

Comparative Studies on Brain Tumor Extraction of MR Images

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Abstract

Brain image segmentation and analysis of different parts of brain is very important research issue. In this paper we proposed a method for segmenting brain tumors by combining Fuzzy C-Means thresholding with watershed segmentation method. We also present a comparative study of different existing segmentation approaches like global thresholding using Otsu method, histogram thresholding and watershed method with addition of some pre- and post-processing methods. Among all the methods Fuzzy C-Means clustering with watershed method gives the best result. These methods allow the segmentation of tumor tissue with accuracy and efficiency as compared to manual segmentation. The tumor is extracted from the brain image and its exact position is also determined. This process calculates the area of tumor for each of the algorithm used. A performance wise comparative study using four number of defected 2D MRI brain images are considered. Several cases under hazy and bad imaging conditions are also studied and good result is obtained.

Keywords: Edge Detection Method, Fuzzy C-Means Clustering, Thresholding Method, Tumor Extraction, Watershed Method

1. Introduction

Brain is an important part of human body. Brain tumors are abnormal mass of tissue in which cells growth and multiply uncontrollably. Brain tumors are classified on bases of tissue of origin, location, primary and secondary or metastatic, grading. Brain tumors are of two main types which are benign tumors (cancerous) and malignant tumors (non cancerous). The task of manually segmentation

of brain tumors from MRI images are time consuming and difficult. In most of the cases, the task is strongly depends on the human rater's view and it produces jaggy images. Present state of art popular approaches are cluster based method^{2,4}, thresholding based method⁶, segmentation using GUI⁸, segmentation using neural network¹⁰, segmentation based on soft computing^{5,12}, hybrid method³, etc. Brain segmentation methods are mainly cluster based methods and threshold based methods. K-means cluster based method is

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widely used for segmentation. Fuzzy C-Means clustering method has an advantage over k-means clustering method. The data points of Fuzzy C-Means clustering method may belong to more than one cluster center².

In the thresholding based segmentation the image is considered as having only two values either black or white. But the bit map image contains 0 to 255 gray scale values. So sometimes it ignores the tumor cells also². In that case suitable thresholding method combined with some post processing method may generate better result. In this paper we proposed a brain tumor segmentation method using 3 class fuzzy c-means thresholding with watershed method and compared with global thresholding Otsu method, histogram thresholding method, watershed method. Some pre- and post-processing methods are also used to enhance and evaluated the tumor parameters like area, execution time etc. more accurately. Comparative study reveals that our proposed method gives the best result.

2. Existing Methods Preliminaries

This section shows the mathematical representation of existing algorithms used in brain tumor segmentation. The algorithm used in Fuzzy C-Means clustering method, global image thresholding using Otsu's method, histogram thresholding method and watershed method are described as follows:

2.1 Fuzzy C-Means Method

Fuzzy C-Means (FCM) is a clustering method of clustering which allows one piece of data belongs to two or more clusters. Fuzzy C-Means clustering method is based on minimization of the following objective function:

$$J_m \sum_{i=1}^N \sum_{j=1}^C U_{ij}^m \|x_i - c_j\|^2 \quad 1 \leq m < \infty \quad (1)$$

Where m is any real number greater than 1, U_{ij} is the degree of membership of x_i in the cluster j , x_j is the d -dimensional measured data, c_j is the d -dimension center of the cluster and $\|*\|$ is any norm expression, the similarity between any measured data and the center $\|x_i - c_j\|$ is the Euclidean distance between i th data and j th cluster center².

The equation of finding the level threshold L1 and L2 is:

$$L1 = \frac{\text{maximum}(D(\text{label}=1)) + \text{minimum}(D(\text{label}=2))}{2} \quad (2)$$

$$L2 = \frac{\text{maximum}(D(\text{label}=2)) + \text{minimum}(D(\text{label}=3))}{2} \quad (3)$$

Thus the Fuzzy C-Means method generates the two output images correspond to the each threshold level L and their performance is compared with the standard Otsu threshold method. The level threshold is calculated by taking mean of maximum or minimum in the class with the smallest center as per distance matrix D as in (2). The threshold is calculated by taking mean of maximum of the cluster 1 or level 1 as in (2) and minimum of cluster 2 or maximum of cluster 2 and minimum of cluster 3. This can be thought as a trade-off between the local and the global features⁷.

2.2 Global Thresholding Otsu Method

In thresholding method the image is divided into two groups. The threshold image $g(x,y)$ is defined as:

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) \geq T \\ 0 & \text{if } f(x, y) < T \end{cases} \quad (4)$$

Where T is the threshold value, (x, y) is any point in the image f . The object pixel value is 1 and background is 0. Optimal global

thresholding using Otsu method is based on the relationship between global variance and between class variance which is defined as $\eta(k)$.

$$\text{The equation } \eta(k) = \frac{\sigma_B^2(k)}{\sigma_G^2}$$

$$\text{where } \sigma_G^2 = \sum_{i=0}^{L-1} (i - m_G)^2 \cdot P_i \text{ and} \quad (5)$$

$$\sigma_B^2(k) = \frac{[m_G P_1(k) - m(k)]^2}{P_1(k)[1 - P_1(k)]} \quad (6)$$

$\sigma_B^2(k)$ For $k=0,1,\dots,L-1$ is the between class variance, is global intensity mean value, $m(k)$ is cumulative means, $p_1(k)$ is cumulative sums, σ_G^2 is global variance i.e. intensity variance of all the pixels in the image¹.

2.3 Histogram Thresholding Method

This process is based on pixel intensity of the image. This work consists of following stages: (1) The brain is divided into two equal parts around its central axis and find the histogram of each part. This will detect the infected side of the brain. If any symmetry is not observed, then the presence of the tumor is detected. (2) Calculate the difference among the two histograms i.e. right half and left half and find the threshold point followed by thresholding. (3) Apply morphological opening and opening by reconstruction on the detected image to find out the tumor region. Segmentation is done by calculating the threshold point^{9,11}.

2.4 Watershed Method

Watershed method applies some morphological operations opening, closing, opening by reconstruction and closing by reconstruction. Opening generally smoothes the contour of an object,

breaks narrow isthmuses, and eliminates thin protrusions. Closing also smooth sections of contours but, as opposed to opening, it combines narrow breaks and long thin gulfs. It fills gaps and eliminates small holes. Opening is erosion followed by dilation, while opening-by-reconstruction is erosion followed by a morphological reconstruction. Dilation is used for expanding an element by using structuring element. Structuring elements can be any size and make any shape.[1] Dilation of A by B and is defined by the following equation:

$$A \oplus B = \{Z | (\check{B})_Z \cap A \neq \emptyset\} \quad (7)$$

Dilation of A by B is the set consisting of all the structuring element origin locations where the reflected and translated B overlaps at least some portion of A. [1] In case of erosion of A by B is defined as

$$A \ominus B = \{z | (B)_z \cap A^c \neq \emptyset\} \quad (8)$$

Erosion of A by B is the set of all structuring element origin locations where the translated B has no overlap with the background of A.[1] The opening of an image f by structuring element s , denoted $f \circ s$ and closing of an image is $f \bullet s$

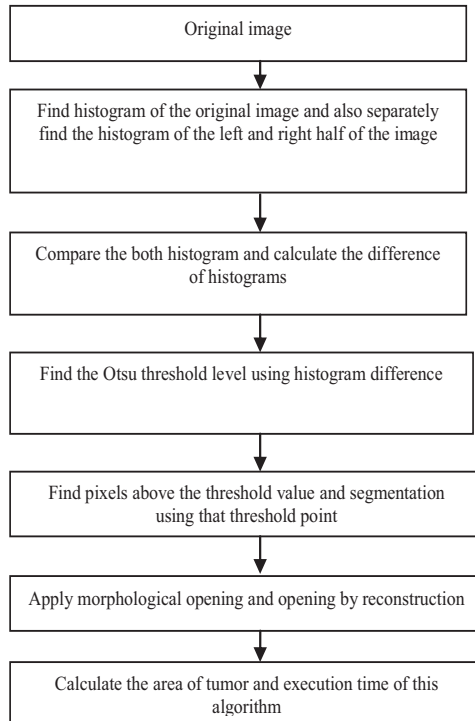
$$f \circ s = (f \ominus s) \oplus s \quad (9)$$

$$f \bullet s = (f \oplus s) \ominus s \quad (10)$$

3. Proposed Method

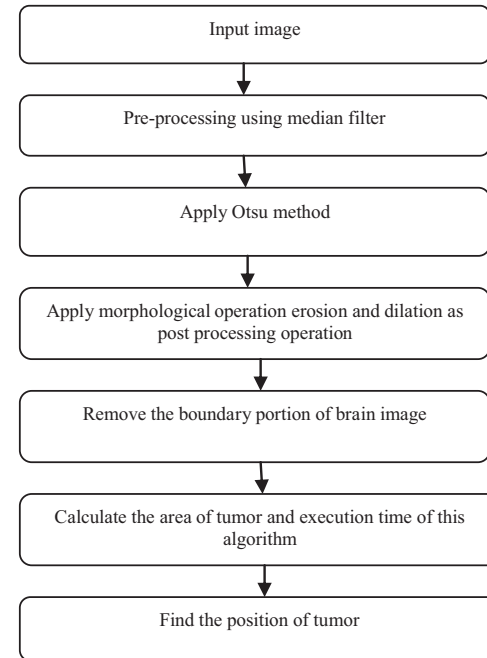
The proposed method consists of analytical study with Fuzzy C-Means thresholding with watershed method, Otsu thresholding method and histogram thresholding method.

3.1 3 Class Fuzzy C-Means Thresholding with Watershed Method



3.2 Global Image Threshold using Otsu's Method

In case of global thresholding method the threshold value is constant all over the image. The object is extracted using Otsu threshold value. If image pixel value is greater than threshold value then take white pixel (tumor region) otherwise take black pixel value. The algorithm of global thresholding using Otsu method with pre- and post-processing method is as follows:



In this paper we apply 'diamond' as a structuring element with radius 1. After segmentation the tumor portion estimates the area of all white pixels in the image.

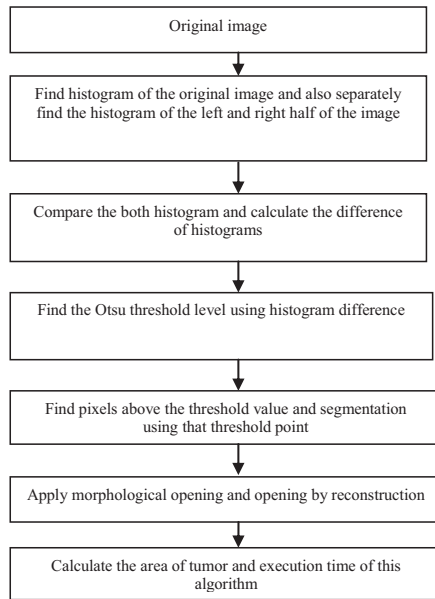
Area of segmented tumor = Σ area of each pixel

Area of each pixel = Σ (Horizontal dimension \times Vertical dimension) of each pixel

The dimension of a single pixel can be found from the horizontal and vertical resolution of the image.

The execution time of each algorithm is calculated from total CPU time (in seconds) using MATLAB.

3.3 Histogram thresholding method



4. Experimental Results

A sequence of four images has been taken for the performance analysis. Figure 1 demonstrates comparison of results of different algorithms. In Figure 1, 1st column shows the original image, 2nd column shows the 3 class Fuzzy C Means thresholding with watershed method, 3rd column represent the result of the global thresholding using Otsu method, 4th column shows the result of the post processing operation (morphological erosion and dilation and boundary elimination operation) on the segmented image using Otsu method, 5th column shows the result of histogram thresholding method, 6th column shows the result of the watershed method. Figures 2a and 2b shows the original image and outlined segmented tumor region of the brain image using Fuzzy C-Means thresholding with watershed method. Result of Otsu

thresholding is not accurate compared to the other two methods. 3 class Fuzzy C-Means thresholding with watershed method automatically removed other blood clot areas which are not the constituent of the tumor image. Figure 3 shows histogram of the brain images. Figure 4 represent the area calculation of each algorithm. As seen in Figure 4 our method extracts maximum affected area of the brain tumor region. Figure 5 shows the execution time comparison of different algorithms on bar chart. As shown in Figure 1, 2nd column i.e. our proposed method gives the best result although the execution time is more than the other methods as shown in Figure 5 from execution time calculation.

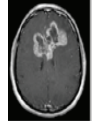



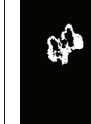

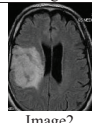





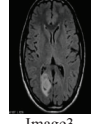



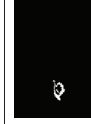

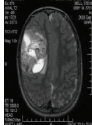





Original image	3 class fuzzy c means thresholding with watershed segmentation	Global thresholding Otsu method	After post processing operation on segmented image using otsu method	Histogram thresholding method	Watershed segmentation
 Image1					
 Image2					
 Image3					
 Image4					

Figure 1. Results of different types of segmentation algorithm applied on 4 no. of sample brain images.

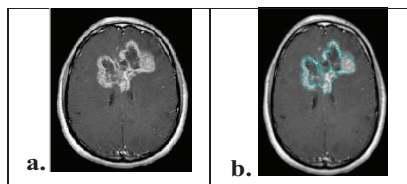


Figure 2. Shows the tumor position of original image.

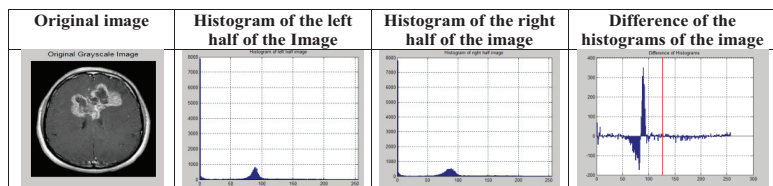


Figure 3. the histogram of the brain image.

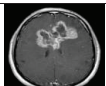
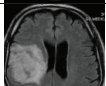
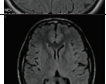
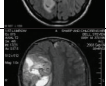
Original image	3 class fuzzy c-means thresholding with watershed method	Global thresholding Otsu method	Histogram thresholding method	Watershed segmentation algorithm
	2.113625e+03 1)	2.25262e+03 2)	2.3432e+03	2.074125e+03 3)
	5.46025e+03 4)	3.668375e+03	3.7631e+03	5.5425e+03
	2.023875e+04 5)	1.86757e+04	2.0558e+04	1.26634e+04
	3.4765e+03	2.0654e+03	1.9345e+03	1.6218e+03

Figure 4. Shows the calculated area of the segmented image.

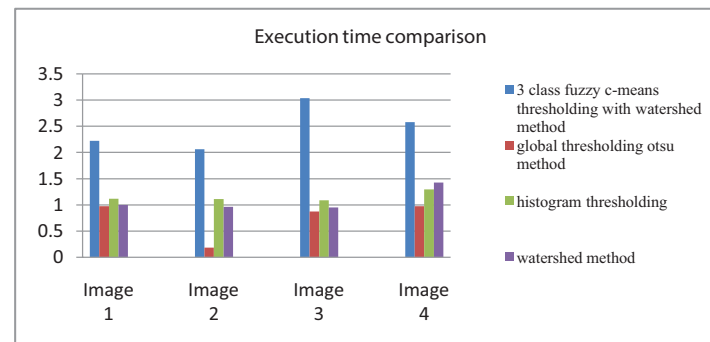


Figure 5. Shows the comparison of execution time.

5. Conclusion and Future Work

Different types of approaches have been proposed in current literature to segment an MRI image, which has its own limitations and merits. This paper provides analytical results of different existing segmentation methods adding some pre- and post-processing method and their respective statistical analysis. The algorithms are applied on four number of sample images of brain. Among all those algorithms our proposed Fuzzy C-Means thresholding with watershed method gives more accurate result.

In future additional textural features like gray level co-occurrence features may be considered to distinguish between malignant and benign tumors.

6. References

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