Computer Aided System for Brain Tumor Detection and Segmentation

Priya Das¹, Sayak Konar², Niharika Puvvula³, Deepali Rai⁴
¹,³,⁴M.Tech (Computer Science & Engineering), VIT University, Vellore, INDIA
²Assistant Professor, Department of Computer Science & Engineering, BIEMS, Kolkata, INDIA

ABSTRACT
Magnetic resonance imaging (MRI) is a radiological method of looking inside the body. MRI provides good contrast between the different soft tissues of the body, and hence quite useful in detecting brain tumor. The purpose of our system is to automate the detection and segmentation of tumor in brain from a MRI. The automation of tumor image detection is a combination of input, processing and output of desired segment. The input is taken from the images generated at pathological labs, the processing is done by our system and the output is processed for further analysis by the concerned people.

Keywords—Brain Tumor, Automate Detection, MRI (magnetic resonance imaging), System

I. INTRODUCTION
In automated medical diagnostic systems, MRI (magnetic resonance imaging) gives better results than computed tomography (CT) as MRI provides greater contrast between different soft tissues of human body. Hence MRI is much more effective in brain and cancer imaging [6]. Detection of brain tumor requires brain image segmentation. Manual brain MRI image segmentation is a difficult task. It requires plenty of time, non-repeatable tasks, non-Uniform segmentation and also segmentation results may vary from expert to expert. So computer aided system is useful in this context. An automated brain tumor detection system should take less time and should classify the brain MR image as normal or tumor accurately. It should be consistent and should provide a system to radiologist which is self explanatory and easy to operate. Automatic brain tumor detection and segmentation faces many issues and challenges. It is a difficult task to segment brain tumor in an automatic computerized system as it involves pathology, physics related to MRI along with intensity and shape analysis of MRI image. The major issue with brain tumor segmentation is that the tumor varies in form of shape, size, location and image intensities. Manual segmentation of brain tumor requires human experts and it takes a lot of time.

II. METHODOLOGY
Step 1:- Getting the samples of MRI images of Brain.
Step 2:- In preprocessing stage the noise removal and gamma law transformation is done.
Step 3:- In segmentation phase the preprocessed image is converted to binary image, and dilation along with erosion is applied.
Step 4:- Image Splitting and segmentation is done.
Step 5:- Analysis is done calculating the Mean Squared Error, Peak Signal to Noise Ratio and Entropy of the images.

III. PRIOR APPROACH
There are several segmentation processes as referred by various research papers. However, each process is preceded by a pre-processing method, where the input image is processed to get rid of input noise or different labeling, to enhance intensity and to filter out the required portion of image. Again the segmentation process can be manual or automated. The automated process may suffer from inefficiency if proper method is not chosen. In the proposed system we apply the manual method. Automated method is our future scope of enhancement as of now.

In [1] the authors have presented the step by step techniques required for automated brain tumor detection and segmentation. In the proposed method there are three steps: pre-processing, segmentation and post-processing.
The proposed method enhances the MR image and segments the tumor using global thresholding. False segmented pixels are then removed using morphological operations and applying windowing technique.

In [2] the authors have presented brain lesion segmentation of diffusion-weighted magnetic resonance images based on thresholding techniques. The proposed technique consists of two steps: pre-processing and segmentation of DWI brain image. Gamma-law transformation algorithm and contrast stretching are evaluated and compared for the segmentation process. They presented that Gamma-law transformation algorithm provides better segmentation than contrast stretching.

IV. OUR APPROACH

Automatic brain tumor detection and segmentation faces many issues and challenges. Our goal is to provide a system which will segment and enhance the brain tumor from the MRI as efficiently as possible.

The detection system is designed to work in three stages. First, the image noise is removed and it is sharpened; next the tumor is segmented and lastly some morphological methods are applied for enhancement of the segmented portion. The system is tested on several input images and their results are compared on the basis of different measurements like entropy, PSNR etc.

A. Pre Processing

To detect the brain tumor from the MRI two stages namely pre processing stage and segmentation stage are implemented. In pre processing stage the noise is removed, background is removed and then gamma law transformation is applied. Gamma-law transformation algorithm is chosen to expand narrow range of low input gray level values DWI to wider range. It has the basic form of 

\[ s = cr^{\gamma} \]

where \( c \) is amplitude and gamma is constant power of input gray level \( r \), \( \gamma=0.4 \).

B. Segmentation

In the second phase segmentation process is done. The pre processed image is converted from grayscale to binary. To that image dilation and erosion are applied. Finally the image is segmented. Erosion generally decreases the sizes of objects and removes small anomalies by subtracting objects with a radius smaller than the structuring element. With grayscale images, erosion reduces the brightness (and therefore the size) of bright objects on a dark background by taking the neighborhood minimum when passing the structuring element over the image. With binary images, erosion completely removes objects smaller than the structuring element and removes perimeter pixels from larger image objects.

Dilation generally increases the sizes of objects, filling in holes and broken areas, and connecting areas that are separated by spaces smaller than the size of the structuring element. With grayscale images, dilation increases the brightness of objects by taking the neighborhood maximum when passing the structuring element over the image. With binary images, dilation connects areas that are separated by spaces smaller than the structuring element.

![Figure 2:-Segmentation Steps](image)

Figure 2:-Segmentation Steps

and adds pixels to the perimeter of each image object.

V. RESULTS

The figures below shows the pre-processed and segmented image on data set of three images. The first row represents all the three original images. Second row shows the filtered image. Third row shows the image after background removal and fourth row represents the image after applying Gamma Law transformation.
VI. ANALYSIS

A. Mean Squared Error (MSE)

For analysis of the image entropy, mean squared error and PSNR is calculated. The MSE is the cumulative squared error between the original and the converted image. The mathematical definition is:

\[
MSE = \frac{1}{MN} \sum_{x=1}^{M} \sum_{y=1}^{N} [I(x, y) - I'(x, y)]^2
\]

where \( I(x, y) \) is the original image, \( I'(x, y) \) is the converted image and \( M, N \) are the dimension of the images.

B. Peak Signal to Noise Ratio (PSNR)

For the PSNR, which is the measure of the peak error, we have,

\[
PSNR = 20 \log_{10} \frac{2B^2}{\sqrt{MSE}}
\]

A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction.

C. Entropy

\[
E = \text{entropy}(I) \text{ returns } E, \text{ a scalar value representing the entropy of greyscale image } I. \text{ Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as}
\]

\[
\text{sum}(p.*\text{log2}(p))
\]

where \( p \) contains the histogram counts returned from imhist. By default, entropy uses two bins for logical arrays and 256 bins for uint8, uint16, or double arrays.

I can be a multidimensional image. If \( I \) has more than two dimensions, the entropy function treats it as a multidimensional greyscale image and not as an RGB image. I can be logical, uint8, uint16, or double and must be real, nonempty, and non sparse. E is double.

For the above stated metrics the following values are found

Table 1:-Analysis of Images

<table>
<thead>
<tr>
<th>Original Image</th>
<th>Operation</th>
<th>Entropy</th>
<th>MSE</th>
<th>PSNR</th>
<th>Threshold</th>
<th>Gamma Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brain.png</td>
<td>Original MRI</td>
<td>3.627</td>
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<tr>
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<td>Filtered</td>
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<td>Background removal</td>
<td>0.8224</td>
<td>6.17</td>
<td>10.26</td>
<td>180</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gamma law transformed</td>
<td>0.8224</td>
<td>6.17</td>
<td>10.26</td>
<td>180</td>
<td></td>
</tr>
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<td>4.374</td>
<td>11.756</td>
<td>180</td>
<td></td>
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<tr>
<td></td>
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<td>4.374</td>
<td>11.756</td>
<td>180</td>
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</tr>
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<td>8.6531</td>
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<td>8.6531</td>
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<tr>
<td>Image3.png</td>
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<tr>
<td></td>
<td>Gamma law transformed</td>
<td>0.1887</td>
<td>5.8947</td>
<td>10.4897</td>
<td>200</td>
<td></td>
</tr>
</tbody>
</table>
VII. CONCLUSION

In this paper brain tumor segmentation and detection is done using MR images. Preprocessing stage is carried out for intensity normalization, background removal and intensity enhancement. Gamma-law transformation algorithm and contrast stretching are evaluated and compared for the segmentation process. The method used enhances the MR image and segments the tumor using global thresholding. False segmented pixels are then removed using morphological operations and applying windowing. The result shows that both enhancement techniques can successfully segment the tumor. Gamma-law transformation algorithm provides better segmentation results.

REFERENCES