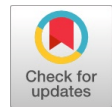# Brain Tumor Detection and Identification Using Histogram Method

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Abstract: Brain tumor is a collection of unwanted cells that grow abnormally in different parts of human brain. Detection of this is done effectively by MR image scanning of human brain. Certain process can be carried out to partition the input MR images into the regions. To convert these regions into coherent segments is done by Histogram Method which can utilize peaks and valleys to analyze the regions into segment of the MR images. This process can be done by program division method to detect the tumor in the earlier stages .This work aims at it.

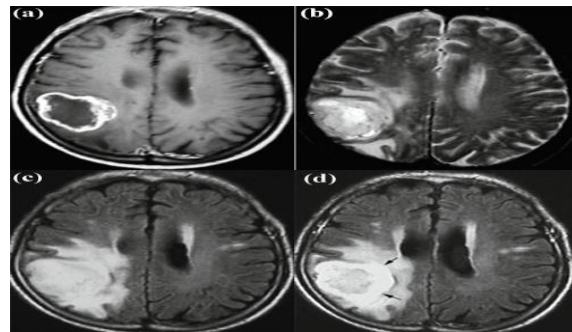*Index terms: Brain tumor, Histogram and Segmentation.*

Figure 1: MRI images

I. INTRODUCTION

A human brain is centre of the nervous system; it is a collection of white mass of cells. A tumor of brain is collection of uncontrolled increasing of these cells abnormally found in different part of the brain namely Glial cells, neurons, lymphatic tissues, blood vessels, pituitary glands and other part of brain which lead to the cancer. Cancer of Brain is of two types. Benign which is not cancerous not danger at all, other one is Malignant which is cancerous tumor; it grows abnormally by multiplying the cells rapidly, which leads to the death of the person if not detected. Manually it is not so easily possible to detect and identify the tumor. Programming division method by MRI is way to detect and identify the tumor. In order to give precise output a strong segmentation method is needed. In this paper we discussed the Histogram segmentation method of the MR Images. The scanned human brain MRI images are taken from the database and experimented in the MATLAB.

II MRI IMAGES OF BRAIN

This magnetic resonance imaging is a very helpful for the brain tumor detection for cancer imaging in which proton and neutron having the angular momentum known as spin, is identified. If the sub atomic particles in nucleus is even there exists no spin. Whereas there exists a spin when the sub atomic particles in the nucleus are odd, this is a base for MR imaging. MRI uses very strong magnets to polarize and excite the hydrogen nucleus which contains the single proton in human tissue to produce the signal, to be detected.

The MRI scan shows a clear view and detailed information inside the human brain which is extraordinary compared to the CT scan and X-Ray.
The contrast of MRI
The different MR Images produce different types of contrast images which provide the valuable structured information to enable the diagnosis and segment the tumor with their sub regions to the medical analysts.

There are four standard MRI models used for Glioma diagnosis which include T1-weighted MRI (T1), T2-weighted MRI (T2), T1-weighted MRI with gadolinium contrast enhancement (T1-Gd) and Fluid Attenuated Inversion Recovery (FLAIR) (see Fig. 1). Although MRI acquisition, can vary from device to device, around one hundred and fifty slices of 2D images are produced to represent the 3D brain volume. Furthermore, when the slices from the required standard various modalities are combined for diagnosis the data becomes very populated and complicated.

The various methods have been developed for MRI to divide the image into number of sub regions in order to identify the tumor at very early stage by pathologists. Here the digital MRI is divided according to their intensity values from 0 to 255. By these intensity values first we should locate object and then identifying the boundaries and their position easily by the MR Imaging techniques.

III PROPOSED METHODOLOGY

The proposed methodology process steps as followed.
- Pre-processing
- Identification
- Segmentation

At the first, we take input image as brain tumor MRI images. The MRI images are pre-processed by using Wiener filter techniques. After that, the histogram based model is used for tumor region identification and segmentation.

Brain Tumor Detection and Identification Using Histogram Method

A. PREPROCESSING

An input MRI image might have noise and unwanted signal which occurred during the movement of the patient or while generating the images.

The image preprocessing steps involve removing the noise. In order to enhance the image for more quality the image segmentation process is carried out. There are also some morphological techniques used to detect the tumor in the medical field but they are not up to the mark in the accuracy. In preprocessing, we smoothen and sharpen the image, by reducing the speckles without destroying its main features of brain MRI for diagnosis.

We apply different filtering techniques to extract image highlights. For this we apply the Wiener filter to reduce the impact of unwanted noise. Wiener filter is preferred since it has the highest Peak Signal to Noise Ratio. This is helpful for MR brain image quality.

Weiner filter

Weiner filter is mostly used in digital image processing. This is frequently used in de-convolution process to reduce the noise, by linear invariant technique. It studies the stationary signal, noise spectra and additive noise. These artifacts are detected and removed. Weiner filter also minimizes the Mean Square Error (MSE) between estimated and desired signals in order to reducing the blurring in the MR images.

A pixel wise Wiener filter is created by pixel wise using the. Eq. 1

$$v(a,b) = \tau + \frac{\eta^2 - p^2}{\eta^2}\left[u(a,b) - \tau\right] \quad ----(1)$$

Where

τ -Mean η -variance

p - is the average of all the local estimated variances

$u(a,b)$ and $v(a,b)$ - are the pixel values in the original image.

B. IDENTIFICATION AND SEGMENTATION

Brain tumor is tissue of mass in the different parts of the brain. Identification by the pathologist is somewhat complicated and tedious, which is prone to error and inaccuracy. We cannot acquire easily the status of the cancer. To avoid this disadvantage, we developed and applied the program division method (PDM) along with MR Images which gives the desired output. To segment the image into regions we use Histogram Based Segmentation method.
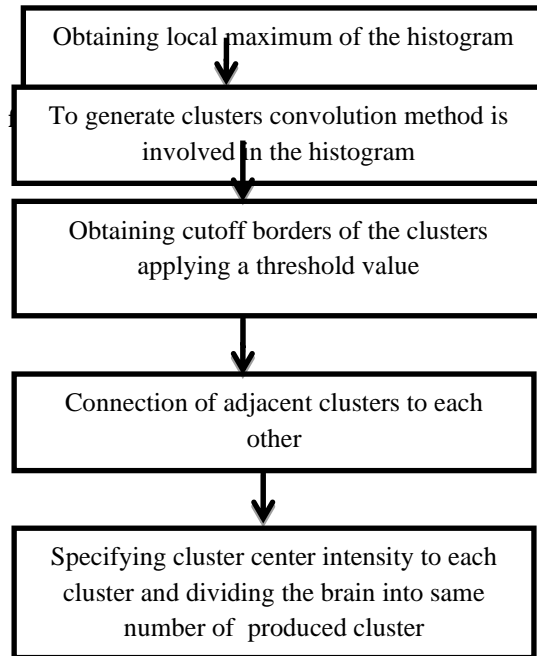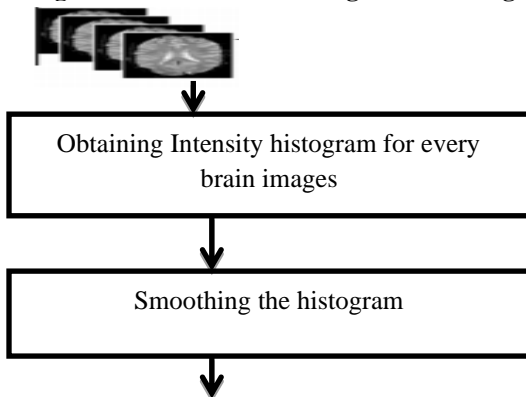
Histogram based brain MRI segmentation algorithm.

[Obtaining Intensity histogram for every brain images] → [Smoothing the histogram]

[Obtaining local maximum of the histogram] → [To generate clusters convolution method is involved in the histogram] → [Obtaining cutoff borders of the clusters applying a threshold value] → [Connection of adjacent clusters to each other] → [Specifying cluster center intensity to each cluster and dividing the brain into same number of produced cluster]

Figure 2: **Seven step analysis of histogram**

Histogram based model scrutinizes peaks and valleys of the input image which uniquely support values of voxel, which can be utilized for image segmentation.

Histogram is shown as seven steps segments, based on the model in the figure 2.

Step 1: The image power of histogram depends on the image intensity. The image values are represented the matrix form from 0 to N1 of the image I. Given H[u] denotes the normalized histogram of I.

$$H[u] = \frac{\text{number of pixels with intensity u}}{\text{total number of pixels}}, u = 0,1,....,N-1$$

-- (2)

Step 2: For smoothen the histogram H[u] we use local weighted techniques using eq 3

$$\overline{H}[u_i] = \frac{\sum_{i}^{i+L} w_i * H[u_i]}{L} \quad ---------$$

$$w_i = \sum_{i}^{i+L} \| u_i - A_w \|^2 \quad ---------(4)$$

(3)

Where

H[u]=Histogram distribution value of ith bin
Wi=weight corresponding to the ith bin
Ai=average of the window
ui= pixel intensity for the ith element

$\overline{H}[u_i]$=local average value of Histogram

Step 3:

The local maximum of smoothed histogram is calculated by:

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$$H_{max-local}[u] = \overline{H}[u_i] | (\overline{H}[u_i] > \overline{H}[u_{(i+1)}]) \cap (\overline{H}[u_i] > \overline{H}[u_{(i-1)}])$$

---(5)

Step 4: The rectangular window is convoluted, the histogram values from previous step, show the intensity values of neighborhood which represents the various fragments in the brain image

The convolution $H_{max-local}[u]$ of rectangular window is employed to connect the local maxima that of each neighborhood.

Let R be the length of rectangle window and A be the length of $H_{max-local}[u]$ then V[u] is vector of length A+R-1

$$V[u] = R_{in}[u] * H_{max-local}[u] = \sum_j R_{in}[j] H_{max-local}[u-j]$$

---(6)

The function V[u] potentially leads many segments, the convolved window produces high no of segments.

Step 5 The threshold values are used in cut of borders to acquire the segments then the convolution of $H_{max-local}[u]$ and a rectangular window, R_{in}, was calculated which results inV[u].The threshold value Th1 controls the cut of boundaries smaller then threshold values and removes as segments. The cut of boundaries are calculated by V[u].

$$U_{low}[u_i] = \{u | V[u_{(i+1)}] > Thl \perp V[u_{(i-1)}] < Thl\}$$

--- (7)

$$U_{high}[u_i] = \{u | V[u_{(i+1)}] > Thl \cap V[u_{(i+1)}] < Thl\}$$ --------

------------------------------------- (8)

Step 6: The upper cut off borders of uth segment is associated with lower cut off border of (u+1)th segment. The gaps between $U_{high}[u_s]$ and $U_{high}[u_{(s+1)}]$. Again every pixel should be assigned of particular section. In this progression, upper cutoff border of one segment reaches to the lower cutoff border of the following one rule

.

$$U_{up-new}[S_u] = U_{low-new}[S_{(i+1)}]$$

-------------------- -----

$$(9) = U_{up}(S_u) + (U_{low}(S_{u+1}) - U_{up}(S_u))$$

--------- ---------------------------- (10)

$$= \frac{LM(S_u)}{LM(S_u) + LM(S_{u+1})}$$

------------------------------------- (11)

Where

S_u = Index of the uth segment

$LM(S_u) = $ local maximum amplitude of the segment S_u

Step 7: One special intensity value is specified for every created section. All intensity values between lower and upper cutoff borders of one segment would be represented

by one intensity value named $U_{center}(S_u)$. The intensity of the S_u segment is defined as:

$$U_{center}(S_u) = \frac{U_{low-new}(S_u) + U_{up-new}(S_u)}{2} \quad (12)$$

The number of the segments which are visible in histogram data is the same as the total number of lower or upper cutoff boundaries of the function V[u].

IV. EVALUATION METRICS

Detection of brain tumor is very important task now days in the present generation. In human brain the mass of tissue spread is abnormal as result of the growth of irregular cells. There is no mechanism to identify them manually. There are several techniques that have been developed till now, but there is lack of accuracy and prone to errors. In this paper we implemented Histogram segmentation method with MRI images using MATLAB experiments for better detection and identification of brain tumor in the earlier stages. The proposed model will definitely help the researchers to go further steps to implement the classification by using the clustering algorithms. Apart from the conventional method this method produced good result in detection and identification. The system performance is analyzed by using the assessment metrics such as Sensitivity, Specificity, Accuracy, PPV, NPV, FPR, FNR and FDR which are depicted in below.

Sensitivity/ Recall

The ratio of a number of true positives to the sum of true positive and false negative is called as sensitivity.

$$Sensitivity = \frac{No.of(TP)}{No.of(TP) + No.of(FN)} \times 100$$

----------------------------- (1)

Specificity

Specificity is the ratio of a number of true negative to the sum of true negative and false positive.

$$Specificity = \frac{No.of(TN)}{No.of(TN) + No.of(FP)} \times 100$$

----------------------------- (2)

Accuracy

Accuracy is calculated by the measures of sensitivity and specificity. It is denoted as follows,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

--(3)

Positive Predictive Value (PPV)/ Precision

The fraction of positive experiment consequences which are considered as the Positive Predictive Value:

$$PPV = \frac{TP}{TP + FP}$$

-----------------(4)

Histogram based method			
Image name	Segmented image	Ground Truth	Segmented portion
HGG_1.jpg			
HGG_2.jpg			
HGG_3.jpg			
HGG_4.jpg			
LGG_11.jpg			
LGG_12.jpg			

Negative Predictive Value (NPV)

The fraction of negative experiment consequences which are considered as the Negative Predictive Value:

$$NPV = \frac{TN}{TN + FN} \quad \text{-----------------(5)}$$

False Positive Rate (FPR)

FPR is calculated as the number of incorrect positive predictions divided by the total number of negatives. It can also be calculated as 1 – specificity.

$$FPR = \frac{FP}{FP + TN} \quad \text{-------------------- (6)}$$

False Negative Rate (FNR)

FNR is calculated as the number of incorrect negative predictions divided by the total number of negatives.

$$FNR = \frac{FN}{FN + TP} \quad \text{----------------------- (7)}$$

False Discovery Rate (FDR)

The FDR is the rate that features called significant are truly empty which is defined as.

$$FDR = \frac{FP}{FP + TP} \quad \text{-----------------------(8)}$$

V PERFORMANCE EVALUATION

In this paper, an improved version for brain tumor segmentation technique of MRI image is proposed. Initially, pre-processing is done for the MRI brain images, and then the pre-processed image is segmented using novel segmentation techniques. Finally, classification algorithm is applied to the segmented image to find out the normal and abnormal portions. This workr exhibits the experimental outcomes obtained for the proposed methodology compared with the existing techniques.Some of the input database MRI images are

HGG1.jpg   **HGG2.jpg**   **HGG3.jpg**

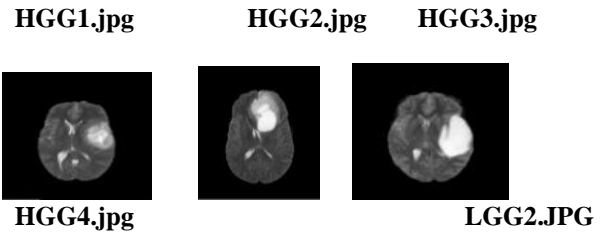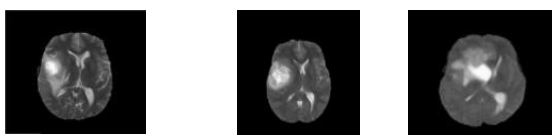**HGG4.jpg**   **LGG2.JPG**

Figure: 3 MR Images From The Database
Histogram Based MR Imagessegmentationdescription
Figure 4: Histogram Segmented Images

The MRI brain images are shown in the above figure (fig 4). Here the segmented image, ground truth portion and the segmented result using proposed histogram based method are highlighted with different colors. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram to locate the clusters in the image. In this histogram seeking segmentation segment-in-segmentation process carried out to produce the smaller segment until no more segments is formed. Histogram-based approaches can also be quickly adapted to apply to multiple frames, while maintaining their single pass efficiency. One advantage of the Histogram method is that it identifies the analysis of peak and valley confinement to compare the values with desired threshold setting value, which leads to division of smaller segments. The threshold values depends on pixel intensity value of every image from (0=black to 255=white). The histogram can be done in multiple fashions when multiple frames are considered. Table below is given which displays histogram MATLAB experimented values using metrics.
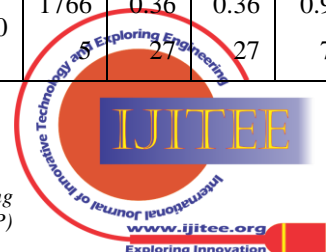
VI. CONCLUSION

The histogram method is very efficient segmentation technique for MR images, since it uses recursive logic to segment the images. The future application is that it helps in making clustering of images and later on we can apply the classification method.

Table 1: MATLAB experimented values

	Histogram based method						
	TP	TN	FP	FN	Recall	prec	Acc
HGG_1.jpg	1483	54332	54	775	0.6568	0.6568	0.9854
HGG_2.jpg	10102	388201	2	3650	0.7346	0.7346	0.9909
HGG_3.jpg	5488	383869	0	18960	0.2245	0.2245	0.9536
HGG_4.jpg	1376	53486	0	833	0.6229	0.6229	0.9850
LGG_11.jpg	18349	388965	17	3546	0.8380	0.8380	0.9913
LGG_12.jpg	10053	385727	0	1766	0.3627	0.3627	0.9573

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