



## Brain Tumor Detection Using Efficient K-Means Clustering Segmentation

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**Abstract-** Brain tumour segmentation is a crucial step in surgical planning and treatment planning. A significant medical informatics task is indexing patient databases according to size, location, and other characteristics of brain tumours and edemas, possibly based on magnetic resonance (MR) imagery. This requires segmenting tumours and edemas within images from different MR modalities. Automated brain tumour or edema segmentation from MR modalities remains a challenging, computationally intensive task. This paper presents a study of k means clustering Approach for to segmenting brain tumor from MRI images.

**Keywords:** Brain tumour segmentation, MRI images, Center calculation K-Mean Clustering

### I. INTRODUCTION

Brain tumour segmentation means segregating tumor from non tumour tissues. In medical imaging, it is one of the crucial steps in surgical and treatment planning. There are various types of malignant tumours such as a stercytoma, and metastatic, which vary greatly in appearance, size and location. Magnetic resonance (MR) sequences such as T1-weighted, T2-weighted and contrast-enhanced T1-weighted scans provide different information about tumours. On these images, brain tumours appear either hypo intense (darker than brain tissue), or isointense (same intensity as brain tissue), or hyper intense (brighter than brain tissue) [5]. The accurate estimation of tumour size is important for clinical reasons, e.g., for treatment planning and therapy evaluation.

Although maximum tumour diameter is widely used as an indication of tumour size, it may not reflect a proper assessment of this tumour attribute because of the 3D nature and irregular shape of the tumour. Tumour volume, on the other hand, may be an appropriate representation of tumour size. Extract the vessel contours. Depending on the image quality and the general image artifacts such as noise, some segmentation methods may require image preprocessing prior to the segmentation algorithm. On the other hand, some methods apply post-processing to overcome the problems arising from over segmentation.

Vessel segmentation algorithms and techniques can be divided into six main categories, pattern recognition techniques, model-based approaches, tracking-based approaches, artificial intelligence- based approaches, neural network-based approaches, and miscellaneous tube-like object detection approaches. Pattern recognition techniques are further divided into seven categories, multi-scale approaches, skeleton-based approaches, region growing approaches, ridge-based approaches, differential geometry-based approaches, matching filters approaches, and mathematical morphology schemes. Clustering analysis plays an important role in scientific research and commercial application. This thesis provides a survey of current vessel segmentation methods using clustering approach and provides both early and recent literature related to vessel segmentation algorithms and techniques.

#### A. Existing system:

Initial centroid value is assumed. Probability of getting a zero matrix. Fail sin larged at a sets

#### B. Proposed system:

K-Means is the one of the unsupervised learning algorithm for clusters. Clustering the image is grouping the pixels according to the some characteristics. In the k means algorithm initially we have to define the number of clusters k. Then k-cluster centre are chosen randomly. The distance between the each pixel to each cluster centres are calculated. The distance may be of simple Euclidean function. Single pixel is compared to all cluster centers using the distance formula. The pixel is moved to particular cluster which has shortest distance among all. Then the centroid is re-estimated. Again each pixel is compared to all centroids.

The process continues until the centre converges The improved K-means algorithm is a solution to handle large scale data, which can select initial clustering center purposefully, reduce the sensitivity to isolated point, and avoid dissevering big cluster. By using this technique locating the initial seed point is easy and which will give more accurate and high-resolution result. By using various techniques we can study or compare the results and find out which technique gives higher resolution Initial centroid algorithm is useful to avoid the formation of empty clusters, as the centroid values are taken with respect to the intensity value of the image. Proposed algorithm is better for large datasets and to find initial centroid. K-Means can be thought of as an algorithm relying on hard assignment of information to a given set of partitions. At every pass of the algorithm, each data value is assigned to the nearest partition based upon some similarity parameter such as Euclidean distance of intensity.

The partitions are then recalculated based on these hard assignments. With each successive pass, a data value can switch partitions, thus altering the values of the partitions at every pass. K-Means algorithms typically converge to a solution very quickly as opposed to other clustering algorithms. Two K-Means algorithms have been implemented. The first clusters the pixel information from an input image based on the RGB color of each pixel, and the second clusters based on pixel intensity. The algorithm

begins with the creation of initial partitions for the data. The clustering based on pixel color will be considered first. In a nearly identical setup, a second K-Means implementation was made using the grayscale intensity of each pixel rather than the RGB color to partition the image. The starting partitions were chosen as equally spaced values from 0 to 255. The number of partitions used, as in the color segmenting setup, was varied in order to increase the number of results available and to study the effects of varying this parameter k-means algorithm that selects k objects randomly from population as the initial centroids. The paper is organized as follows. In the next section we review the standard k means algorithm and give an example to illustrate how we get the initial centroids

## II. CLUSTERING ANALYSIS

K-Means clustering algorithm –similar to nearest neighbor techniques (memory-based-reasoning and collaborative filtering)– depends on a geometric interpretation of the data Organizing data into clusters how internal structure of the data Ex. Clusty and clustering genes above Sometimes the partitioning is the goal Ex. Market segmentation Prepare for other A techniques Ex. Summarize news(cluster and then find centroid) Techniques for clustering is useful in knowledge discovery in data

## III. K-MEANS ALGORITHM

### A. Algorithm of K-Mean Clustering:

- a. Give the no of cluster value as k.
- b. Randomly choose the k cluster centres.
- c. Calculate mean or centre of the cluster.
- d. Calculate the distance b/w each pixel to each cluster centre.
- e. If the distance is near to the centre then move to that Cluster.
- f. Otherwise move to next cluster.
- g. Re-estimate the centre.
- h. Repeat the process until the centre doesn't move

### B. K-means clustering:

K-means (Macqueen, 1967) is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters)fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and a nearly group age is done. At this point we need to recalculate k new centroids as bary centers of the clusters resulting from the previous step

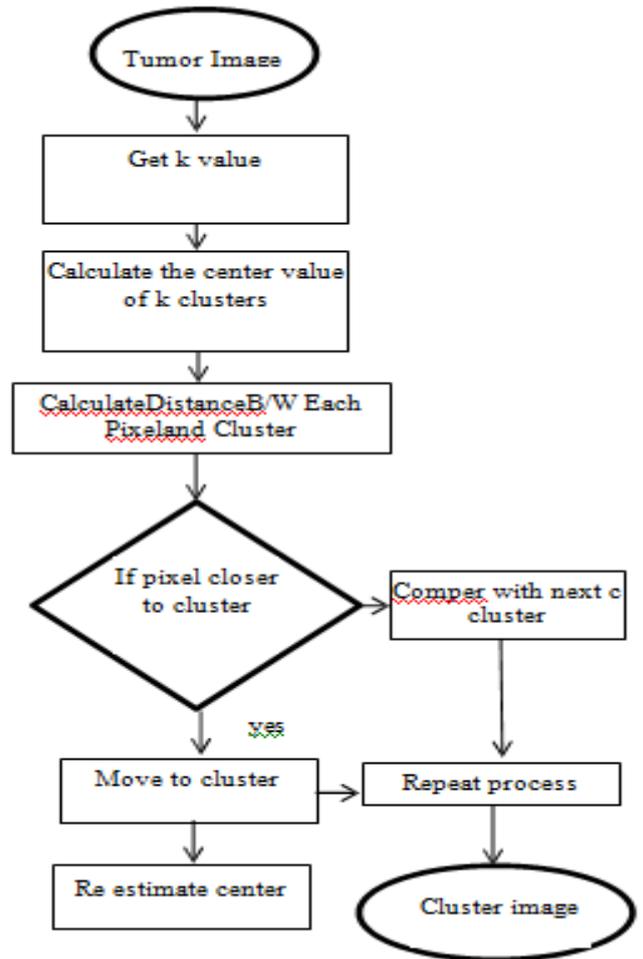


Figure:-Flow chart for K-Means Algorithm

### C. K-means overview:

There are always K clusters. There is always at least one item in each cluster. The clusters are non-hierarchical and they do not overlap. Every member of a cluster is closer to its cluster than any other cluster because closeness does not always involve the 'centre' of clusters. K-means clustering in particular when using heuristics such as Lloyd's algorithm is rather easy to implement and apply even on large data sets. As such, it has been successfully used in various topics, ranging from market segmentation, computer vision and astronomy to agriculture. It often issued as a preprocessing step for other algorithms, for example to find a starting configuration. In statistics and data mining, k-means clustering is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean. Figure1 shows the flow chart of k-means algorithm which is relatively efficient and applicable only when mean is defined. Figure1 shows the flow chart of k-means algorithm which is relatively efficient and applicable only when mean is defined.

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of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and a nearly group age is done. At this point we need to recalculate  $k$  new centroids as bary centers of the clusters resulting from the previous step. After we have these  $k$  new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop had been generated. As a result of this loop we may notice that the  $k$  centroids change their location step by step until no more changes are done. In other words centroids do not move anymore. K-Means clustering generates a specific number of disjoint, flat clusters. K-Means method is numerical, unsupervised, non-deterministic and iterative. Hierarchical clustering is also widely employed for image segmentation. The most popular method for image segmentation is  $k$ -means clustering.

#### IV. FEATURE EXTRACTIONS

The issue of choosing the features to be extracted should be Guided by the following concerns. The features should carry enough information about the image and should not require any domain-specific knowledge for their extraction. They should be easy to compute in order for the approach to be feasible for large image collection and rapid retrieval. An image is partitioned into  $4 \times 4$  blocks, a size that provides a compromise between texture granularities, computation time and segmentation coarseness as a part of preprocessing; each  $4 \times 4$  block is replaced by a single block containing the average Value over the  $4 \times 4$  block. To segment an image into objects, some features are extracted from each block. Texture features are extracted using Haar Wavelet Transform. After obtaining features from all pixels on the image, perform  $k$ -means clustering to group similar pixel together and form objects. Feature extraction has been done using MATLAB Image Processing tool. The advantage of  $k$ -means algorithm is that it works well when clusters are not well separated from each other, which is frequently encountered in images. However  $k$ -means requires the user to specify the initial cluster centers. Image clustering consists of two steps, the former is feature extraction and these cond. Part is grouping. For each image in the data base, a feature vector capturing certain essential properties of the image is computed and stored in a feature base. Clustering algorithm is applied over this extracted feature to form the group. In terms of performance the algorithm is not guaranteed to return a global optimum. The quality of the final solution depends largely on the initial set of clusters, and may, in practice, be much poorer than the global optimum.] Since the algorithm is extremely fast, a common method is to run the algorithm several times and return the best clustering found. Starting point for these cond. phase. The second phase uses *online updates*, where points are individually reassigned if doing so will reduce the sum of distances, and cluster centroids are recomputed after each reassignment. Each iteration during these cond phase consists of one pass though all the points. The second phase will converge to a local minimum, although there may be other local minima with lower total sum of distances. The problem of finding the global minimum can only can be solved in general by an

exhaustive(or clever, or lucky) choice of starting points, but using several replicates with random starting points typically results in a solution that is a global minimum.

#### A. K-means functions:

Standard  $k$ -means clustering algorithm and give our improved version which partitions a data set into clusters according to some defined distance measure. Images are considered as one of the most important medium of conveying information. Understanding images and extracting the information from them such that the information can be used for other tasks is an important aspect of Machine learning. An example of the same would be the use of images for navigation of robots. One of the first steps in direction of understanding images is to segment them and find out different objects in them. To do this, we look at the algorithm namely  $K$ -means clustering. It has been assumed that the number of segments in the image is known and hence can be passed to the algorithm.  $K$ -Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The functions of  $k$ -means are as follows.  $IDX = k\text{-means}(X, k)$  partitions the points in the  $n$ -by- $p$  data matrix  $X$  into  $k$  clusters. This iterative partitioning minimizes the sum, overall clusters, of the within-cluster sums of point-to-cluster-centroid distances. Rows of  $X$  correspond to points, columns correspond to variables.  $K$ -means returns an  $n$ -by-1 vector  $IDX$  containing the cluster indices of each point. By default,  $k$ -means uses squared Euclidean distances [8,9]. When  $X$  is a vector,  $k$ -means treats it as an  $n$ -by-1 data matrix, regardless of its orientation.  $[IDX, C] = k\text{-means}(X, k)$  returns the  $k$  cluster centroid locations in the  $k$ -by- $p$  matrix  $C$ .

#### V. SIMULATION RESULT

#### VI. CLUSTER ALGORITHM

$K$ -Means uses a two-phase iterative algorithm to minimize the sum of point-to-centroid distances, summed overall  $k$  clusters: The first phase uses *batch updates*, where each iteration consists of reassigning points to the irnearest cluster centroid, all at once, followed by recalculation of cluster centroids. This phase occasionally does not converge to solution that is a local minimum, that is, a partition of the data where moving any single point to a different cluster increases the total sum of distances. This is more likely for small data sets. The batch phase is fast, but potentially only approximates a solution as a

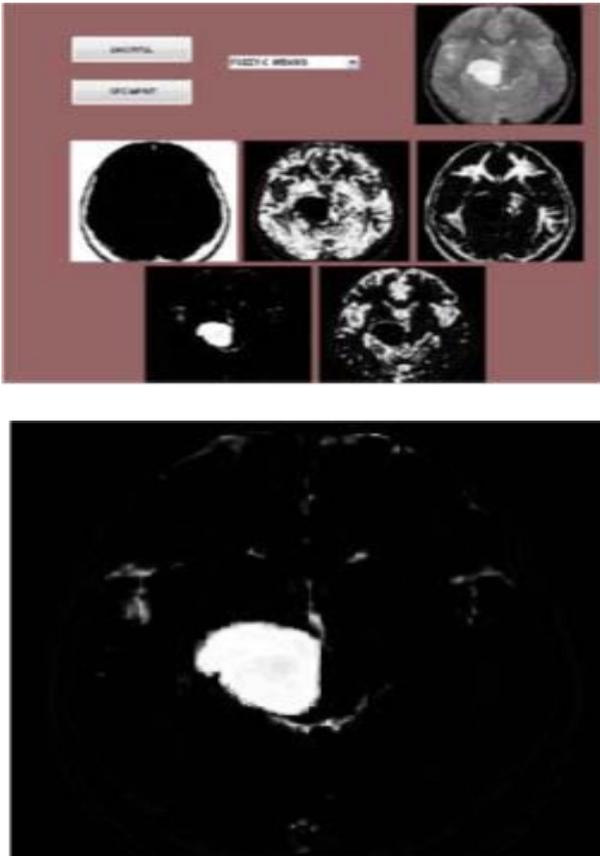


Figure: Out Put tumor

## VII. CONCLUSION

Tumor segmentation methods have been a heavily researched area in recent years. Even though many promising techniques and algorithms have been developed, it is still an open area for more research. This algorithm does not require any user interaction, not even to identify a start point. Here seed points are selected randomly which determines the main branches of the vessel structure.

Random selection of seed points does not yield accurate segmentation. Accuracy of the segmentation process is essential to achieve more precise and repeatable radiological diagnostic systems. Accuracy can be improved by incorporating a priori information on vessel anatomy and let high level knowledge guide the segmentation algorithm. K means algorithm is a popular clustering algorithm applied widely, but the standard algorithm which selects k objects randomly from population as initial centroids cannot always give a good and stable clustering. Experimental results show that selecting centroids by our algorithm can lead to a better

clustering. Along with the fast development of database and network, the data scale clustering tasks involved in which becomes more and more large. K-means algorithm is a popular partition algorithm in cluster analysis, which has some limitations when there are some restrictions in computing resources and time, especially for huge size

## VIII. REFERENCES

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