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3D MRI Image Segmentation for Brain Tumor Boundary Detection using Kapur Entropy Measure

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Abstract—Boundary detection of brain tumor from the MRI is a time consuming task. This is due to the diversity in shape, size and appearance of the tumors. Boundary detection in MR image with brain tumor is an important image processing technique applied in Radiology for 3D reconstruction. To segment the boundary of the brain tumor region, many segmentation techniques have been emerged in image processing like the region based segmentation, the boundary based segmentation. Moreover, even in some of the normal tissue region, edge created by this method has also been encompassed. In this paper, Kapur Entropy measure method is used for boundary detection of brain tumor segmentation and its earlier detection. In the proposed approach threshold selection is done on the basis of different Kapur entropy measure. Simulation results for different MRI Images are also presented and it is observed that in 3D MRI Images, Kapur entropy is able to detect the brain tumor at its earlier stage.

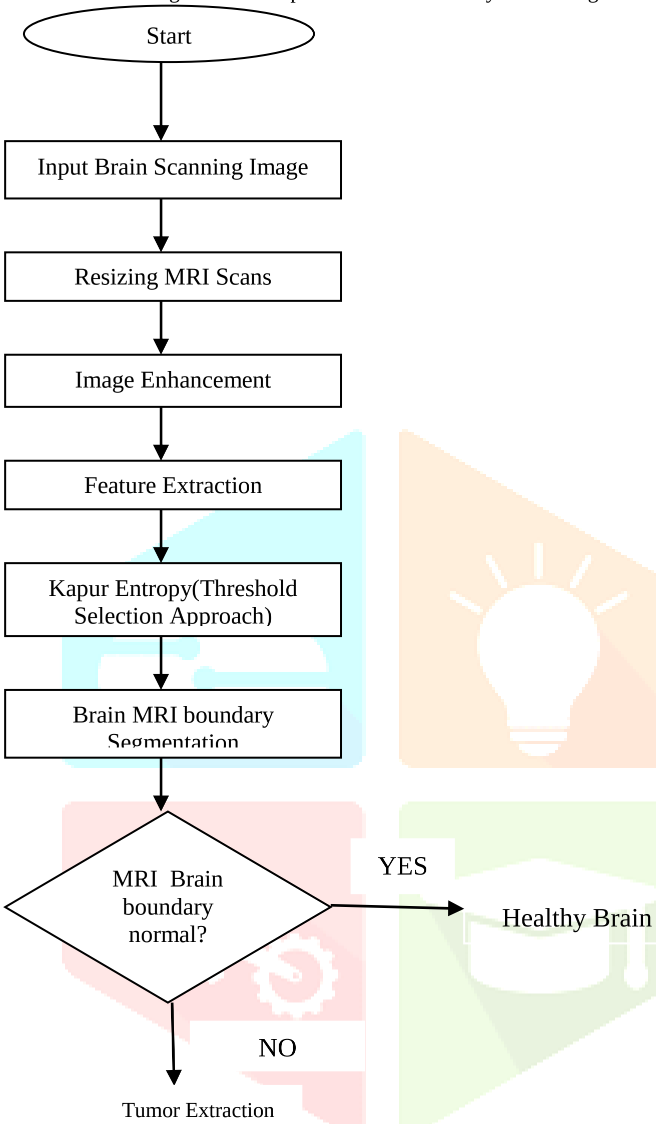
Keywords— MRI , Segmentation,Radiology, Kapur Entropy

I. INTRODUCTION

In 3D reconstruction of MR image with brain tumor, boundary detection in each 2D image slice of magnetic resonance (MR) can be located by the features in the edge of the brain tumor. For the sensitivity of the edge, the fine edge denotes one pixel in the width of the edge. If more than one, the worst sensitivity of the edge is obtained. Now, we are based on these two factors to measure which methods can be satisfied in edge detection for the non homogeneities density tissue of brain tumor. Tissue in homogeneity [l] as an additional noise surrounds the tumor is the problem for searching the boundary of tumor. Previous studies [2-4] proposed the contour deformable model (snake) and adaptive thresholding to solve this problem in MR image. However, these kinds of the methods cannot detect the boundary reliably. It is invalid in the nonhomogeneous region while the term of external energy attracts the contour toward the object in the image. Now, we propose a simple but efficient edge detection method that is based on Generalized Fuzzy Operator (GFO) [7]. The special properties of this GFO can search the boundary in high accuracy and obtain the fine edge based on its generalized fuzzy set. Evaluation between Contour Deformable Model (CDM) and our method with MR image are also presented. Our brain is central processing unit of the human body, is delicate, soft, and spongy mass of the tissues. It is basically a steady place for the signals to enter and then being processed. The brain directs the things we choose to do. The human brain which functions as center for control of all the parts of human body is a highly specialized organ that allows human being to adapt and to endure the varying environmental condition. The human brain allows a human to articulate the words, execute our actions, and share the thoughts and feelings. Under certain conditions, brain cell grow and multiplies it uncontrollably because of some reasons the mechanism that control normal cells is unable to regulate growth of brain cells. The abnormal mass of the brain tissue is the brain tumor that occupies space in the skull, interrupts normal functions of brain and creates an increasing pressure in brain. Due to the increased pressure on brain, some brain tissues get shifted and pushed against the skull and responsible for the damage of the nerves of the other healthy brain tissues. Tumors are created by an abnormal and uncontrolled cell division in the brain. Scientists have classified the brain tumor according to location of the tumor, type of the tissues involved classified the tumor as whether they are non-cancerous or cancerous. World Health Organization (WHO) classified brain tumor into 120 types. This classification of tumor is done on the basis of cell origin and the behavior of the cell from less aggressive to more aggressive behavior. Even, some tumor types are graded ranging from grade I that is less malignant to grade IV that is more malignant. This represents the rate of the growth despite of variations in grading systems which depends on the type of the tumor. ***Grade I:*** The tissues are benign and the cells look nearly like normal brain cells, and they grow slowly. This type of brain Tumors are rare in adults. ***Grade II:*** The tissue is relatively slow growing and sometimes spread to the nearby normal tissues and become malignant. The cells look less like normal cells than do the cells in a Grade1 Tumor. ***Grade III:*** These are the malignant tissue and have cells that look very different from normal cell. The abnormal cell is actively growing. ***Grade IV:*** These cover the most malignant tissue and have cells that look like most abnormal and tend to grow quickly. Tumor forms new blood vessels to maintain rapid growth. Magnetic resonance (MR) images are useful tool in order to detect the tumor growth in the brain. It is used in radiology to investigate the anatomy and the physiology of body in both health and disease. Eventually, MRI became the most preferred imaging technique in radiology because MRI enables the internal structure be visualized in some detail. In MRI signal processing considers signal emissions. The imaging processes do not involve use of the ionizing radiation and hence does not have associated potential harmful effects. Photons and neutrons of the nucleus of an atom have an angular momentum which is known as a spin. These spin will cancel when the number of sub atomic particles in a nucleus are even. Nuclei with the odd number will have resultant spin. This basically forms the base of magnetic resonance imaging. Actually, many medical imagery diagnosis systems faced the problem of cells and their nuclei separation from the rest of the image content. As the process of separation is important, much attention in a construction of the expert diagnosis system has to be paid to the segmentation stage

II. THE PROPOSED METHOD

In MRI the good contrast between different soft tissues of the body can observed. The MRI brain image is acquired from patient's database. This makes MRI suitable for providing the better quality images for brain, muscles, heart and cancerous tissue compared with the other medical imaging techniques as the computed tomography (CT) or X-rays. MRI scanners use the magnetic fields and the radio waves to form images of body. This technique widely used in the hospitals for medical diagnosis, staging of disease or for accurate detection, shape and size of the tumor. In medical image processing segmentation of the anatomical regions of brain is basically the fundamental problem. MRI images are extremely rich in information content. The image pixel values can considered as a function of a host of parameters. The flexibility in data acquisition and rich contrast mechanisms of the MRI endow technique with the superior scientific and diagnostic value. Image segmentation is process of partitioning the digital image into a multiple segments (set of pixels, known as super pixels). Segmentation is the crucial step in image processing tasks. The goal of segmentation is to simplify and change the representation of image to something that is meaningful and easier to analyze. Segmentation is typically used to locate the objects, boundaries (lines, curves, etc.) in images. Precisely, image segmentation is a process of assigning the label to every pixel in an image so that pixels with the same label share certain features. The result of the image segmentation is the set of segments that collectively cover the whole image, a set of contours is extracted from image. Each pixel in the region is similar with respect to some characteristic or computed property, such as the color, the intensity, or texture. The purpose of segmentation is to separate an image information into clear meaningful parts by placing the boundaries and separating the area of the healthy brain from the area of the cancerous and tumorous brain. The proper detection and segmentation of the tumor leads to exact extraction of features and classification of tumors. A large number of techniques have been developed for medical image analysis in the last decade. It is the purpose of the paper to investigate the tumor affected area and to present the comparative study based on the different entropies for threshold selection purpose in MRI Images using Co-Occurrence matrix. Here we will compute the threshold for the each gray plane using the minima of each entropy measures. In this paper different MR scans of patients are taken having abnormality in their brain. On the bases of their comparisons, the result is obtained and then represented in tabular form indicating whether the presence of abnormality in the image.



III. Methodology Based on Kapur Entropy Measures

The methodology of image segmentation using the gray level co-occurrence matrix and probability matrix is discussed. The basic steps of algorithm are reproduced here for sake of convenience

(i) The co-occurrence matrix $C_{m1,m2}$ of the image to be segmented is computed first for each color channel.

(ii) The probability distribution $P_{m1,m2}$ is then calculated from its co-occurrence matrix as $P_{m1,m2} = C_{m1,m2}/MN$.

(iii) The entropy is then calculated for each gray level image for each entropy definitions.

(iv) The numbers of minima points are then determined from the entropy function versus gray level (t) plot.

Probability Matrix:- Probability Matrix is the normalized GLCM (Gray Level Co-occurrence Matrix) over all offsets or directions that are under the considerations.

Co-occurrence matrix:- Co-occurrence is the matrix or the distribution that is always defined over the image to the distribution of the co-occurring values at the given offset.

Entropy:- The measure of the degree of the randomness that can be used to characterize the texture of the input image. Entropy are of different types and those are discussed below

The Kapur entropy is defined as:

Kapur Entropy: Kapur entropy was defined by $H_k(p_{m1,m2})$ of the order of α and type β and is defined as,

$$H_k(P_{m1,m2}) = \frac{\sum_{m1}\sum_{m2} P_{m1,m2}^{\propto+\beta-1}}{2^{1-\propto}-1} - 1 + \frac{1}{2^{1-\propto}}\left[\sum_{m1=t+1_1}^{L-1}\sum_{m2=0}^{t} P_{m1,m2}^{\propto} - 1\right]$$

Below we are discussing the different Entropies and also the different entropies mathematical representation. Basic approach of the paper was to select the threshold from the entropy function which will then calculate the minimum value of the threshold. The entropy function of the various Entropies are as follows.

Table1: Entropy functions

Entropy	Entropy Function Entropy(t)
Kapur	$\sum_{m1=0_1}^{t}\sum_{m_2=t+1}^{L-1}\left(\frac{P_{m_1,m_2}^{\propto+\beta-1}}{P_{m_1,m_2}^{\beta}}\right)-1\left(2^{1-\alpha}-1\right)^{-1} + \sum_{m_1=t+1}^{L-1}\sum_{m_2=0}^{t}\left(\frac{P_{m_1,m_2}^{\propto+\beta-1}}{P_{m_1,m_2}^{\beta}}\right)-1\left(2^{1-\alpha}-1\right)^{-1}$

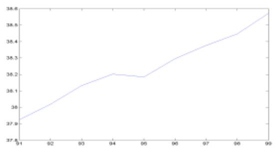
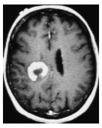
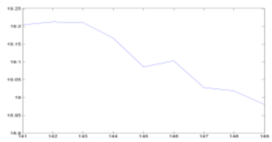
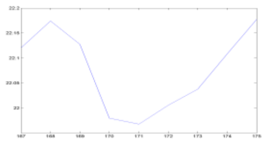
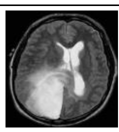
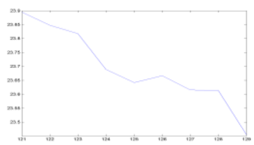
The above entropy was calculated for each value of $t \in [0, 1, 2, 3....L-2]$ that was on the basis of the basic Gray Co-occurrence Matrix C_{m1m2} which was in turn actually used to calculate probability density function p_{m1m2}. P_{m1m2} that always plays a vital role which usually represents the image. In this the L represented the max number of the gray level that was present in a particular image.

iv. Simulation Results

A. *Entropy Plots*

In this section we present the simulation results performed in MATLAB. The experiment was basically conducted on the MRI Images on windows 7. In the below mention table the entropy versus the gray value plots for the different entropy functions represented by the below different figure for few selected MRI Images.

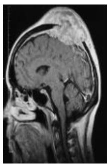
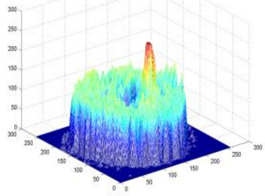
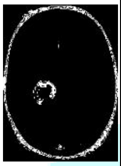
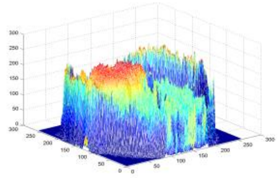
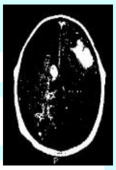
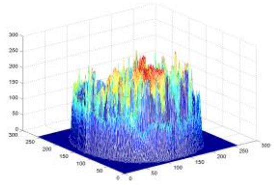
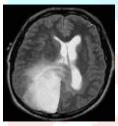
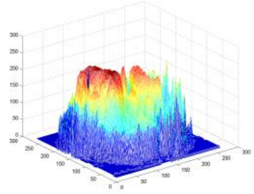
Table2: Kapur Entropy Graphs

Image	Graph
 Grade1 Tumor MRI Image	
 Grade2 Tumor MRI Image	
 Grade3 Tumor MRI Image	
 Grade4 Tumor MRI Image	

B. *Brain Tumor Boundary Detection for MRI Images and 3D Implementation Results*

The tumor detection 3D images for different stages of MRI images is tabulated below -

Table 3: Result from Different stages of Tumor Images

1	 Grade1 Tumor MRI Image		
2	 Grade2 Tumor MRI Image		
3	 Grade3 Tumor MRI Image		
4	 Grade4 Tumor MRI Image		

In this, the Kapur Entropy Threshold technique was tested on different stages of MRI brain images taken of patients with brain tumors. Experimental results show that the detected tumor blocks were marked accurately at stage 1 and it is enough to produce a 3D visualization for linking and differentiating different tumor blocks with different brain illnesses using a brain model that was able to enhance the detection and interpretations.

C. *Detection Results on multiple MRI Images*

Table 4: Result from Grade I Tumor Images

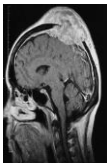
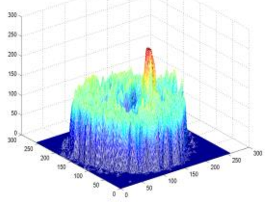
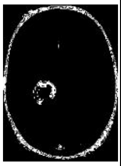
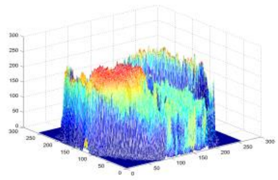
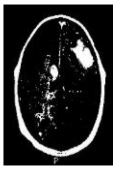
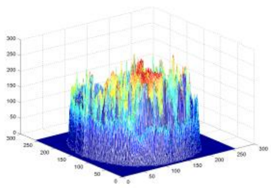
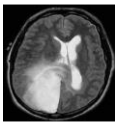
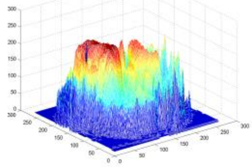
1	 Grade I Tumor MRI Image_A		
2	 Grade I Tumor MRI Image_B		
3	 Grade I Tumor MRI Image_C		
4	 Grade I Tumor MRI Image_D		

Table 5: Result from Grade II Tumor Images

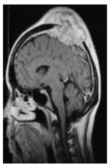
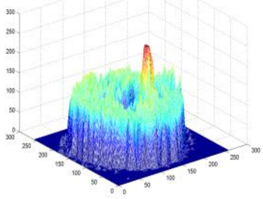
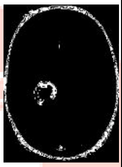
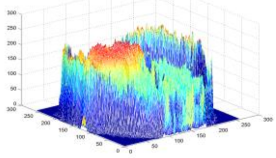
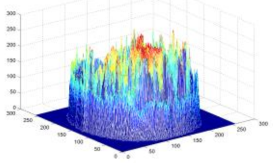
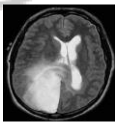
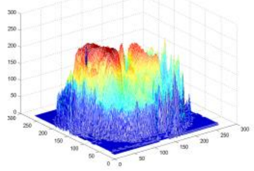
1	 Grade II Tumor MRI Image_A		
2	 Grade II Tumor MRI Image_B		
3	 Grade II Tumor MRI Image_C		
4	 Grade II Tumor MRI Image_D		

Table 6: Result from Grade III Tumor Images

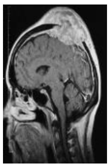
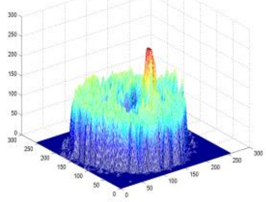
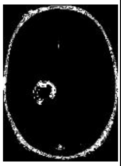
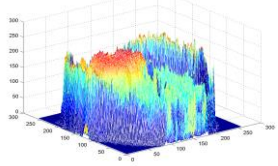
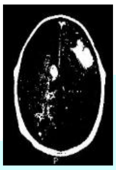
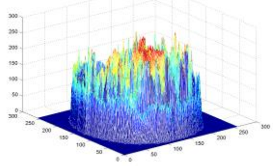
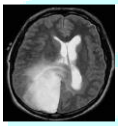
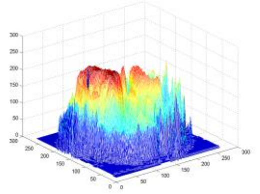
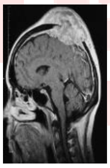
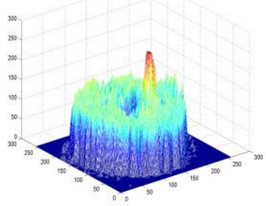
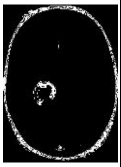
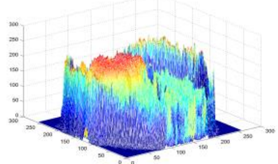
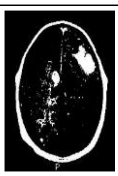
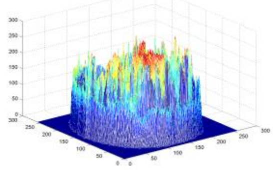
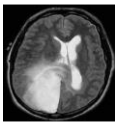
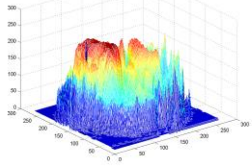
1	 Grade III Tumor MRI Image_A		
2	 Grade III Tumor MRI Image_B		
3	 Grade III Tumor MRI Image_C		
4	 Grade III Tumor MRI Image_D		

Table 7: Result from Grade IV Tumor Images

1	 Grade IV Tumor MRI Image A		
2	 Grade IV Tumor MRI Image B		
3	 Grade IV Tumor MRI Image C		
4	 Grade4 Tumor MRI Image D		

D. Performance Parameters

Different texture features of MR Images including Contrast, Homogeneity, Dissimilarity, Entropy have been calculated.

1.Contrast

A local gray level variation that is basically in the gray level co-occurrence matrix. It could be thought of the linear dependency of gray levels of the neighboring pixels

$$Contrast = \sum_{i,j} |i-j|^2 p(i,j)$$

i, j are horizontal cell cordinate and vertical cell cordinate and the p in the formula is the cell value. In this, if the neighbouring pixels are very similar with their gray level values, then the contrast in the image is found to be very low. In the case of the texture, the variation of the gray level shows the variation in the texture itself. The values of the high contrast was expected for the heavy textures and the low for the soft and the smooth textures.

2. Homogeneity

The uniformity of the non-zero entries in GLCM is measured in Homogeneity. By the inverse of the contrast weight, it weight the values

$$\text{Homogeneity} = \sum_{i,j} \frac{1}{1-(i-j)^2} p(i,j)$$

The GLCM homogeneity of any texture is high if GLCM concentrates along the diagonal, means that there are lot of pixels with the same or very similar gray level value. The larger the changes in gray values, the lower the GLCM homogeneity making higher the GLCM contrast.

3. Dissimilarity

Dissimilarity is a measure that defines the variation of a gray level pairs in an image. It is closest to Contrast with a difference in the weight – Contrast unlike Dissimilarity grows quadratically.

$$\text{Dissimilarity} = \sum_{i,j} |i-j| p(i,j)$$

It is expected that these two measures behave in the same way for same texture because they calculate same parameter with different weights. Contrast will always give slightly higher values than the Dissimilarity. Dissimilarity obtain maximum when the gray level of the reference and neighbor pixel is at the extremes of the possible gray levels in the texture sample.

4) Entropy

Entropy in any system represents disorder, where in case of the texture analysis is a measure of its spatial disorder

$$Entropy = -\sum_{i,j} p(i,j)\log(p(i,j))$$

This feature can be useful to tell us if the entropy is bigger for a heavy texture or for the smooth textures giving us information about which type of texture can be considered statistically.

Table8: Performance Parameter Table for Grade I Tumor Image

MRI Images	*Contrast*	*Homogeneity*	*Entropy*	*Dissimilarity*
Grade I Tumor MRI Image A	135.7585	0.3125	0.3521	9.9773
Grade I Tumor MRI Image B	190.1020	0.2945	0.0629	6.7534
Grade I Tumor MRI Image C	182.4849	0.0260	0.3159	8.8541
Grade I Tumor MRI Image D	171.0384	0.3421	0.0595	9.0762

Table9: Performance Parameter Table for Grade II Tumor Image

MRI Images	*Contrast*	*Homogeneity*	*Entropy*	*Dissimilarity*
Grade II Tumor MRI Image A	177.4890	0.3721	0.1501	8.0273
Grade II Tumor MRI Image B	212.1103	0.0324	0.3094	5.4712
Grade II Tumor MRI Image C	200.6475	0.4173	0.2094	6.0387
Grade II Tumor MRI Image D	190.1284	0.2019	0.4612	4.1732

Table10: Performance Parameter Table for Grade III Tumor Image

MRI Images	*Contrast*	*Homogeneity*	*Entropy*	*Dissimilarity*
Grade III Tumor MRI Image A	199.0362	0.2734	0.1483	3.1645
Grade III Tumor MRI Image B	279.6471	0.1253	0.2876	9.0212
Grade III Tumor MRI Image C	245.0093	0.2091	0.3093	2.1829
Grade III Tumor MRI Image D	215.3748	0.4231	0.5362	5.1605

Table11: Performance Parameter Table for Grade IV Tumor Image

MRI Images	*Contrast*	*Homogeneity*	*Entropy*	*Dissimilarity*
Grade IV Tumor MRI Image A	212.3748	0.1021	0.2899	123.16
Grade IV Tumor MRI Image B	302.0034	0.3807	0.2932	198.02
Grade IV Tumor MRI Image C	290.5327	0.7364	0.3184	220.18
Grade IV Tumor MRI Image D	245.6739	0.2736	0.4978	193.05

IV. CONCLUSION

In this paper, the kapur Entropy functions is applied for tumor boudary detection and the image segmentation is done on various MRI images. The different threshold values are obtained depend on the particular different grades of MRI Tumor images. The threshold values are dependent on the different MRI images which in turn affects the segmented results. It is a simple but effective method using in boundary detection. The texture analysis of medical images is also performed in order to get a better accuracy and it was found that the best result are obtained by applying Kapur Entropy in sense of detecting tumor's boundary. It is very accurately in searching the boundary of the brain tumor, and is a useful method in pre-processing for 3D reconstruction. and it will help in the earlier detection of the tumors and the pro treatment can be provided to the patients by the early detection of the tumors and thus, the disease can be cured.

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