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Brain Tumor Extraction in MRI images using Clustering and Morphological Operations Techniques

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Abstract

In this paper, Magnetic Resonance Images,T2 weighted modality , have been pre-processed by bilateral filter to reduce the noise and maintaining edges among the different tissues. Four different techniques with morphological operations have been applied to extract the tumor region. These were: Gray level stretching and Sobel edge detection, K-Means Clustering technique based on location and intensity, Fuzzy C-Means Clustering, and An Adapted K-Means clustering technique and Fuzzy C-Means technique. The area of the extracted tumor regions has been calculated. The present work showed that the four implemented techniques can successfully detect and extract the brain tumor and thereby help doctors in identifying tumor's size and region.

Keywords: MRI, Brain Tumor, Clustering, Morphological Operations, K-Means and FCM

1 Introduction

Imaging is an essential aspect of medical science to visualize the anatomical structures of the human body. Several new complex multidimensional digital images of physiological structures can be processed and manipulated to help visualize hidden diagnostic features that are otherwise difficult or impossible to identify using planar imaging methods **[1]**. Magnetic Resonance Imaging (MRI) is a significant technique for examining the human body, it helps to clarify and distinguish the neural architecture of the human brain. It is unharmed method of obtaining images of the specific structure in the human body. MRI scanner employs magnetic field and radio waves to generate exhaustive images of the human brain, its data is most relevant in the studies of a head, specifically, for tracking the size of brain tumor and other brain related problems. It helps for early detection of intracranial tumors and precise estimation of tumor boundaries. Analytical, MRI scan can also been used to assess the maturity of the central nervous system and diagnose malformations. The resonance is also crucial for imaging of vascular changes. Using this method of diagnostic, imaging allows obtaining information about aneurysms and accompanying symptoms. It is also helps in showing seditious changes of the central nervous system and gives accurate assessment of the degree of brain atrophy . The automatic classification of brain's MRI can thus be used to identify regions having various brain diseases like cerebro-vascular, Alzheimer, brain tumor, inflammatory, etc **[2].**

The segmented MR images used in the medical diagnostic process depends on a combination of two, often conflicting, requirements; i.e. the removal of the unnecessary information present in the original MR images and the maintenance of the significant details in the resulting segmented images. MRI segmentation methods are usually evaluate based on their ability to differentiate: i) between cerebro-spinal fluid (CSF), white matter, and gray matter, and ii) between normal tissues and abnormalities. Many segmentation techniques have been proposed in the recent years, which were used for segmentation of brain tissues from MRI, are classical pattern recognition methods, rule-based systems, image analysis methods, crisp and fuzzy clustering procedures, feed-forward neural networks, fuzzy reasoning, geometric models to determine lesion boundaries, connected component analysis, deterministic annealing, atlas based methods and contouring approaches**[3].** Lots of researches have been performed for the segmentation of MR brain images to detect and extract tumor regions from these images. Some of these related works regarding the segmentation of brain tissues using clustering and other methods can be found in [**3]**-[**8].**

2 Image segmentation

Image segmentation methods can be classified into three categories: edge-based methods, region-based methods, and pixel-based methods. For Brain segmentation, two types of segmentation techniques have been adopted in the literature; i.e. ***region detection methods*** and ***boundary detection methods***. Mostly, the existing methods are dedicated for specific objects. The K-means clustering technique is a pixel-based method, it is one of the most simple techniques, it's complexity is relatively lower than other region-based or edge-based methods. Furthermore, K-means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy. Combined with the existing methods and aiming to get better results, it is useful to take soft segmentation methods into account. In soft segmentation, pixels are classified into different classes with various degrees of uncertainty which are specified by functions. The larger the value of function for a specific pixel, the larger the possibility that this pixel belongs to that cluster. The fuzzy C-means (FCM) clustering algorithm is soft segmentation method, and has aroused comprehensive attention. There have been many different families of fuzzy clustering algorithms proposed, for instance see [**1]** and **[5].**

3 Clustering

Clustering is the process of grouping feature vectors into classes in the self-organizing mode. Let $\{\mathbf{x}(q): q = 1,\ldots,Q\}$ be a set of Q feature vectors. Each feature vector $\mathbf{x}(q) = (x_1(q), \ldots, x_N(q))$ has N components. The process of clustering is to assign the Q feature vectors into K clusters $\{\mathbf{c}(k): k = 1, \ldots, K\}$, usually by the minimum distance assignment principle. Choosing the representation of cluster centers (or prototypes) is crucial to the clustering. Feature vectors that are farther away from the cluster center should not have as much weight to those are close. These more distant feature vectors are outliers usually caused by errors in one or more measurements or a deviation in the processes that formed the object. The simplest weighting method is arithmetic averaging; it adds all feature vectors in a cluster and takes the average as prototype. Because of its simplicity, it is still widely used in the clustering initialization. The arithmetic averaging gives the central located feature vectors the same weights as outliers. To lower the influence of the outliers, median vectors are used in some proposed algorithms. To be more immune to outliers and more representatives, the fuzzy weighted average is introduced to represent prototypes **[1]**:

$$Z_n^{(k)} = \sum_{\{q:q\in k\}} W_{qk} X_n^{(q)} \tag{1}$$

Rather than a Boolean value "1-True" (means it belongs to the cluster), or 0-False (does not belong),

- The weight W_{qk} in equation (1) represents partial membership to a cluster. It is called a fuzzy weight. There are different means to generate fuzzy weights.
- One way of generating fuzzy weights is the reciprocal of distance **[1]**; i.e.

$$W_{qk} = \frac{1}{D_{qk}}, \qquad (\mathrm{W_{qk}} = 1 \quad \text{if} \quad \mathrm{D_{qk}} = 0) \tag{2}$$

The earlier fuzzy clustering algorithms; when the distance between the feature vector and the prototype is large, the weight is small, and it is large when the distance is small. Using Gaussian functions to generate fuzzy weights is the most natural way for clustering. It is not only immune to outliers but also provides appropriate weighting for more centrally and densely located vectors. It is used in the fuzzy clustering and fuzzy merging (FCFM) algorithm **[1].**

4 K-Means Clustering

It is one of the simplest unsupervised learning algorithms to 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. Occasionally the extracted features that used affect the clustering method response. In this work, **an adaptive K-Means Clustering algorithm is proposed, the intensity and the location distance from the center of the skull is used**. The nature of the skull creature reflect a Centro or near Centro symmetry with organized tissues layer alike; which can be defined by a distance, **to segment MRI images of brain in order to detect the tumor,** since the detection of brain tumor through MRI images can provide the valuable outlook and accuracy of earlier brain tumor detection.

5 Fuzzy Clustering Algorithms

The fuzzy C-means (FCM) is widely used method like the K-means algorithm **[9].** It aim is minimizing an objective function. It is more preferable than the K-means because in the K-means the feature vectors of a data's set is partitioned into hard clusters, and the feature vector can exactly be a member of one cluster only, while the fuzzy C-means relax the condition by allowing the feature vector to have multiple membership grades to multiple clusters. Suppose the data set with known clusters and a data point which is close to both clusters but also equidistant to them. Fuzzy clustering gracefully copes with such dilemmas by assigning this data point equal but partial memberships to both clusters; i.e. the point may belong to both clusters with some degree of membership grades varies from 0 to 1**[6].** It uses reciprocal distance to compute fuzzy weights. It computes the cluster's center using Gaussian weights, uses large initial prototypes, and adds processes of elimination, clustering and merging. The FCM algorithm was introduced by J. C. Bezdek **[10]**, using weights that minimize the total weighted mean-square error, i.e.;

$$J(W_{qk}, Z^{(k)}) = \sum_{k=1}^{K}\sum_{k=1}^{K}(W_{qk})\left\| X^{(q)} - Z^{(k)} \right\|^{2} \tag{3}$$

Where $$\sum_{k=1}^{K} W_{qk} = 1, \qquad for\ \ each\ \ q \tag{4}$$

and $$W_{qk} = \frac{\left(\frac{1}{D_{qk}{}^{2}}\right)^{\frac{1}{(p-1)}}}{\sum_{k=1}^{K}\left(\frac{1}{D_{qk}{}^{2}}\right)^{\frac{1}{(p-1)}}} \tag{5}$$

The FCM allows each feature vector to belong to every cluster with a fuzzy truth value (between 0 and 1), which is computed using Equation (5). The algorithm assigns a feature vector to a cluster according to the maximum weight of the feature vector over all clusters **[1]** .

5.1 K-Means Based Fuzzy C-Mean Clustering

It is well known that the output of K-Means algorithm depends hardly on the initial seeds number as well as the final clusters number. Therefore to avoid such obstacle K-Means based FCM is suggested. The idea behind this suggestion is to supply the K-Means with well defined clusters centers based on optimal calculation instead of random ones. In addition to that it is well known that the fuzzy C-Mean algorithm assign probability for each point to be classified rather than deterministic class assignment by K-means; therefore one can switch form probability to deterministic by this algorithm.

6 Bilateral Filters

In this work the bilateral filter that introduced by Manduchi *et al*. (1998) **[11]**, has been adopted. It performs nonlinear smoothing on image to reduce the noise and retaining the edge information. Nonlinear smoothing is performed by combining the geometric and intensity similarity of pixels. The filtering operation is given by**[11]**

$$I_b(x,y) = \frac{\sum_{n=-N}^{N}\sum_{m=-N}^{N} W(x,y,n,m)\ I_g(x-n,y-m)}{\sum_{n=-N}^{N}\sum_{m=-N}^{N} W(x,y,n,m)} \tag{6}$$

If $I_g(x , y)$ be a grayscale image having values in the range [0, 1] , $I_b(x, y)$ will be the bilateral filtered version of $I_g(x, y)$. This equation is simply a normalized weighted average of a neighborhood of $(2N + 1)$ *by* $(2N + 1)$ pixels around the pixel location (x, y). The weight $W(x, y, n, m)$ is computed by multiplying the following two factors **[11]**:

$$W(x,y,n,m) = W_S(x,y,n,m) \times W_r(x,y,n,m) \tag{7}$$

Where: $W_S (x, y, n, m)$ is the geometric weight factor. It is based on the Euclidean distance between the center pixel (x, y) and the $(x - n, y - m)$ pixel as **[11]**:

$$W_S(x,y,n,m) \ = \exp[\frac{(x-n)^2 + (y-m)^2}{2\sigma_z^2}] \tag{8}$$

The second weight $W_r(x, y, n, m)$ is based on the grayscale intensity distance between the values at (x, y) and $(x - n, y - m)$. Again , it is based on the Euclidean distance between intensity values as **[11]** :

$$W_r(x,y,n,m) = \exp[-\frac{(I_g(x,y) - I_g(x-n,y-m))^2}{2\sigma_r^2}] \tag{9}$$

For discarding noise terms without disturbing object boundaries, the I_b function should be normalized by W(x, y, n, m).

7 Morphological Operations

Morphological operators have been used in the field of image processing and are known for their robust performance in preserving the shape of a signal, while suppressing the noise. Image morphology provides a way to incorporate neighborhood and distance information into algorithms. The basic idea in mathematical morphology is to convolve an image with a given mask (known as the structuring element) and to binaries the result of the convolution using a given function. Choice of convolution mask and binarization function depends on the particular morphological operator being used. Shrinking or expanding a binary image based on iterative neighborhood transformations or a “mathematical morphology” as applied by *G. Matheron and J. Serra* **[12]** allows processing of an image based on its shape. Morphological operations may be viewed as shape filters which remove information from an image based on the shape of objects in the image, and how they relate to the shape of the filter retaining only the information of interest in the image. There are two basic morphological operators: ***erosion*** and ***dilation***, opening and closing are two derived operations in terms of erosion and dilation **[13]**.

8 Material and Datasets

The samples of images adopted in this work have been supplied by ***AL-Shiek Zayed Hospital***. They have been obtained with 1.5 Tesla magnetic resonance**,** MRI device (Siemens, syngo fast view, standard viewing tool for the Digital Imaging and Communications for Medicine (DICOM) standard was created by the National Electrical Manufacturers Association (NEMA) to aid the distribution and viewing of medical images. The used samples of MRI were 4-slices for T2-wieghted axial orientation (5, 6, 7, and 8) for a patient of an abnormal case, named as 5T2, 6T2, 7T2&8T2 images. Each image has size equals to 166 × 276 pixels per slice (spatial resolution 1mm), with slice thickness of 5mm. The reason behind the selection of these images belongs to the distinguishable appearance of the tumor which is the important requirement in this work, because our techniques can be applied on images with tumor of high intensity rather than other regions or tissues in the brain.

9 Methodology

The processes involved in this work can be summarized by the following block **diagram, shown in fig-1:**

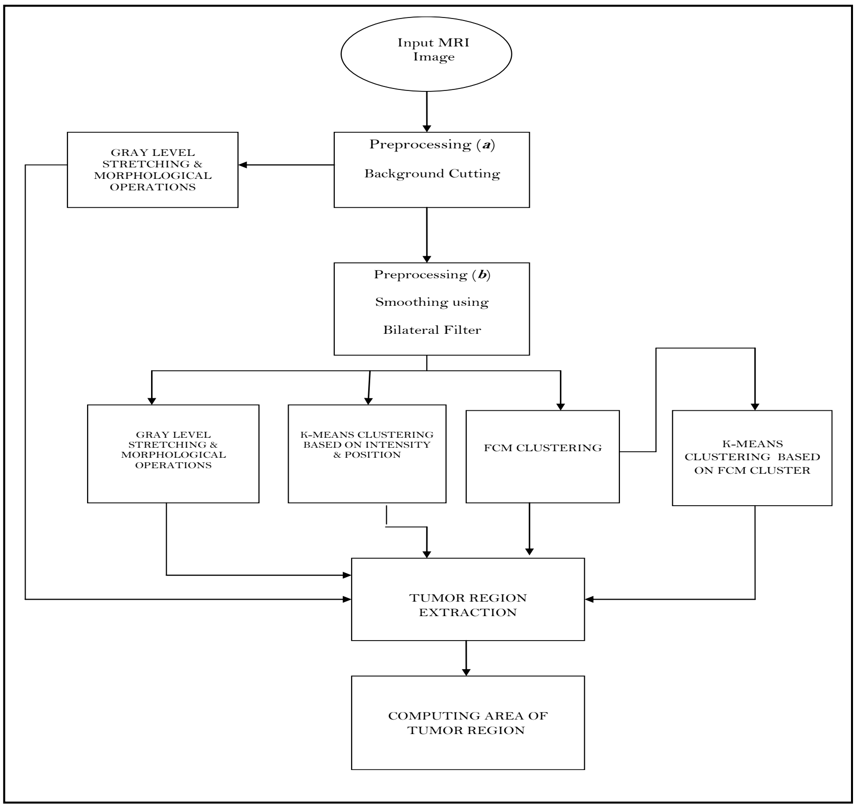


Figure-1: Block Diagram of the proposed work.

10 Experiments and Results

The proposed techniques are applied on images with tumor of high intensity rather than other regions or tissues in the brain.

Preprocessing Stage: included;
a- Automatically cutting the background of the images.
b- Implementing bilateral filter to smooth images.
Image segmentation follows the preprocessing operation, utilizing the four mentioned techniques; i.e.

10.1 Gray Level Stretching; includes

a. Gray Level Stretching: performing contrast adjustment to stretch the gray level of the input image from the range [0.3-0.7] to the range [0 1].

b. Morphological Operation: after converting the image into binary form by choosing threshold value (depending on the image intensity), many morphological operations have been applied using structural element of 'disk-shape', of 6-pixels diameter, these operations are:
1-Erosion: applied on the binary image.
2-Dilation: applied on the resultant image from the previous step.
The dilated image then convolutes with the input reduced intensity image (0.03 of its original intensity value).
c. Edge Detection
In this step, the Sobel operator is implemented on the resultant image from the previous steps, followed by filling process to represent the final image of the tumor. The last step involves contouring the tumor region, are illustrated in figs-2&3.

d. Surface Area of the Tumor Region:
The last step was computing the surface area of the tumor region in pixel unit, as listed Table-1. All the above processes have been applied without smoothing the original image; the results are shown in fig-2.

10.2 K-Means Clustering Based on Intensity and Location:

In this technique, the K-Means clustering algorithm was implemented on the input MRIs (with six clusters). The segmented image included the cluster of the tumor then selected, using opening morphological operation with structure element of shape disk (five pixels diameter), and the resulted image then convoluted with the original image to acquire the image of the tumor region, shown in fig-4. The tumor region's surface area is presented in Table-1.

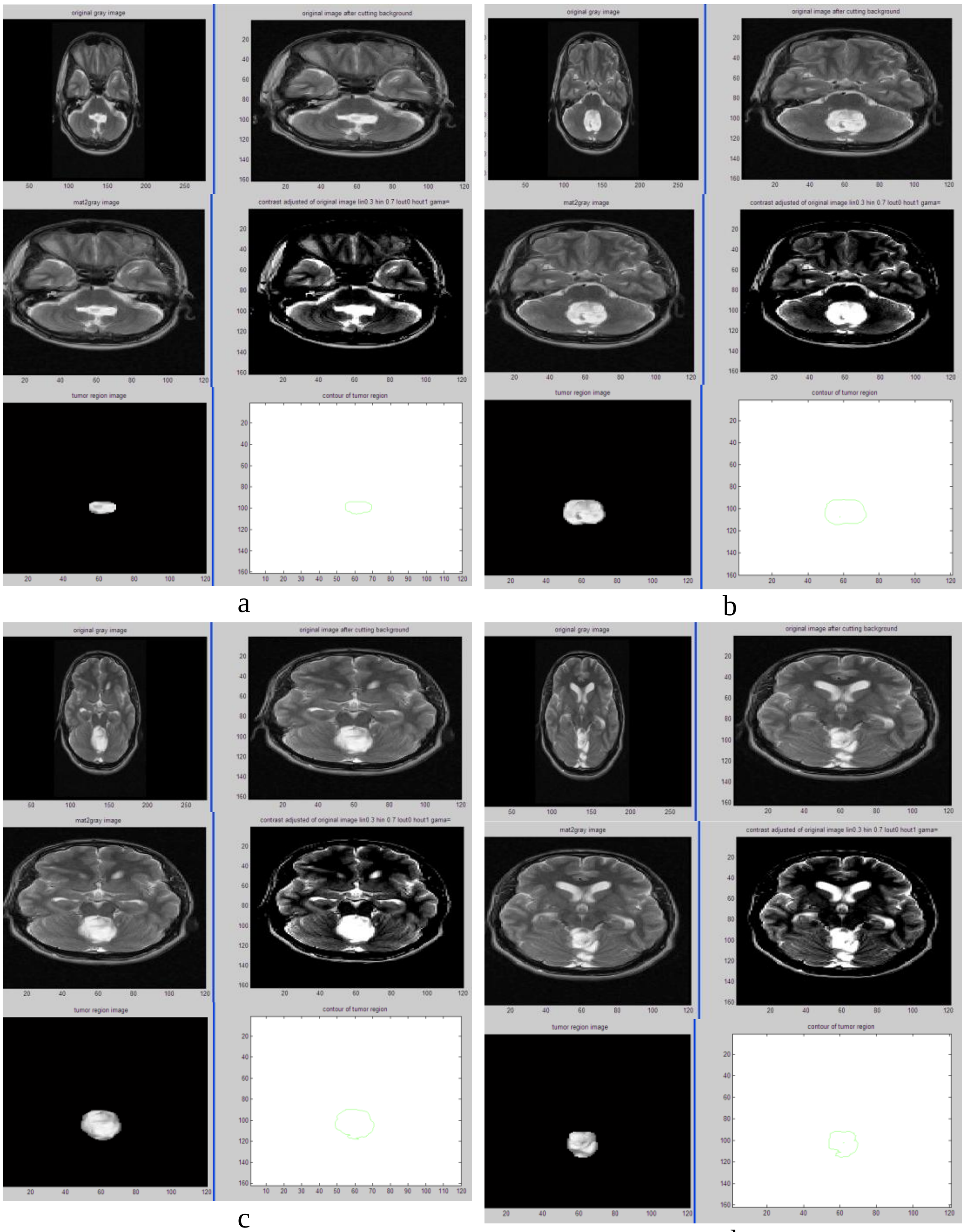
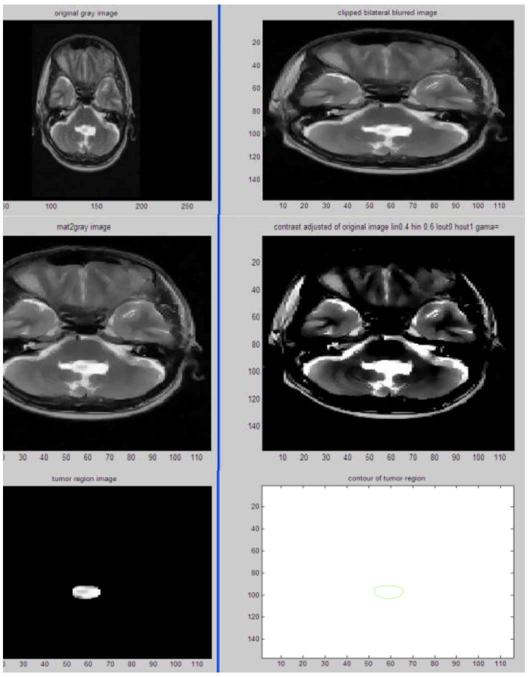
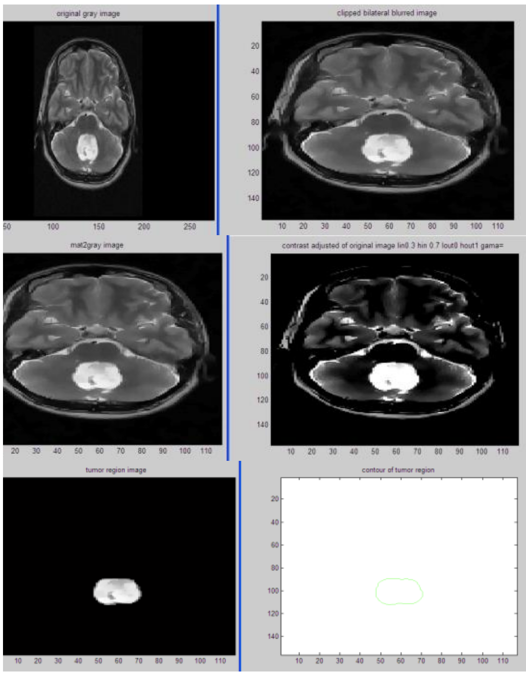


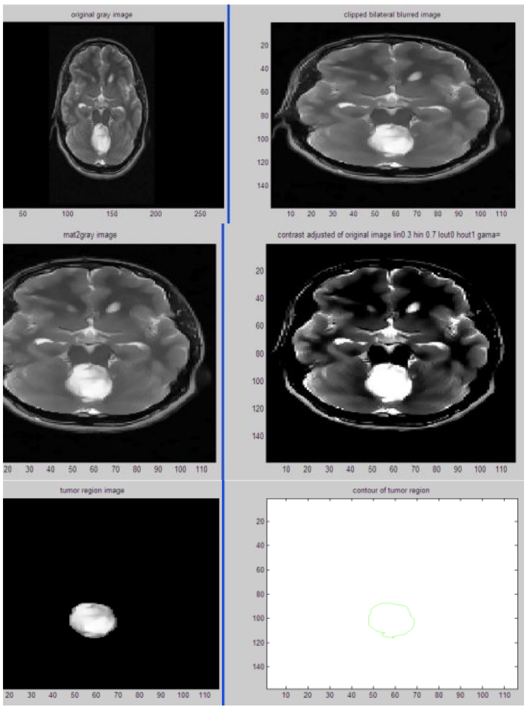
Figure-2: *Gray Level Stretching*, left to right: 1st line , original image & original image after cutting background ; 2nd line, mat-to-gray of the background cutting image & contrast adjusted image; 3rd line, extracted tumor image & contour of tumor region. a ,b , c & d for 5T2,6T2,7T2 &8T2 images respectively.



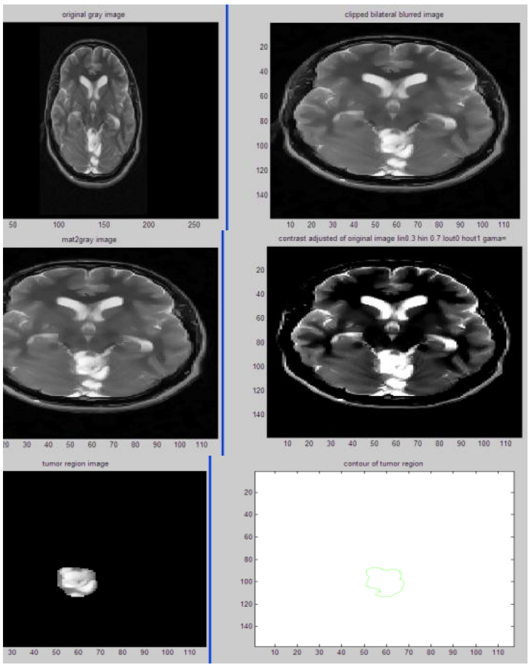
a



b



c



d

Figure-3: *Gray Level Stretching after applying bilateral filtering*, left to right : 1st line, original image & original image after cutting background and smoothing ; 2nd line , mat-to-gray of the background cutting and smoothed image & contrast adjusted image; 3rd line, extracted tumor image & contour of tumor region. a ,b , c & d for 5T2, 6T2, 7T2 & 8T2 images respectively.

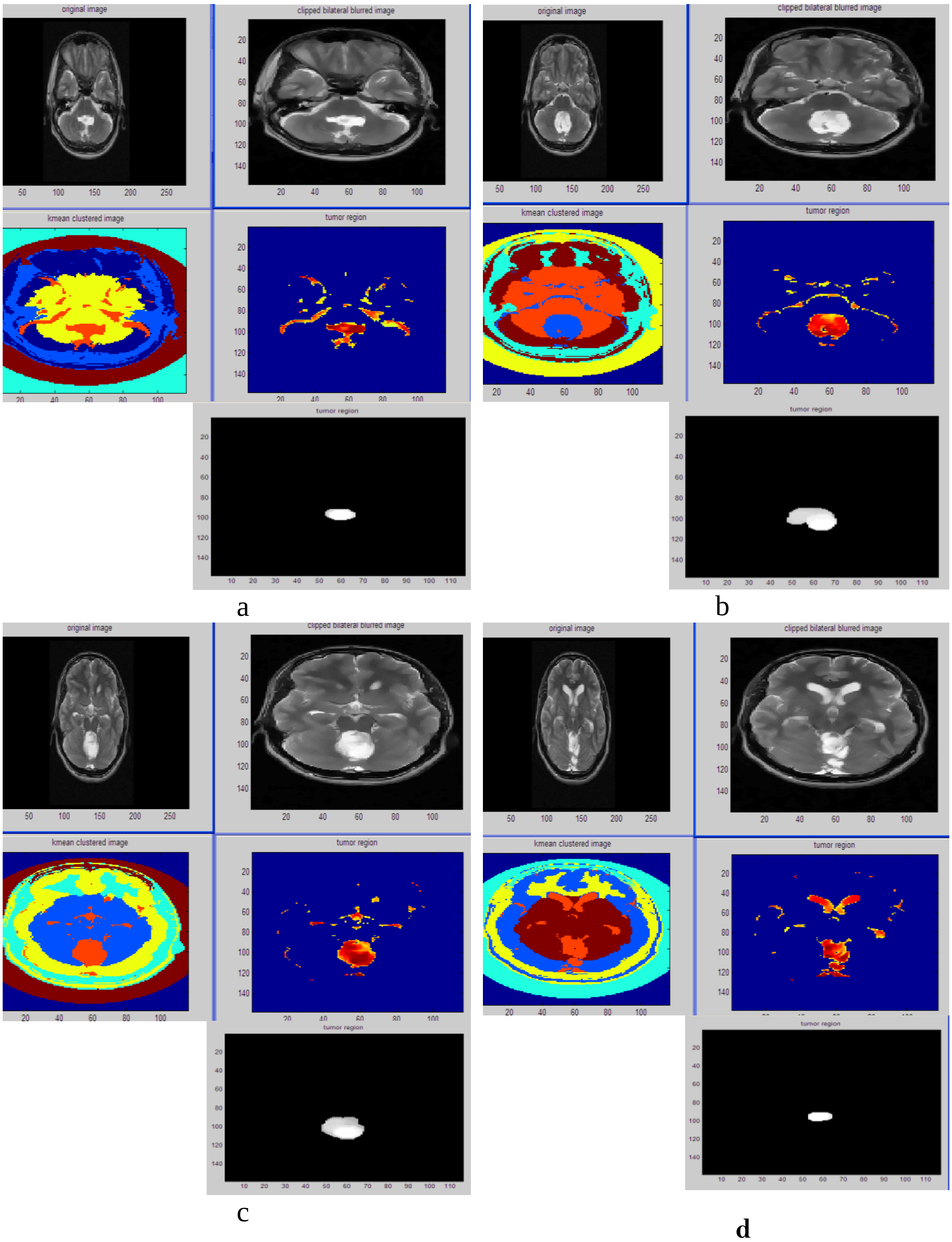


Figure-4: *K-Means Clustering based on intensity and Location*, left to right: 1st line , original image & original image after cutting background and smoothing ; 2nd line , K-means clustering based on intensity and position of the background cutting and smoothing image & tumor cluster image ; 3rd line ,extracted tumor image after applying morphological operation on the tumor cluster image . a ,b , c & d for 5T2 ,6T2 ,7T2 & 8T2 images respectively.

s technique is implemented on the input MRIs (with cluster number equals to 6) . The segmented image including the cluster of the tumor was selected and opening morphological operation with structure element of shape disk (four pixels diameter) for images 5T2, 6T2, 7T2 & 8T2. The resulted image is then convoluted with the original image to acquire the image of the tumor region, shown in fig-5. The tumor region's surface area is listed in Table-1.

10.4 K-Means Clustering Based on the Centers' values of the clusters of Fuzzy C-Means algorithm

In this adaptive technique, Fuzzy C-Means (FCM) clustering algorithm was implemented on the input MRIs (six clusters). The segmented image with center values of the clusters then passed to the K-Means clustering algorithm (with also six clusters), the resulted image then segmented. The image of the cluster of the tumor is selected by applying the opening morphological operation with structure element of disk shape (four pixels diameter size), the images 5T2,6T2,7T2 and (three pixels diameter size) for 8T2 image, then convoluted with the original image to obtain the image of the tumor region, shown in fig.6. The tumor region surface area is given Table-1.

Table-1: illustrates the values of the surface area of tumor regions for the implemented techniques .

Image name	Surface area of tumor region (pixel)				
	Contrast adjustment & morphological operations (without Smoothing	Contrast adjustment & morphological operations (with Smoothing)	K-Means clustering depending on intensity & position of pixels	FCM clustering	FCM clusters ' center passed to K-means clustering
5T2	159	135	128 *	143	143
6T2	473	470	375	319	319
7T2	523	508	394	300	300
8T2	341	395	85**	163	262

* The tumor region area equals 165 pixels, using structure element of radius 4. ** When using radius of the structure element, the ventricles are contained with the tumor

11 Conclusions

In this work, four different techniques have been implemented to extract and calculate the area of the tumor region for four successive slices of T2 weighted MR images. As it has been evidenced, the morphological method produced extensively different results than that fabricated by the adopted probabilistic calculation. The smoothing operation changed the results of the Fuzzy C-means when fuzzy grouped with K-means. This behavior may be utilized to improve the classification accuracy as expected due to the dependency of K-mean method on the initial seeds. However, more work may be required to improve the segmentation results, this may be achieved by implementing certain supervised classification method.

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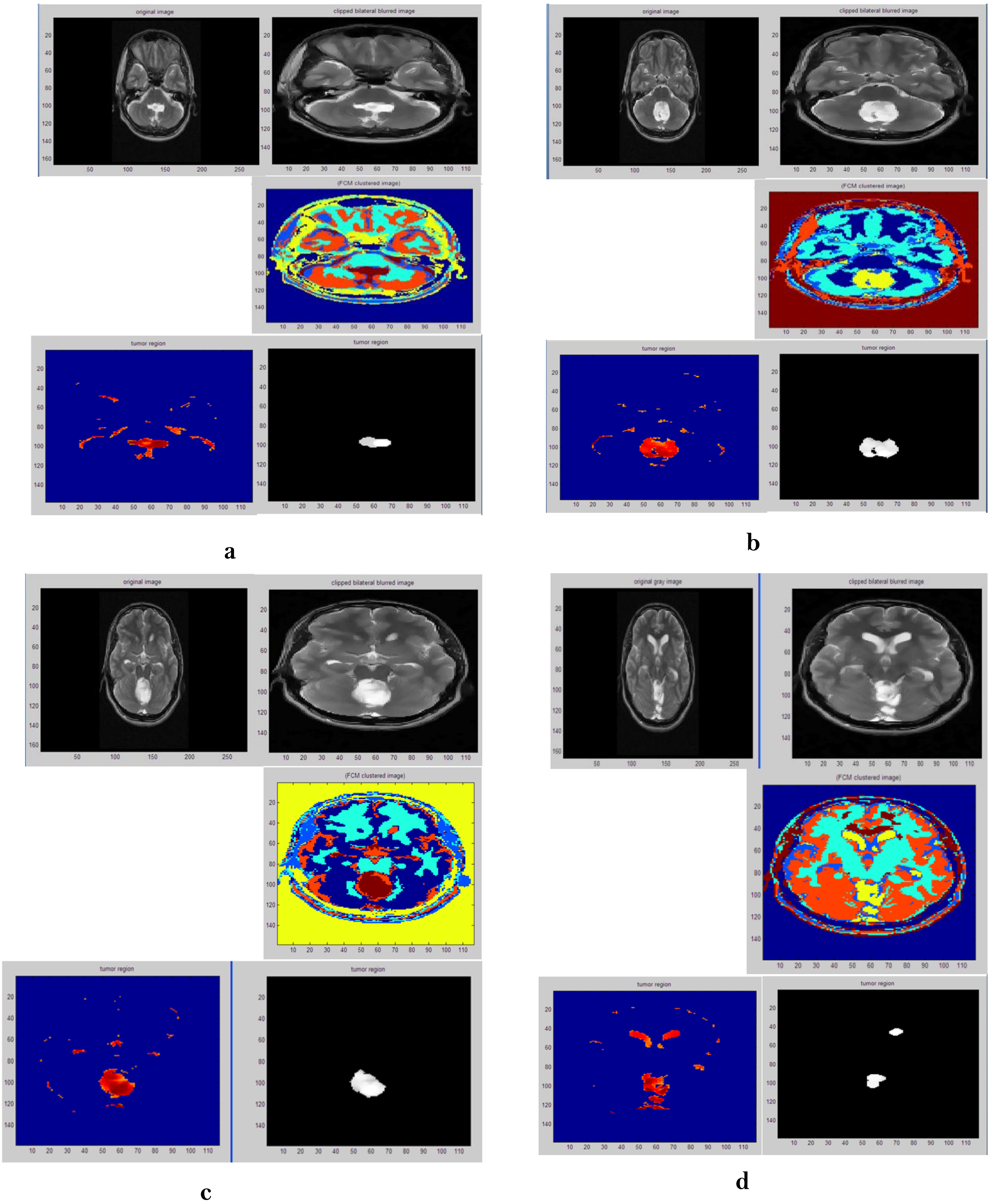

Figure-5: *Fuzzy C-Means Clustering*, left to right: 1st line , original image & original image after cutting background and smoothing; 2nd line Fuzzy C-means clustering of the background cutting and smoothing image; 3rd line, tumor cluster image & extracted tumor image after applying morphological operation on the tumor cluster image. a ,b , c & d for 5T2,6T2,7T2 &8T2 images respectively.

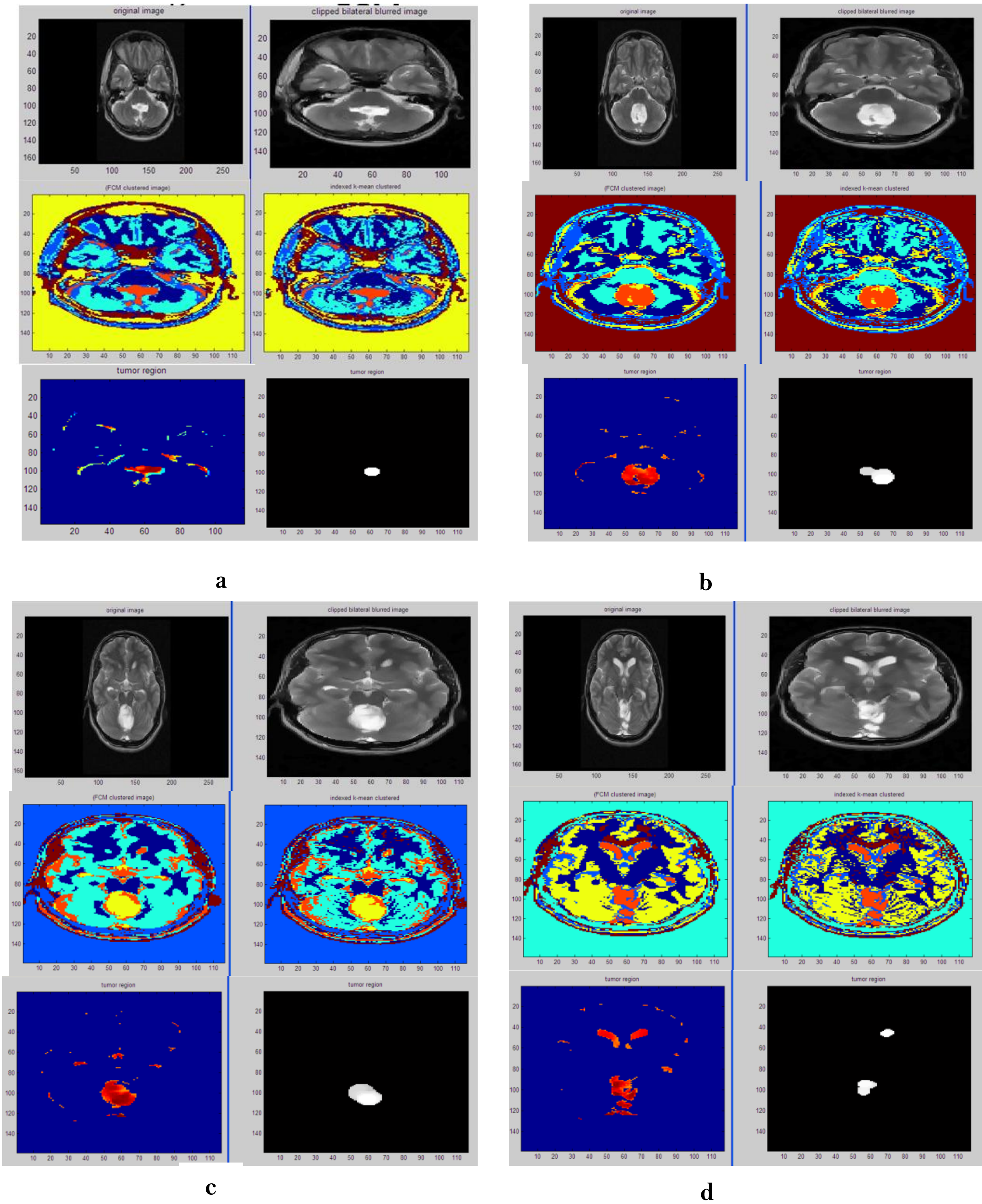

Figure-6: *K-Means Clustering based on the centers' values of the clusters of Fuzzy C-Means algorithm*, left to right: 1st line, original image & original image after cutting background and smoothing ; 2nd line, Fuzzy C-means clustering of the background cutting and smoothing image & K-means clustering of the background cutting and smoothing image based on clusters' centers values of FCM algorithm; 3rd line, tumor cluster image & extracted tumor image after applying morphological operation on the tumor cluster image . a, b, c& d for 5T2, 6T2, 7T2 & 8T2 images respectively.

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