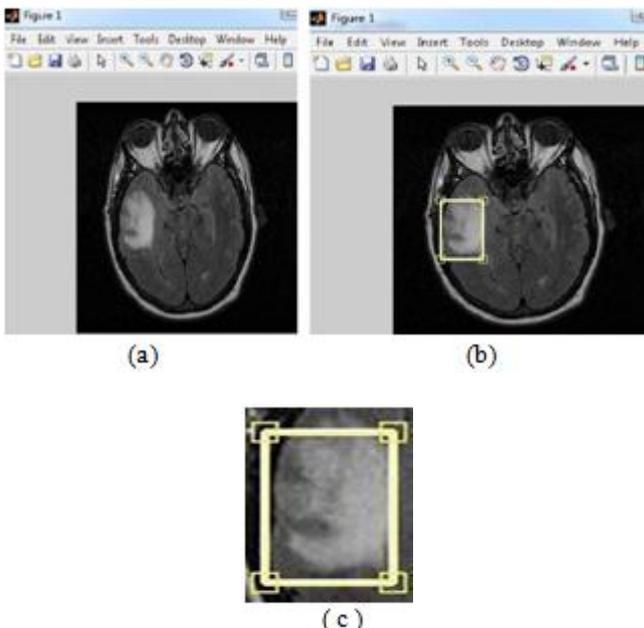


Figure 5: (a) Original image (b)Tumour Region that is been selected (c)The selected region is been cropped for further calculation

3. Result

The two algorithm namely K-Means and Fuzzy C means was performed for 100 iterations and the result was tabulated into (a) Performance and Execution Time of clustering techniques in RGB and (b) Performance and Execution Time of clustering techniques in $L^*a^*b^*$. The data distribution and the resulting values are represented by histogram

Table 1: performance of clustering techniques in RGB

Type of clustering	Recall	Execution time(s)
K-Means Clustering	94.5	1.875
Fuzzy C-Means Clustering	84.3	55.922

Table 2: Performance of clustering techniques in $L^*a^*b^*$

Type of clustering	Recall	Execution time(s)
K-Means Clustering	95.1	6.75
Fuzzy C-Means Clustering	84.6	17.340

Performance of Clustering Technique in RGB color space

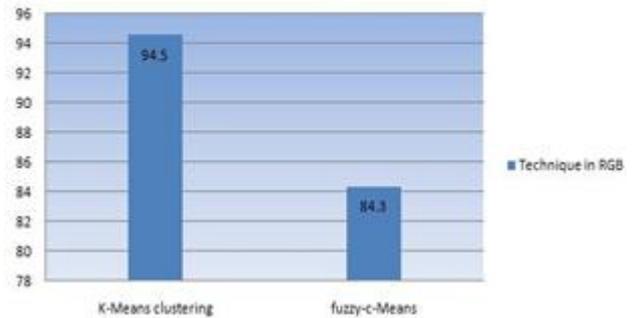


Figure 6: (a) Histogram representing recall(%) in RGB

Performance of clustering technique in $L^*a^*b^*$ color space

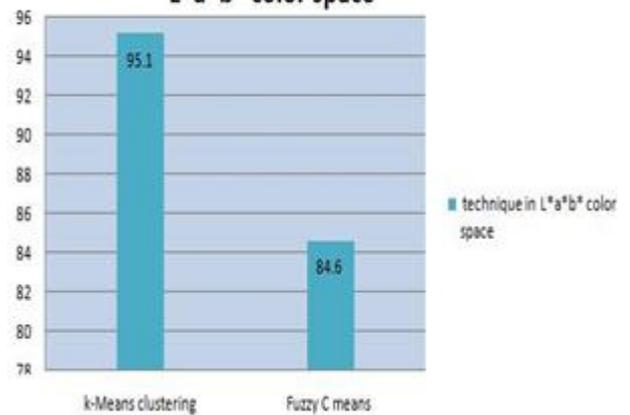


Figure 6: (b) Histogram representing recall(%) in $L^*a^*b^*$

Execution Time (in sec) in RGB Color space

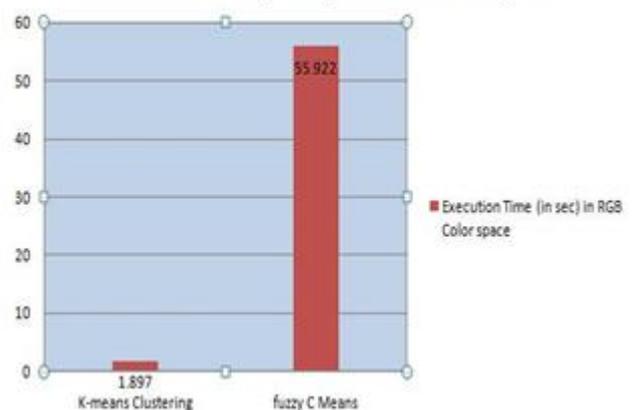


Figure 6: (c) Histogram representing execution time in RGB



Figure 6: (d) Histogram representing execution time in L*a*b*

From the values of the histogram, we can see that the time of execution is considerably lesser in K-Means Clustering than Fuzzy C Means. The following were tested with a database of 100 MRI brain images. K-means clustering achieved about 95% result. Fuzzy C Means achieved a result of about 80%.

4. Conclusion

This paper presents that the results from K-Means clustering method is better than the Fuzzy C Means method because, fuzzy C Means is semi-supervised method. Therefore, preprocessing is required, Whereas K-Means Clustering does not require preprocessing since it is unsupervised method and number of iteration is less. Maximum lossless compression is achieved by K-Means Clustering. It also provides accurate results with minimal amount of data. Hence, it is efficient and is less error sensitive.

In summary, we have described the characteristics of two widely used algorithm for segmentation. The area of the tumour is calculated manually. In order to achieve the higher accuracy rate, some other statistical features may have been introduced. This remains for future work

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