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Brain Tumour Segmentation Using Clustering and Em Segmentation

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Abstract

Tumour is a mass of cells growing in or on a part of the body where they should not, usually causing medical problems. Brain Tumor is an intra-cranial solid neoplasm occurs within the brain or the central spinal canal. Image analysis is generally a process where digital image processing is utilized to process digital images in order to extract significant statistics or information from the images. In this paper, we discuss about methods and techniques being proposed and developed first two categories of image analysis i.e., image segmentation and edge detection. Segmentation of medical images has the significant advantage that interesting characteristics are well known up to analysis the states of symptoms. Here clustering algorithm is used for segmenting medical images. Detection of brain tumor in early stages can enhance the prevention mechanism to stronger level. Detection of brain tumor from digital image processing techniques is one of the most essential parts for work. Here, we are using canny edge detector algorithm for detecting such a medical images.

Keyword: Image analysis, segmentation, clustering, edge detection, canny edge detection.

Introduction

Brain tumor is one of the common diseases which are treated in medical science. Primary brain tumors are those that begin in the brain and tend to stay in the brain. Metastatic brain tumors begin as a cancer elsewhere in the body and migrate, or metastasize, to the brain. There are more than 120 different types of brain tumors; some are malignant (cancer), many are benign (noncancerous). The cause of brain tumors is unknown. Benign or malignant, primary or metastatic, brain tumors are treatable. More knowledge about brain tumors has been gained in the last ten years than in the past hundred years due to involvement of high resolution techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), functional MRI (fMRI), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) in medical imaging. Imaging techniques to diagnose, stage, and follow patients with brain tumors are central to the clinical management. MRI is the most commonly used technique for lesion detection, definition of extent, detection of spread and in evaluation of either residual or recurrent disease.

The existing tumor detection methods broadly classified into three categories: atlas-based methods [1], [2], symmetry property-based methods [3]–[5] and feature-based methods [6]–[9]. Most of the methods are semi-automatic and require user intervention either to initiate or to refine the results.

Image analysis is a process mainly utilized to extract facts confined in the images. This process basically goals at identifying, analyzing and labeling the texture together with the geometry of digital images. The facts, statistics and subsequently the significance of the image are purpose of the procedures used on behalf of its development and achievement. The features by which a digital image is recognized and characterized are of spectral and symmetrical environment. Brain image analysis is a subfield of image analysis and comprises a huge range of applications [10] in detecting, diagnosing and treating brain related issues and diseases. The following figure 1 shows the structure of image analysis:

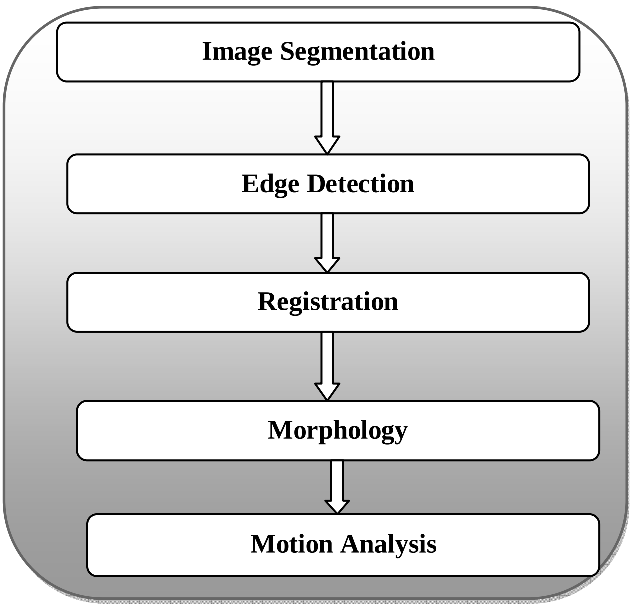

Figure 1: Steps in Image Analysis

(a) Image Segmentation: A vital problematic domain, termed segmentation, is to differentiate substances commencing background or states to the procedure of dividing a digital image into numerous parts. For intensity images, there exist four general methods which are: threshold procedures, edge-based approaches, region-based practices and connectivity-preserving relaxation procedures.

(b) Edge Detection: Edge detection is an essential instrument in image processing, principally in the capacities of feature detection and extraction which target on classifying facts in a digital image at which the image illumination fluctuates suddenly or further has breaks and gaps.

(c) Image Registration: It is the procedure of aligning and arranging two or further images having identical prospect or vision.

(d) Morphology: Morphology is a comprehensive traditional process of image processing procedures that course images centered on shapes. A morphological process utilizes a structuring component to an input image while generating an output image of equal dimension.

(e) Motion Analysis: Motion analysis is a subject in image processing that lessons approaches and methods in which two or additional successive images from an image arrangement are treated to produce material centered on the deceptive motion in the images.

Literature Survey

The brain image analysis [12] process is discussed from the viewpoint of MRI brain imaging types which are given in the figure below:

Table 1: MRI Brain Images Analysis Methods Comparison

S. No	Application	Pros	Cons	Results
1	MRI brain segmentation [12]	Has application to MRI as well as to EEG and MEG	-	It has been shown through results that the technique handles MRI segmentation in an effective way.
2	MRI volume visualization [13]	Handles both 2D and 3D data	-	The results show that the method gains a powerful ability of structural manipulation and volume visualization
3	Segmentation of MRI images [14]	Feature segmentation of even noisy images	Difficult formulation	Results of this technique show that it is better, fast and accurate as compared to other algorithms
4	Segmentation of MRI	The advantage is that the	Less accurate with noisy	Average differences are 1.7% and 2.7%

	medical images [16]	proposed method is very fast in segmentation and automatic as well	images	
5	MRI images registration of medical sector [17]	If there is a picture with less information, it will handle it	-	Results show that the proposed method is better for dealing missing information pictures
6	MRI brain segmentation in medical sector [20]	Advantage of this method is that it can segment and detect brain as well as contour	Limitation is that calculation is difficult for contour detection	Proposed method shows better results for contour and brain detection as well as for segmentation
7	MRI brain sector [18]	Advantage is that it is more robust as compared to the individual implemented techniques	Limitation is that data is complex because of 3D images	Improved results are obtained through 3D segmentation of MRI Brain Images
8	MRI brain sector [19]	Advantage of this method is that it is fast and easy to understand	-	The proposed method is tested and compared with ordinary algorithms and it shows better results.
9	Brain images of MRI [21]	Advantage of this method is that it is fast and easy to understand	Limitation is that it has greater tile of computations	The proposed method shows better results as compared to other methods and algorithms.
10	Medical MRI brain department [22]	Advantage of the work is that it does not require any manual data	Limitation of this method is that it shows less accurate results on adult brain images	The suggested technique gives more accurate experimental results in comparison with existing methods
11	MRI brain department [23]	It has greater speed and accuracy and it	Limitation is not mentioned	Results show that the method proposed is fast and more accurate as

		is simple as well		compared to algorithms already existing
12	MRI abdominal images department [24]	Advantage is that it is fast	-	The proposed technique gives more precise and reliable results
13	3D segmentation of medical images [25]	This method is very efficient to volume estimation and segmentation	It shows less accuracy if quality of image is low	Experimental results show that novel method is more accurate rather than the ordinary methods
14	Medical sector [26]	Advantage is that it is used for both manual and automatic segmentation	Limitation of this method is that it has very complex calculations	Results show that the segmentation procedure added with the volume visualization has strong ability to segment brain
15	Medical sector [27]	Advantage is that it segments the brain from even noisy images	Limitation is that it involves different algorithms and thus it is complex	The extensive experiments are conducted to validate the results and proposed method shows better results

Brain Image Analysis Technique

Basically different brain image types are MRI, CT, PET, and EEG/MEG. In this section we will analyze MRI methods and techniques that have been proposed in the perspective of brain image analysis.

MRI (Magnetic Resonance Imaging): The first paper in this regard is a MRI brain segmentation method [12]. The procedure presented is for finding brain and contours. Also genuine computation form for EEG and MEG investigation is proposed. The work proposed in [13] is a 3D volume information segmentation centered on 2D image segments. By utilizing the customer presented image mask containing the concerned regions or structural data, the half automatic segmentation method is able to produce segmented fresh volume dataset and regional data. The object centered volume apparition procedure is capable of using this segmented dataset and regional data to carry out structural centered treatment and visualization. The method described in [14] presents the geometric active contour models for detecting the edges and segmentation [15] of MRI and CT images. Method defined is based on feature matrices and then added to the novel snake paradigm. Another automatic brain segmentation of MRI images is addressed in paper [16]; proposed method follows two steps: i) initial model is created first ii) secondly that model deformation to map the precise contour of brain. Automatic segmentation is thus performed by following these two steps. The method described in [17] is the process of registration of brain images. The images are multimodal of MRI and SPECT. This was the big problem because of non availability of any land mark. To overcome this problem, the method uses the anatomic invent brain properties. The method is also presented for missing information i.e., pathological cases. A hybrid method in [18] is introduced for brain segmentation in 3D MRI images. Fuzzy region growing and edge detection is introduced. The proposed technique combines the edge detection method and region growing method. In [19] a novel system is presented to segment automatically from the MRI brain images. Different algorithms are used to extract different types of data. Proposed graph cut atlas based method uses that prior data or information and automatically calculates the atlases and boundaries from the image.

Proposed System

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. So we apply the segmentation on the MRI loaded image.

1. After that we develop the code for the Clustering segmentation and apply on the loaded image. This algorithm is used to segment the non-segmented portion of brain.
2. At the last we develop the code for average detection of tumor from the results of these two algorithms.
3. In our proposed method we implement detection and segmentation of brain tumor through Magnetic Resonance Image.

The following figure shows the system architecture of our proposed system.

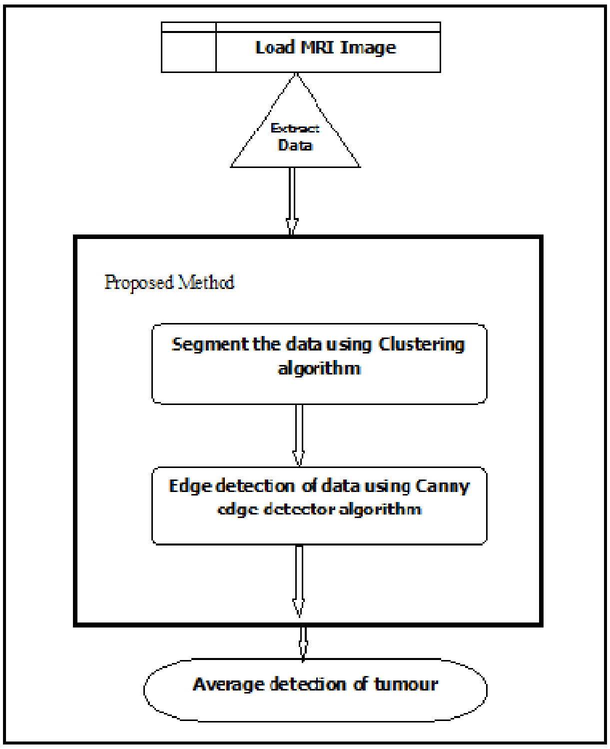

Figure 1: System Architecture

Algorithms Used

A. Fuzzy C-means Clustering Algorithm

Fuzzy c-means (FCM) is the clustering algorithm which allows one piece of data may be member of more than one clusters. Fuzzy clustering is basically a multi valued logic that allows intermediate values i.e., member of one fuzzy set can also be member of other fuzzy sets in the same image. There is no abrupt transition between full membership and non membership. The membership function defines the fuzziness of an image and also to define the information contained in the image. These are three main basic features involved in characterized by membership function. They are support, Boundary. The core is a fully member of the fuzzy set. The support is non membership value of the set and boundary is the intermediate or partial membership with value between 0 and 1.

It is based on reducing the following function,

$$Xm = \sum_{i=1}^{L} \sum_{j=1}^{N} M_{ij}^{m} \left\| X_i - C_j \right\|^2$$

Where

m - any real number greater than 1,

M_{ij} - degree of membership of X; in the cluster j,

X_i - data measured in d-dimensional,

R_j - d-dimension center of the cluster,

B. K-Means Clustering

The K-means clustering is an algorithm to group objects based on attributes into numbers of groups where k is a positive integer. The Clustering is done by minimizing the Euclidean distance between data and the corresponding cluster centroid. Thus the purpose of k-means clustering is to cluster the data. K-means algorithm is one of the simplest partitions clustering method.

Algorithm:

1. Give the no of cluster value as k
2. Randomly choose the k cluster centers
3. Calculate mean or center of the cluster
4. Calculate the distance between each pixel to each cluster center
5. If the distance is near to the center then move to that cluster
6. Otherwise move to next cluster

Adaptive K-Means Clustering:

The adaptive k- means clustering algorithm starts with the selection of K elements from the data set. The K elements form the seeds of clusters and are randomly selected. The properties of each element also form the properties of the cluster that is constituted by the element. It is also called as Threshold-Based Clustering Algorithm. In the threshold-based clustering algorithm, the number of clusters is unknown. However, two elements are classified to the same cluster if the distance between them is below a specified threshold.

Segmentation Using EM Algorithm:

Expectation:

With an initial guess for the parameters of the GMM (Gaussian Mixture Model distribution) partial membership of each image voxel in each distribution is estimated by computing expectation values for the membership variables of each data voxel. For each data voxel x_j and distribution Y_i, the membership value $y_{i\,j}$.

Maximization:

Once the expectation values are computed for group membership, estimates are re-calculated for the distribution parameters. The blending coefficients are the means of the membership values over the N data voxels

Experimental Results

The following figure 2 shows is the input image that has been uploaded for the Preprocessing. Figure 3 shown below is the histogram for the input image whose peaks value shows the tumor portion.

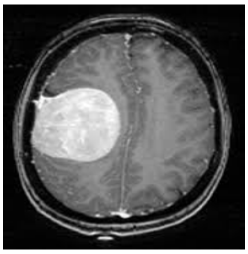

Figure 2: Input Image

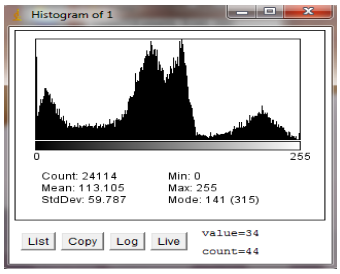

Figure 3: Histogram of input image

The first step in the segmentation is Thresholding the input image which is nothing but converting the input image into Black & White image or Binary image. The Figure 4 is the threshold image. The pixel value from 0 to 200 signifies 0 and is shown by white region. The pixel value from 200 to 255 signifies 1 and is shown by black region. The Figure 5 is the image obtained from FCM clustering in which the tumor can be seen clearly. To get this FCM clustered image a number of layers has been segmented to get the final image. The set of clusters obtained in the FCM clustering is shown below:

Figure 4: Threshold Image

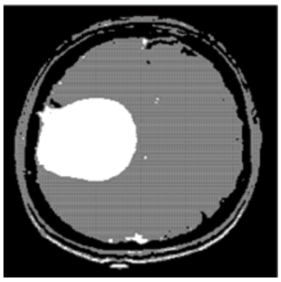

Figure 5: FCM Clustered Image

The Figure 6 is the set of clusters obtained from the FCM Clustering. In the set there are three clusters which are also called as the object. In the Figure 6 the 3rd cluster shows the tumor but, along with the tumor some noise is also present which needs to be filtered. After filtering the 3rd cluster alone, the resulted image is shown below.

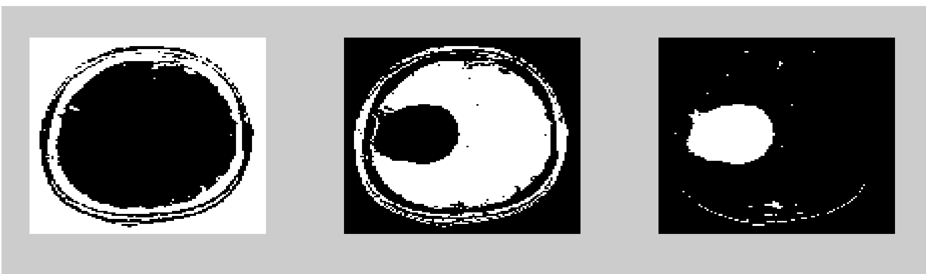

Figure 6: Clusters Obtained From FCM Clustering

The size of the tumor portion by FCM Clustering is 6303 which is shown in the Figure7.

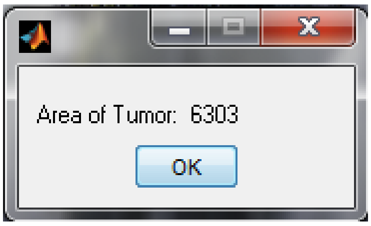

Figure 7: Size of Tumor Portion by FCM Clustering

In the Figure 8 there are four clusters and each cluster has different pixel value. The 4th cluster shows the tumor part which is same as obtained from FCM clustering but it looks smaller than the tumor region obtained from FCM clustering. Also along with the tumor some additional noise is present that is filtered out to get the exact size of the tumor which is stated below

Figure 8: Clusters Obtained From K-Means Clustering

The size of the tumor obtained from K-Means is 6020 μm^2 shown in Figure 9

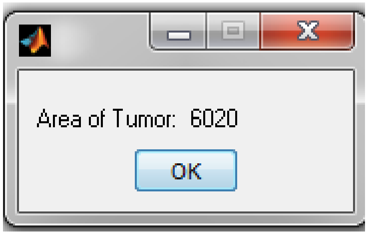

Figure 9: Size of Tumor Portion by K-Means Clustering

The time elapsed in the segmentation by K-Means is 0.076355 seconds. It is lesser than the time taken by the FCM.

Figure 10 shows the set of clusters obtained from Adaptive K-Means Clustering. In this figure there are four clusters but only 3rd cluster shows the tumor. When the 3rd cluster is again segmented, the tumor part get vanished this show that the Adaptive K-

Means clustering takes larger pixel value in each cluster. The size obtained from this Algorithm is smaller than the size obtained from earlier two algorithms.

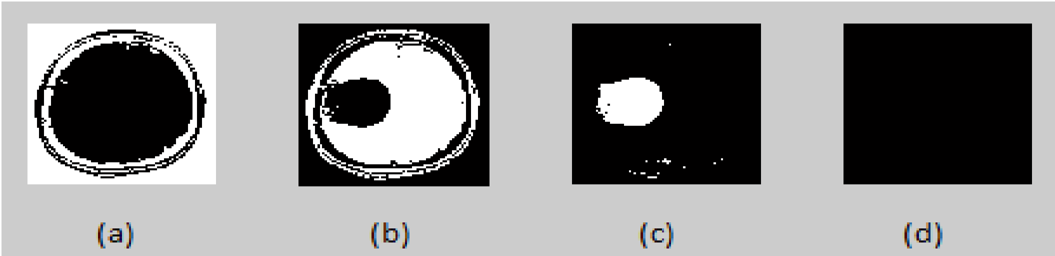

Figure 10: Set of Clusters Obtained From Adaptive K-Means Clustering

The size of the tumor is 5788µm^2 shown in Figure 11

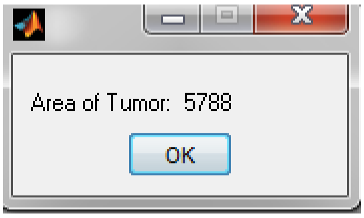

Figure 11: Size of Tumor by Adaptive K-Means Clustering

Figure 12 is the set of clusters obtained from EM-Segmentation. There are five clusters present in the set in which fifth clusters shows the tumor location. The EM segmentation gives the highest number of clusters for the same image. This shows that it takes smaller range of pixel value for each cluster and that's the reason, this algorithm is considered as the best one and also due to its convergence approach it takes less time to segment the tumor region. The size of the tumor obtained after the segmentation is approximately equivalent to the size given by the expert.

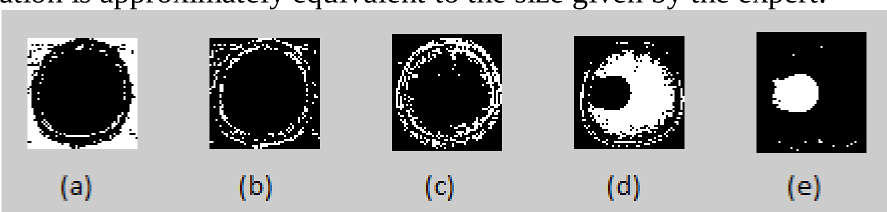

Figure 12: Clusters from EM Segmentation

The size of the tumor by EM Segmentation is 5886 µm^2 shown in Figure 13

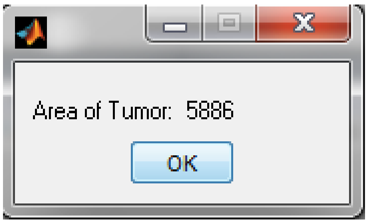

Figure 13: Size of Tumor by EM Segmentation

Outputs from all the four algorithms

The Figure 14 shows the set of images obtained from all the four Algorithms. The first image is the input image, the 2nd is the threshold image, 3rd one is the FCM image, 4th is the K-Means clustered image, the 5th image is adaptive k-means segmented image and the last image is the EM Segmented image. On comparing all the clustering the k-means clustering is sharpest and gives the clear vision of the tumor.

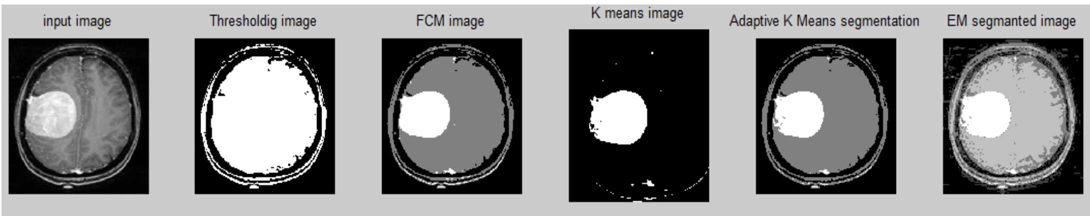

Figure 14: Set of Images obtained from all the four algorithms

Conclusion

The research compares the performance of the Fuzzy C-Means, K-Means, Adaptive K-Means and Expectation Maximization Algorithm for the Brain tumor segmentation. The algorithms are developed in MATLAB for analysis and comparison. K-means clustering produces fairly higher accuracy and requires less computation. Fuzzy C means clustering produces close results to K-means clustering, yet it requires more computation time than K-means, because of the fuzzy measures calculations involved in the algorithm. Whereas in adaptive K- means clustering, there is no need to assign the k's value. It gives more accurate result than the k-means clustering. In FCM and Adaptive K-Means clustering the tumor is present in the third Cluster but k-means clustering and EM segmentation shows the tumor part in fourth and fifth clusters. The size of the tumor varies in all the four algorithm. The Adaptive K-Means Algorithm gives the lesser size for the same case.The major drawback Of the FCM Algorithm is The Huge Computational Time Required for Convergence. The Effectiveness of the FCM Algorithm in terms of Computational Rate is improved by modifying the Cluster centre and membership value updating criterion.

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