

Development of Automated Brain Tumor Extraction from MRI Images

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Abstract

The brain is one of the largest and most complex organs in the human body. Some abnormal and uncontrolled growth of tissue taking place in human brain called “brain tumor”. The objective of biomedical image processing is that the image will be enhanced to support doctors more easily in diagnosing and treating. The detection of brain tumor can be performed by using various image processing techniques like brain Magnetic Resonance Imaging (MRI), Computer Tomography (CT), Positron Emission Tomography (PET), Electroencephalography (EEG) etc. Among these techniques the brain MRI is widely adopted in the world due to its significant features. Its correct detection and identification at an early stage is the only way to get cure. Brain tumor tissues may become malignant (cancerous) if not diagnosed. This paper deals with the various aspects of the brain tumor detection. The paper discusses the significant researches which are meant for the brain tumor detection through MRI quality enhancement.

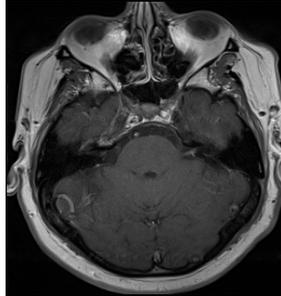
KEYWORDS

Biomedical MRI, Brain, Otsu segmentation, K-means, Fuzzy C-means.

1 | INTRODUCTION

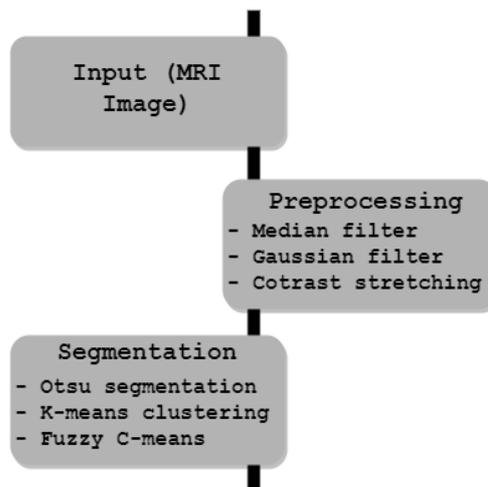
The brain is made up of a complex network of billions of nerve cells called neurons, as well as other kinds of cells, all protected by the bones of the skull. As with all other organs, the tumor is made up of cells in the brain. Normally, cells grow, grow and aging or die, and new cells are formed instead of these cells. However, in abnormal cases, when this formation-destructive activity begins to function differently than normal, unnecessary cells begin to form, or when the cells formed are not destroyed in time, the excess cells begin to group so that a structure called the tumor appears at the organ level. Because not all tumors can be called cancer, tumors formed in the brain are called brain tumors. Primary brain tumors may be benign (meningioma, scwanoma, epidermoid dermoid cysts) or malignant (glial tumors, anaplastic multiforme and glioblastoma).

1 Fig1 indicates the magnetic resonance imaging (MRI) of brain. The MRI gives a perfect
2 visualization of brain anatomic structure like deep structures, brain tissues by generating the
3 3D image. But for segmentation and detection of brain tumor more number of MRI scans are
4 need to be taken for each patient. Thus to overcome the problem of manual segmentation the
5 computer based brain tumor segmentation and detection is required.



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11 **Figure 1** Input MRI image of brain

12 In this research study, an automated approach has been proposed where MRI gray-scale images
13 were incorporated for brain tumor detection. Brain tumor images were taken as input and
14 medical image processing techniques such as pre-processing and post-processing were
15 incorporated to identify the tumor region only. The pre-processing includes enhancement, filter
16 operation, and segmentation and post-processing includes feature extraction and identification.
17 The phases of image processing are shown in fig2.



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26 **Figure 2** Block diagram for image processing

28 **2 | BRAIN TUMOR DETECTION**

29 The brain tumor detection is mainly an image processing technique. The proper diagnosis or
30 brain tumor can make easy to save the patient life to some extent [1]. The brain MRI is most
31 commonly used techniques for brain tumor detection. There are mainly five basic steps in
32 brain tumor detection [2, 3, and 4].

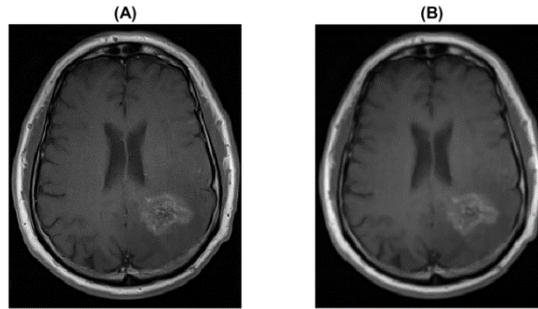
34 **2.1 | PRE-PRCESSING**

35 The MRI image can be obtained from the patient data base on the computer when the person

1 undergoes the MRI scanning. Grayscale is a range of shades of gray without apparent color.
2 The darkest possible shade is black, which is the total absence of transmitted or reflected light.
3 The lightest possible shade is white, the total transmission or reflection of light at all visible
4 wavelengths. So because of the above reasons first we convert our MRI image to be pre-
5 processed in grayscale image. A preprocessing stage considered to remove noise and enhance
6 of an image before segmentation.

7 *A. Median Filter*

8 Median Filter is used for noise reduction by removing salt and pepper noise. The main idea of
9 the median filter is replacing each pixel with the average of neighboring pixels [5,7]. Fig. 3
10 indicates the result.



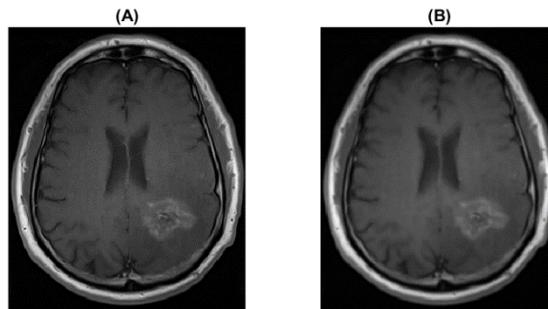
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16 **Figure 3** A, Gray image. B, Image after median filter.

17 *B. Gaussian Filter*

18 The Gaussian smoothing operator is a convolution operator that is used to blur an image. Its
19 kernel represents the shape of a Gaussian bell-shaped [6,7]. Fig. 4 indicates the result. Gaussian
20 filter can be expressed as

$$21 \quad I(X) = \frac{1}{2\pi\delta^2} \cdot e^{-\frac{x^2+y^2}{2\delta^2}} \cdot I(Y) \quad (1)$$

22 where x is the distance from the origin in the horizontal axis, y is the distance from the origin
23 in the vertical axis, and δ is the standard deviation of the Gaussian distribution.

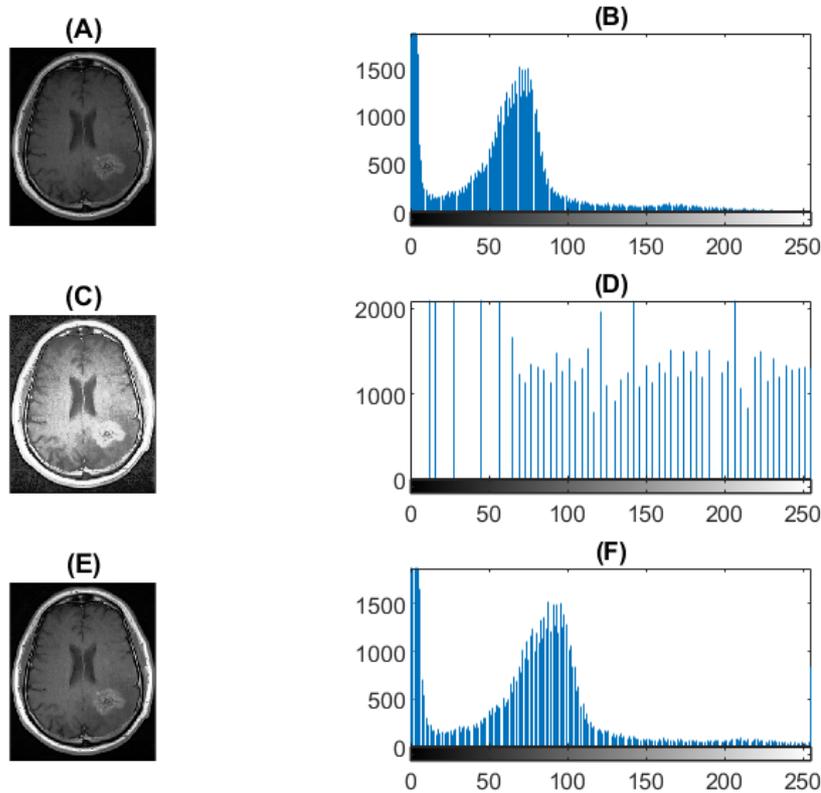


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30 **Figure 4** A, Gray image. B, Image after Gaussian filter.

31 *C. Image Enhancement*

32 Image enhancement is used as the first step of image preprocessing for this study for this study.
33 This study used contrast stretching as it comparatively performs better on the gray scale image
34 as contrast increased without distorting relative gray level intensities. As a result, it does not

1 yield any artificial looking image like histogram equalization. Contrast stretching increases the
2 contrast of the image by stretching the range of intensity values of the image to span the desired
3 range from 0 to 1. It eliminates the ambiguity which may appear in different regions in the
4 image of the dataset [8]. Fig. 5 indicates the results of image enhancement for this study test
5 image.



20 **Figure 5** (A), Gray image, (B), Histogram of (A), (C) Histogram equalization,
21 (D) Histogram of (C), (E) Contrast enhancement (contrast
22 stretching), (F) Histogram of (E).

24 2.2 | SEGMENTATION

25 The image segmentation in DIP is a major process required to define the Region Of Interest
26 (ROI) in image. The segmentation can be done manually, semi-automatic or automatically. The
27 drawback of manual segmentation is that it consumes huge time and its accuracy is depending
28 on the operator knowledge whereas automatic segmentation is apart from this [9,10]. The
29 segmentation with image processing for brain MRI is divided in many techniques as Otsu
30 segmentation, K-means clustering, Fuzzy C-means and other methods etc.

31 A. Otsu Segmentation

32 Otsu's method is one of the effective processes employed for the selection of threshold and is
33 well known for its rare time consumption. Otsu's thresholding method involves iteration along
34 the entire probable threshold values and evaluation of standard layout for the entire pixel levels
35 that occupy each side of the threshold. The algorithm involves iterating through all the possible

1 threshold values and calculating a measure of spread for the pixel levels each side of the
2 threshold, the pixels that either fall in foreground or background. The aim is to find the
3 threshold value where the sum of foreground and background spreads is at its minimum. We
4 can define the within-class variance as the weighted sum of the variance of each cluster:

$$\sigma_w^2(I) = W_f \sigma_f^2(I) + W_b \sigma_b^2(I) \quad (2)$$

6 where $\sigma_w^2(I)$ is within-class variance, $\sigma_f^2(I)$ the variance of the foreground $\sigma_b^2(I)$ is the
7 variance of the background, W_f the weight of the foreground, W_b the weight of the background.

9 *B. K-means Clustering*

10 K-means is a widely used clustering algorithm to partition data into k clusters. Clustering is
11 the process for grouping data points with similar feature vectors into a single cluster and for
12 grouping data points with dissimilar feature vectors into different clusters. Let the feature
13 vectors derived from l clustered data be $X = \{x_i \mid i=1,2,\dots, l\}$. The generalized algorithm
14 initiates k cluster centroids $C = \{c_j \mid j=1,2,\dots,k\}$ by randomly selecting k feature vectors are
15 grouped into k clusters using a selected distance measure such as Euclidean distance so
16 that, [11] :

$$d = \|x_i - c_j\| \quad (3)$$

18 The next step is to recompute the cluster centroids based on their group members and then
19 regroup the feature vector according to the new cluster centroids. The clustering procedure
20 stops only when all cluster centroids tend to converge [11].

22 *C. Fuzzy C-means*

23 The FCM algorithm [5], [9], attempts to partition a finite collection of pixels into a collection
24 of “C” fuzzy clusters with respect to some given criterion. Depending on the data and the
25 application, different types of similarity measures may be used to identify classes. This
26 algorithm is based on minimization of following objective function [11]:

$$J = \sum_{i=1}^N \sum_{j=1}^C \mu_{ij}^m \|x_i - c_j\|^2 \quad (4)$$

28 where m is any real number greater than 1, μ_{ij} is the degree of membership of x_i in the cluster
29 J, x_i is the ith of d-dimensional measured data, c_j is the d-dimension center of the cluster.

31 **3 | RESULT AND DISCUSSION**

32 These figures show the result of previous techniques. Grayscale image, contrast stretching, otsu
33 segmented image, k-means clustering algorithm and fuzzy c-means algorithm. Because off
34 these methods the tumor become very easy to locate and extract it from a MRI image.

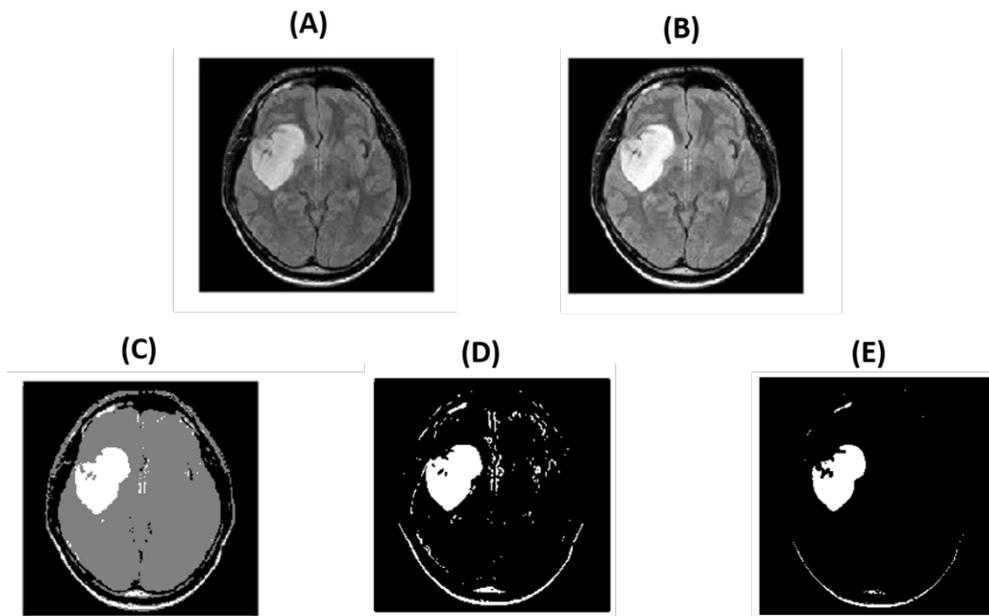


Figure 6 (A), Gray image, (B), Filtered image, (C), Otsu segmented image
,(D) K-means clustered image,(E) Fuzzy C-means clustered
Image.

4 | FUTURE WORK

In future we can adjust the algorithm to be more advanced where tumor can be classified depending on its type.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

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