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IJIEMR Transactions, online available on 28th July 2017. Link :

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Volume 06, Issue 05, Page No: 2163 – 2168.

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SEGMENTATION OF IMAGES IN EXTRACTION OF BRAIN TUMOUR FROM MRI.

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ABSTRACT:

There are various segmentation methodology for extraction of specific brain tumour from Magnetic Resonance Imaging (MRI). Here in this paper I used appropriate segmentation method for extraction of specific objects from Magnetic Resonance Imaging (MRI). A specific attention is paid to detection and extraction of particular tissues. This could be a pressing issue for physicians because MRI reveals usually damage to explicit cartilage which is shown by a minor modification during a brightness scale. The image segmentation will give a close color map which shows distribution of the tissue densities. Medical image processing is the foremost difficult and emerging field currently a days. Processing of MRI images is one amongst the half of this field. The proposed strategy to detect & extraction of brain tumour from patient's MRI scan images of the brain. This technique incorporates with some noise removal functions, segmentation which are the fundamental ideas of image processing. Detection and extraction of tumour from MRI scan pictures of the brain is done by using MATLAB software..

Keywords: Image Segmentation, Image Processing, Brain Tumour Segmentation, MRI Image Processing.

I. INTRODUCTION

The incidence of brain tumors is increasing rapidly, particularly within the older population as compared to younger population. Brain tumor is largely developed as a group of abnormal cells that grows inside the brain or around the brain. Tumors can directly destroy all healthy brain cells and will also indirectly harm healthy cells by crowding other elements of the brain and inflicting inflammation, brain swelling and pressure inside the skull. MRI is that the noninvasive and very a lot of sensitive imaging test of the brain in routine clinical apply [1,2]. MR imaging uses a robust magnetic field, radio

frequency pulses and a computer to provide detailed pictures of organs, soft tissues, bone and nearly all other internal body structures. It will not use ionizing radiation (x-rays) and provides detailed pictures of brain and nerve tissues in multiple planes while not obstruction by overlying bones.

Brain tumor segmentation may be a recent research in field of biomedical application that is the process of partitioning an image into completely different clusters [3]. The goal of image segmentation could be a domain independent decomposition of a picture into

distinct regions like color, intensity, brightness, textures etc. An vital step in segmentation is to extract the region of area in which we have a tendency to are interested in.

Clustering could be a technique that classifies patterns in such a way that true positive pixels of same cluster who truly belongs to cancer than false positive pixels who will not belong to tumor belongs to totally different group.

A brain tumor is any intracranial mass created by abnormal and uncontrolled cell division. This paper analyses 2 different clustering techniques to detect tumor objects in magnetic resonance (MR) brain pictures. The optimized genetic algorithm based mostly clustering is used to change traditional k-means and c-means that clustering. A genetic algorithm-based mostly clustering technique, called GA-clustering enhances the looking out capability to go looking for appropriate cluster centers within the feature area such that a similarity metric of the ensuing clusters is optimized. The chromosomes, which are represented as strings of real numbers, encode the centers of a fixed range of clusters. This paper is organized into four sections mentioned as under.

II. SYSTEM MODEL

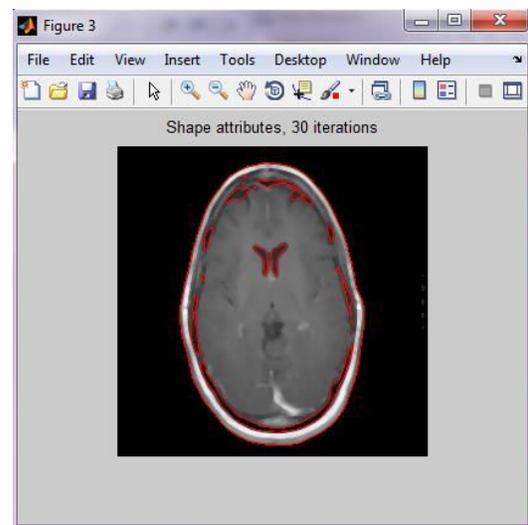
In this paper we have analyzed three different clustering techniques to detect tumor objects in MRI brain images. The Optimized Theshold, Fuzzy k-Means and Fuzzy c-Means Clustering Methods.

2.1 THRESHOLDING :

Threshlodng is one in every of straightforward image segmentation technique. It is method of

separating pixels in numerous classes depending on their pixels grey levels. A thresholding methodology determines an intensity value, referred to as the brink, which separate the desired categories. The segmentation is achieved by taking threshold price.

Based on threshold value, pixels are grouping with intensity bigger than the brink into one class and stay pixels grouping into another category. The mains disadvantage are that, in the simplest type solely two categories are generated and it can not be applied to multichannel images. In thresholding technique, image having only 2 values either black or white. MR image contains 0 to 255 gray values. So, thresholding of MR images ignores the tumor cells [1].



2.2 FUZZY C MEANS CLUSTERING

(FCM)

The FCM algorithm assigns pixels to each category by using fuzzy memberships. Let $X=(x_1, x_2,..,x_N)$ denotes an image with N pixels to be partitioned into c clusters, where x_i represents multispectral (features) data. The

algorithm is an iterative optimization that minimizes the cost function defined as follows [19]

$$J = \sum_{j=1}^N \sum_{i=1}^c u_{ij}^m \|x_j - v_i\|^2$$

where u_{ij} represents the membership function of pixel x_j in the i th cluster, v_i is the i th cluster center, and m is a constant. The parameter m controls the fuzziness of the resulting partition, and $m = 2$ is used in this study.

The value operate is minimized when pixel close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data way from the centroid.

The membership operate represents the probability that a pixel belongs to a selected cluster. Within the FCM algorithm, the probability is dependent solely on the space between the pixel and every individual cluster center in the feature domain. The membership functions and cluster centers are updated by the following.

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|x_j - v_i\|}{\|x_j - v_k\|} \right)^{2/(m-1)}}$$

And

$$v_i = \frac{\sum_{j=1}^N u_{ij}^m x_j}{\sum_{j=1}^N u_{ij}^m}$$

Where $u_{ij} \in [0, 1]$.

Starting with an initial guess for each cluster center, the FCM converges to a solution for v_i representing the local minimum or a saddle point of the cost function. Convergence will be detected by comparing the changes within the membership function or the cluster center at two successive iteration steps.

One of the necessary characteristics of a picture is that neighboring pixels possess similar feature values, and the chance that they belong to the identical cluster is nice.

This spatial relationship is important in clustering, but it's not utilised in a commonplace FCM algorithm. To exploit the spatial data, a spatial function is defined as.

$$h_{ij} = \sum_{k \in NB(x_j)} u_{ik}$$

where $NB(x_j)$ represents a square window centered on pixel x_j in the spatial domain. A 3 x 3 window was used throughout this work. Just like the membership function, the spatial function h_{ij} represents the probability that pixel x_j belongs to i th cluster.

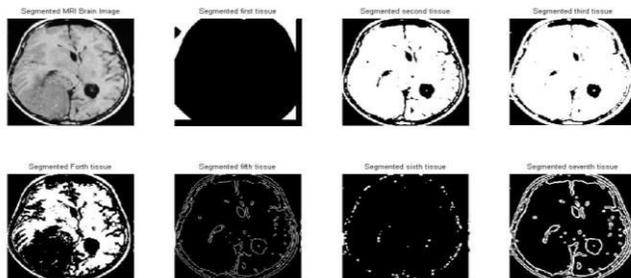
The spatial function of a pixel for a cluster is large if the majority of its neighborhood belongs to the same cluster. The spatial function is incorporated into membership function as follows:

$$u_{ij} = \frac{u_{ij}^p h_{ij}^q}{\sum_{k=1}^c u_{kj}^p h_{kj}^q}$$

where p and q are parameters to regulate the relative importance of both functions. In a standardized region, the spatial functions fortify the first membership, and also the clustering result remains unchanged. However, for a noisy pixel, this formula reduces the weighting of a loud cluster by the labels of its neighboring pixels. As a result, misclassified pixels from noisy regions or spurious blobs can simply be corrected. The spatial FCM with parameter p and q is denoted FCMS p,q . Note that FCMS $1,0$ is a dead ringer for the traditional FCM.

The clustering is a 2-pass process at every iteration. The first pass is the identical as that in customary FCM to calculate the membership perform in the spectral domain. Within the second pass, the membership information of every pixel is mapped to the spatial domain, and the spatial operate is computed from that.

The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations is less than a threshold ($\epsilon=0,02$). After the convergence, defuzzification is applied to assign each pixel to a specific cluster for which the membership is maximal.



2.3 FUZZY K MEANS CLUSTERING

K-means may be a heuristic methodology and conventional, which provides higher output in information clustering. “K-means clustering is an interactive procedure”. The K-suggests that clustering technique cluster the information by repeatedly finding the statistical mean value for every cluster after segmenting the image through classifying each pixel within the cluster with nearest mean. The steps concerned in the K-suggests that algorithm are given below:

1. Select K initial clusters $z_1(l), z_2(l), \dots, z_k(l)$
2. The K^{th} recursive step, take the samples between k clusters given below $x \in C_j(k)$ if $\|x - z_j(k)\| < \|x - z_i(k)\|$ For $i = 1, 2, \dots, k, i \neq j$, where, $C_j(k)$ denotes the deposit of samples whose cluster center is $z_j(k)$
3. Obtain the new cluster centers $z_j(K+1), j = 1, 2, \dots, k$, such that the Euclidean distance from points in $C_j(K)$. Therefore, the innovative cluster is given by:

$$Z_j(k+1) = \frac{1}{N_j} \sum_{x \in C_j} x, j = 1, 2, \dots, k. \text{ where } N_j \text{ is the number of samples in } C_j(k)$$

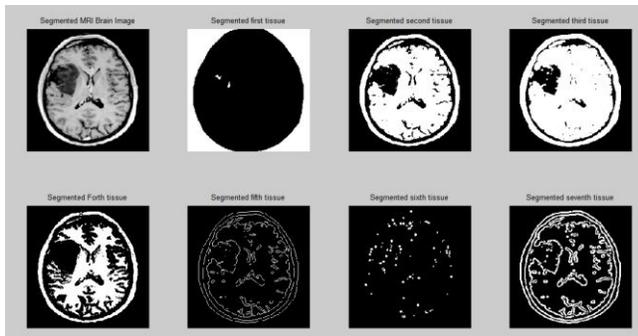
If $z_j(k+1), j = 1, 2, \dots, k$, the computation will be converged at the end else go to step 2

After segmentation of brain MR image, we can find out boundaries of the image using canny edge detection. After that, we find out labeling of the image and finally exact location of the tumor in the image.

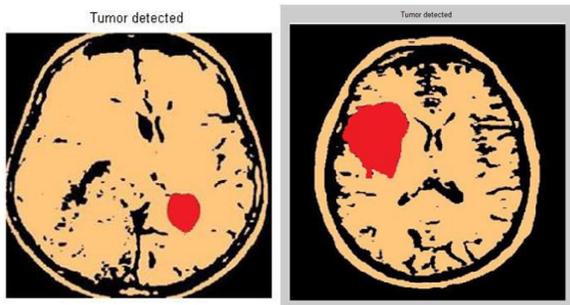
Advantages of K-means technique are:

- 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 Limitations of K-means algorithm:
- It will be always terminated
- Always return K number of clusters
- It is sensitive to noise
- It requires high configuration for energy minimization



III. SIMULATION/EXPERIMENTAL RESULTS



The error rates of second brain MR image with SNR 3, 5 and 7% obtained by K-means algorithm, Fuzzy c-means algorithm.

Noise levels%	K-means	Expectation maximization	Spatial Fuzzy
3	3.65	2.06	1.75

5	4.06	3.06	3.09
7	6.13	5.23	4.36

IV. CONCLUSION

This paper describes varied segmentation ways. This strategies makes is possible to make color maps of biological tissues with rather complex tissue structures. Standard exhausting-thresholding strategies are very efficient for segmentation of such image information. A particular attention has been paid to pictures of an articular cartilage as it's rather difficult for a physician to spot pathological findings in primary information. It is usually a pressing issue for the physician to detect locations subject to pathological changes as those locations are typically presented by a minor amendment within the brightness scale which is nearly impossible to recognise for an individual's eye. The solely probability to boost visibility of pathological changes is supply of a distinction substance which, however, hundreds a person's organisms with a radiation dose and effects of such examination don't seem to be too satisfactory. The proposed segmentation method will efficiently separate each tissue structure and determine locations subject to pathological changes. This is of a significant benefit for the physicians who might perform a better diagnosis even with pathological changes being in an early stage. This technique makes it possible to analyse highly efficiently continuity of the analysed tissue and to reveal arisen defects. the first purpose of our interest being detection of pathological formations on the basis of colour maps and optimising of color maps.



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