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# Hybrid Clustering for Automatic Tumor Extraction from MR Brain Images

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**Abstract**

In radiology, magnetic resonance imaging (MRI) is used to investigate the human body processes and functions of organisms. These images can be formed by using the magnetic fields and radio waves. In hospitals, this technique has been using widely for medical diagnosis, to find the disease stage and follow-up without exposure to ionizing radiation. MRI has a broad range of applications in medical diagnosis and in all over world there are over 25,000 scanners to be in use. It has an impact on diagnosis and treatment in many specialties although the effect on improved health outcomes is uncertain. MRT is more preferable over computed tomography (CT) since it does not use any ionizing radiation, when either modality could yield the same information. The sustained increase in demand for MRI within the healthcare industry has led to concerns about effectiveness of cost and over diagnosis. Segmenting an image is an effort to group similar colors or elements of an image into a cluster or group. This can be achieved by clustering, which clusters the number of colors or elements into several clusters based on the similarity of color intensities and gray intensities of an image.

Segmentation is a process of partitioning the image into several objects. It plays a vital role in many fields such as satellite, remote sensing, object identification, face tracking and most importantly in medical field. Here in this project, a hybrid clustering approach is proposed for detecting the tumor with improved performance in terms of precision time and accuracy from given MR brain images.

**Keywords:** Tumor extraction, MR brain images, hybrid clustering.

## 1. Introduction

In radiology, magnetic resonance imaging (MRI) [1] is used to investigate the human body processes and functions of organisms. These images can be formed by using the magnetic fields and radio waves. In hospitals, this technique has been using widely for medical diagnosis, to find the disease stage and follow-up without exposure to ionizing radiation. MRI has a broad range of applications in medical diagnosis and in all over world there are over 25,000 scanners to be in use. It has an impact on diagnosis and treatment in many specialties although the effect on improved health outcomes is uncertain. MRT is preferable over computed tomography (CT) since it does not use any ionizing radiation, when either modality could yield the same information. The sustained increase in demand for MRI within the healthcare industry has led to concerns about effectiveness of cost and over diagnosis. Segmenting an image is an effort to group similar colors or elements of an image into a cluster or group. This can be achieved by clustering, which clusters the number of colors or elements into several clusters based on the similarity of color intensities and gray intensities of an image.

Main objective of clustering an image is dominant colors extraction from the images. By extracting the information from images such as texture, color, shape and structure, the image segmentation can be very important to simplify. Because of the information extraction in any images, the segmentation has been used in many fields such as Enhancing the image, compression, retrieval systems i.e., search engines, object detection, and medical image processing [2].

From the past decades, there are so many approaches developed for the image segmentation. Among those, Fuzzy c-means (FCM) is a well-known method and very popular clustering scheme, which will segment the image into several parts based on the membership function [4] and [5]. After FCM, the K-means algorithm has been proposed to reduce the computational complexity of FCM. Because of its ability to cluster huge data points very quickly, K-means has been widely used in many applications [4], [7], [8] and [9]. Later years the Hierarchical clustering is also widely applied for image segmentation. Then after, Gaussian Mixture Model has been used with its variant Expectation Maximization for segmenting the images.

Here in this, hybrid clustering with estimate arguing algorithm is proposed for detecting the multi tissues in brain images with an improved performance over conventional segmentation techniques such as fuzzy c means (FCM), K-means and even that of manual segmentation in terms of accuracy. This system has mainly four modules: pre- processing, segmentation, Feature extraction, and estimate arguing. Pre-processing is done by median filtering. Segmentation is carried out by unified iterative partitioned fuzzy clustering (Hybrid Clustering). Area estimation is done by calculating tissue area and number of cells it occupied.

## 2. IMAGE SEGMENTATION

### 2.1 Segmentation

In computer vision, segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

### 2.2 Clustering methods

**Types of Clustering**

Hierarchical algorithms find successive clusters using previously established clusters. These algorithms can be either agglomerative ("bottom-up") or divisive ("top-down"). Agglomerative algorithms begin with each element as a separate cluster and merge them into successively larger clusters. Divisive algorithms begin with the whole set and proceed to divide it into successively smaller clusters.

Many clustering algorithms require specification of the number of clusters to produce in the input data set, prior to execution of the algorithm. Barring knowledge of the proper value beforehand, the appropriate value must be determined, a problem for which several techniques have been developed they are given below:

- Distance measure
- Hierarchical clustering
- Agglomerative hierarchical clustering
- Concept of clustering

## 3. Literature survey

Idanis Diaz introduced automatic brain tumour segmentation (ABTS) method for segmenting different constituents of the tumour in the brain. The approach was applied on four magnetic resonance image modalities to find the edema and gross tumour volume (GTV). The ABTS segmentation algorithm uses a histogram multi-thresholding technique and morphological operations like geodesic transformations. The registered images containing the standard MR sequence was applied as input. The first step was thresholding, followed by Skull, Edema, and gross tumour volume (GTV) segmentation. The method is fast and accurate for images produced from different scanners as it automatically identifies thresholds based on the histograms.

Author in [3] presented a segmentation algorithm that was based on improved watershed approach. This approach provided some better enhancements over manual segmentation algorithms, but it was suffering from few restrictions like over segmentation and sensitive to false edges. In [4], a fuzzy implementation has been presented by the author named fazel. Fuzzy is a set of rules and regulations, in which the segmentation depends on the membership values. However, fuzzy wasn't without drawbacks, it suffers from the computational complexity due to its dependency on membership function. Later, many researchers tried to implement hybrid combos with the integration of FCM algorithm. Author in [5] presented an effective segmentation of tissue in brain images by utilizing the combo of spatial information and FCM, this resolved the issue found in [4], but it was also taking more computational time to segment an image and also suffer from false edges. To overcome the limitations of above-mentioned segmentation algorithms, the author in [6] proposed an efficient segmentation algorithm which utilized k-means clustering for segmenting MR brain image. This approach was an extended version for the watershed, manual segmentation and FCM based algorithms. Segmented output of k-means is quite better over those algorithms, and this takes very less time to compute the segmented images. From then many researchers tried to implement the integrated algorithms with the combination of k-means clustering to get the enhanced performances in [7-10]. However, this K-means depends on the selected centroids initially. It needs new centroids to be updated by calculating the mean of obtained clustered points in the first iteration. The mean of these values provides the floating values which were not favorable for replacing as a new centroid. Therefore, K-means must need to optimize for the integer or scalar centroid to be replaced with the existed centroid.

**4. Proposed method**

Here in the proposed clustering algorithm, AIPMSC is utilized which employs Hybrid Clustering algorithm for optimizing the k- means clustering. Therefore, K-means must need to optimize for the integer or scalar centroid to be replaced with the existed centroid. In, the author has proposed a pillar-based approach to optimize the K-means clustering, in which the maximum value is selected instead of calculating the mean value to replace the initial centroid.

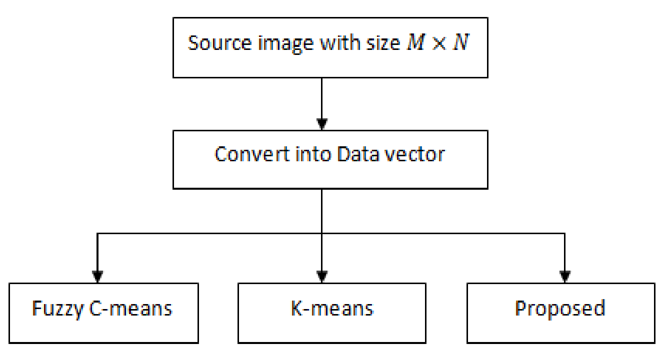


Fig. 1: Brain Tumour segmentation flow diagram.

Proposed segmentation algorithm consists of both iterative partitioned (IP) clustering and fuzzy clustering (FC) approaches. First, IP clustering is applied to the pre-processed MR brain image to obtain the segmented output having tissue in it. As discussed in earlier sections, IP clustering doesn’t provide the accurate segmentation results. Since IP clustering depends on the selected centroids initially. and requires new centroids to be updated by computing the obtained clustered points mean in the primary iteration. Usually, mean values render the floating-point values which are not suggestable in digital imaging to reposition as a new centroid.

**Algorithm 1**

Step 1: First, source image ‘I’ is to be chosen and read.

Step 2: Convert it into a data sets of column vector for grouping of similar elements.

Step 3: Choose the cluster quantity i.e., centroids.

Step 4: Now, compute the distance of every picture element form the cluster element.

Step 5: Calculate the number of data points those are near to the chosen clusters.

Step 6: Choose the cluster with a minimal distance and then mover the data point to the relevant cluster centroid.

Step 7: Now, re-estimate the new centroid by finding the mean of obtained data from step 6 and replace the initial centroid with the new one.

Step 8: Repeat this process iteratively until the attainment of symmetry of previous and new cluster point.

**Algorithm 2**

Source image = ‘J’

Segmented image = ‘O’

Step 1: Recall the outcome of algorithm 1 and read as an input MR brain image.

Step 2: Now, employ fuzzy clustering and apply it to the obtained image of Step 1.

Step 3: Show the obtained multi tissues of MR brain image and separate them as primary (T1) and secondary (T2) tumors.

Step 4: Apply 3D rendering and compute the volume of each tumor.

Step 5: Finally, compute the execution time to disclose the comparative analysis with existing clustering algorithms.

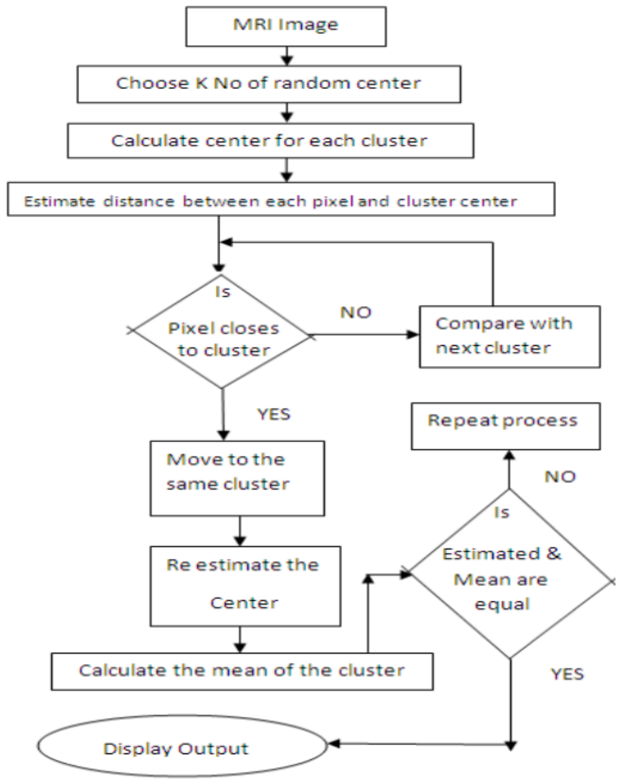



Fig. 2: Iterative partitioned clustering.

**Hybrid Clustering algorithm**

Our proposed Hybrid Clustering is described in this section briefly. Fig. 3 show that the block diagram of proposed segmentation methodology. Algorithm 1 and 2 explained the complete procedure for obtaining the segmented tissues of brain images by utilizing the proposed approach. Median filter is utilized as a pre-processing step to eliminate the noise from input MR brain image. Obtained denoised MR brain image is converted into data vector then k-means clustering is applied to segment this vector into several clusters. Now, the segmented output is optimized by fuzzy algorithm to enhance the segmentation accuracy and perfect tissue detection. At last, estimate arguing is applied to estimate the area of obtained tissue image by utilizing the typography and digital imaging units. Here, we considered the images of size 256 x 256 and the pixels in the segmented image having only two values i.e., either black or white, where the pixel value 0 denotes the black and 1 denotes the white.

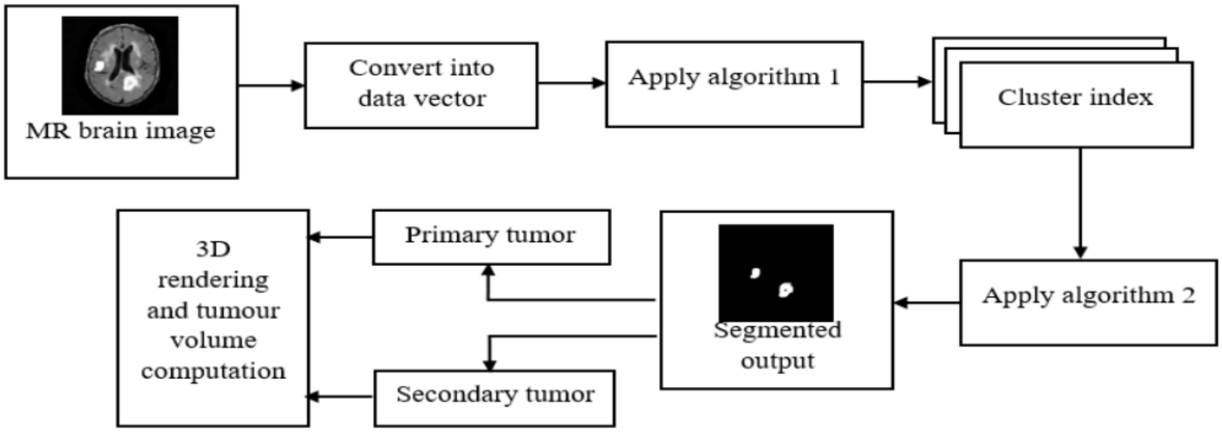



Fig. 3: Block diagram of proposed model.

**Area Estimation**

Hence, we can represent the segmented output image as a summation of total number of white and black pixels.

$$M = \sum_{x=1}^{L}\sum_{y=1}^{L}[f_{x,y}(0) + f_{x,y}(1)]$$

where L=1, 2, 3…256

$f_{x,y}(0)$ = black pixel having the value of zero,

$f_{x,y}(1)$= white pixels having the value of one

$$P = \sum_{i=1}^{L}\sum_{j=1}^{L} f_{x,y}(1)$$

Where,

P = number of white pixels

Now, by using the above equation, we can calculate the area of the segmented tumor based on the typography and digital imaging units [20], where one pixel is equal to 0.264583 millimeters. i.e., 1 pixel = 0.264583 mm

Then the area of tumor can be expressed as follows:

$$A_{Tumor} = (\sqrt{P})*0.2646mm^2$$

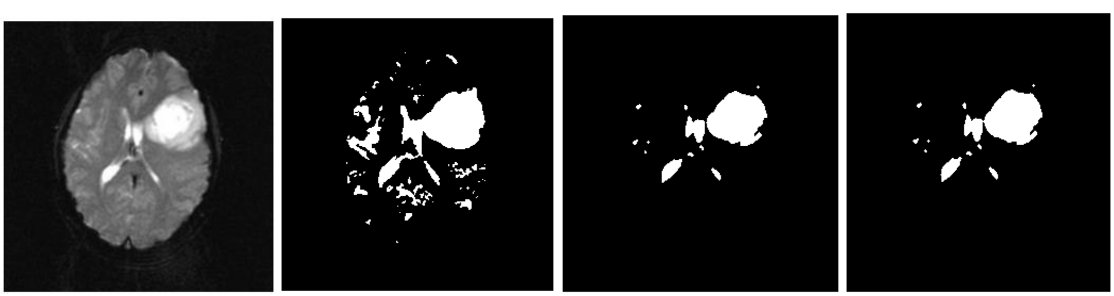
## 5. Results

In this section, we had given an overview of conventional and proposed segmented results with the area of tumor. All the experiments have been done in MATLAB 2016b64-bit version with 4GB RAM. We tested five set of images with various sizes such as 400x400, 512x512 and 600x600, which have the different stages of tumors. Then we evaluated the performance of conventional schemes Fuzzy c means, K-means and manually segmented algorithms with the proposed hybrid clustering algorithm for detection of single and multi-tissues in MR Brain images. The experimental results of MRI tumor detection using proposed hybrid algorithm and existing algorithms will be shown in below figures. By comparing the results our proposed approach is more effective and accurate. Fig5.1 and 5.2 shows that the segmented outputs of single tissue of MR brain images with manual segmentation, FCM clustering, K-means clustering and proposed hybrid clustering algorithms. From the obtained outputs, we can observe that the proposed hybrid clustering algorithm has detected the tumor more effectively with higher accuracy. Although, our proposed algorithm running time will be quite bit of more than the k-means clustering but however the accuracy of segmented output will be more i.e., tumor area will be estimated more precisely to diagnosis further.

(a) (b) (c) (d)

(e)

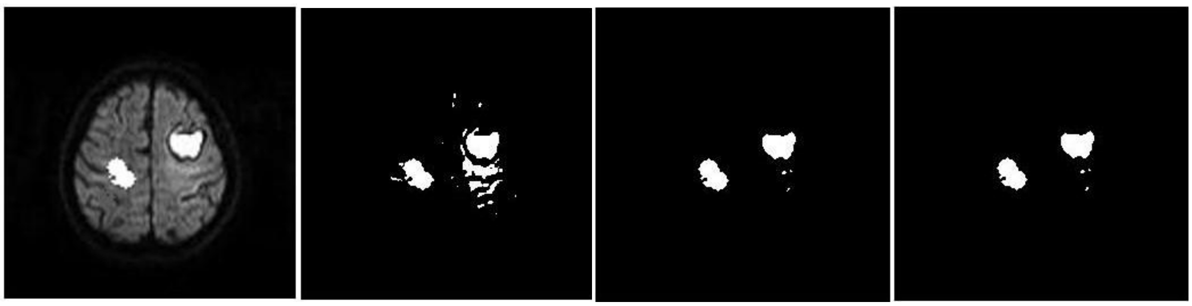
Fig. 4: (a) Original Image (b) manual segmentation (c) Fuzzy C Means clustering (d) K-means clustering (e) proposed hybrid clustering.



(a) (b) (c) (d)

(e)

Fig. 5: (a) original image (b) manual segmentation (c) fuzzy C means clustering (d) K-means clustering (e) proposed hybrid clustering.



(a) (b) (c) (d)

(e)

Fig. 6: Segmented multi tissues obtained (a) original image (b) manual segmentation (c) FCM clustering (d) K-means clustering and (e) proposed hybrid clustering.

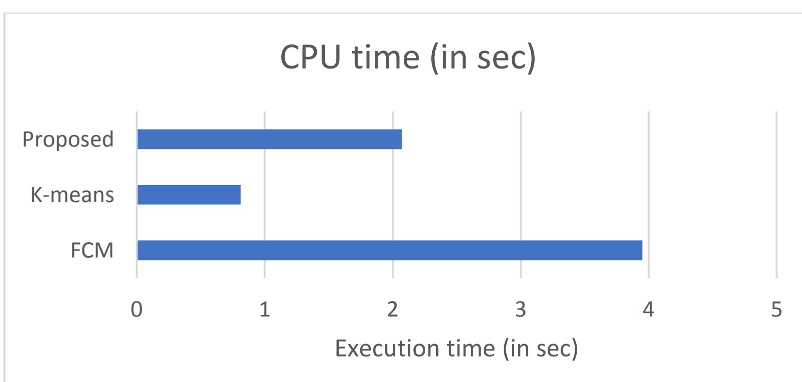



Fig. 7: Performance evaluation with CPU running time for multi tissues detection.

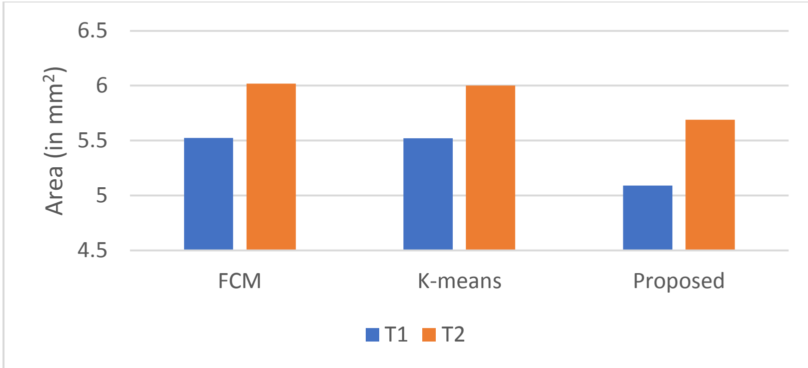



Fig. 8: Estimated area of segmented tissues T1 = tissue 1 and T2 = tissue 2.

Above figures demonstrates that the performance evaluation of proposed hybrid clustering algorithm with comparison to the conventional clustering algorithms presented in the literature. We calculated execution time in seconds and tissues area in mm2

**6. Conclusion**

The implementation of detecting single and multi-tissues in MR brain images and to estimate the area of the tissue has done with an improved accuracy and reduced computational time. Utilization of unified iterative partitioned fuzzy clustering and estimation of the area in terms of $mm^2$ based on the typography and digital imaging units has done successfully. We also compared the simulation results with the existing algorithms. Furthermore, this can be extended to 3D multi modal medical image segmentation with more effective and accurate clustering algorithms.

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