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VISUALIZATION OF 3D VIEW OF DETECTED BRAIN TUMOR AND CALCULATION OF ITS VOLUME

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Abstract— **A tumor also known as neoplasm is a growth in the abnormal tissue which can be differentiated from the surrounding tissue by its structure. A tumor may lead to cancer, which is a major leading cause of death and responsible for around 13% of all deaths world-wide. Cancer incidence rate is growing at an alarming rate in the world. Great knowledge and experience on radiology are required for accurate tumor detection in medical imaging. Automation of tumor detection is required because there might be a shortage of skilled radiologists at a time of great need. We propose a Visualization of 3d View of Detected Brain Tumor and Calculation of its Volume that can detect and localize brain tumor in magnetic resonance imaging. The proposed brain tumor detection and localization framework comprises five steps: image acquisition, pre-processing, edge detection, modified histogram clustering and morphological operations.it also include tumor detection with comparisons and finally 3D model is obtain of tumor detected portion with its volume. Proposed method developed a tumor detection method using three parameters; edge (E), gray (G), and threshold value (T) values. The method proposed here studied the EGT parameters in a supervised block of input images. These feature blocks were compared with standardized parameters (derived from normal template block) to detect abnormal occurrences, e.g. image block which contain lesions or tumor cells. The proposed method shows more precision among the others. Processing time is less also proposed system implement more than one edge detection system i.e. sobel edge detection and canny edge detection method. Result also compared of implemented both methods. This will help the physicians in analyzing the brain tumors accurately and efficiently. It is used to segment the brain tumor from 2D images and then converting it into 3D for further model analysis and volume calculation.**

Index Terms— **3D,Brain Tumor, Segmentation, MRI, Image Registration, and Brain Structures.**

I. INTRODUCTION

Tumor is one of the most common brain diseases, so its diagnosis and treatment have a vital importance for more than 400000 persons per year in the world (based on the World Health Organization (WHO) estimates). On the other hand, in recent years, developments in medical imaging techniques allow us to use them in several domains of medicine, for example, computer aided pathologies diagnosis, follow-up of these pathologies, surgical planning, surgical guidance, statistical and time series (longitudinal) analysis .The analysis and study of the brain is of great interest due to its potential for studying early growth patterns and morphologic changes in the cancer process. Recent studies have demonstrated the potential of a decision support system for detecting tumors in medical images, providing radiologists with a second pair of highly trained eyes. It gives doctors access to additional information present in images that have characteristics generally accepted to be associated with cancer, clusters of bright spots that are suggestive of lesions, patterns suggestive of tissue masses or distortions, and mark regions that have the characteristics of lesions or tumors. Magnetic Resonance Imaging (MRI) techniques are still developing, and recent efforts have been directed primarily at improving image quality and speed of acquisition. MRI provides non-invasive, high quality images of neuro-anatomy and disease processes. Through its ability to detect contrast in the density of soft tissues, MRI is well suited to monitor and evaluate cerebral tumors as they develop and respond or, as the case may be, fail to respond to therapy. There are many sequences that can be used on MRI and the different sequences often provide different contrast between tissues so the most appropriate sequence should be chosen according to disease and what the clinicians want to detect. For this study T2 and T1 (contrast enhanced) weighted MRI images are used. This paper focuses on analysing T2-weighted MRI images because medical specialists often can diagnose whether a brain tumour exists within a T2-weighted MRI images with sensitivity of 94%.

II. OBJECTIVES

The first aim of this work is to develop a framework for a robust and accurate segmentation of a large class of brain tumors in MR images. Most existing methods are region-based. They have several advantages, but line and edge information in computer vision systems are also important. The proposed

method tries to combine region and edge information, thus taking advantage of both approaches while cancelling their drawbacks. 3D contrast enhanced T1-weighted and FLAIR images are the inputs to perform an automatic segmentation of the solid part of tumor and the potential associated edema and necrosis .We first segment the brain to remove non-brain data. However, in pathological cases, standard segmentation methods fail, in particular when the tumor is located very close to the brain surface. Therefore we propose an improved segmentation method, relying on the approximate symmetry plane. Then we developed two new and original methods to detect and initially segment brain tumors. The first one is a fuzzy classification method which combines membership, typicality and neighborhood information. The second one relies on a symmetry-based histogram analysis. The approximate sagittal symmetry plane is first computed, and the tumor is then extracted by comparing the histograms of the two cerebral hemispheres. To refine the initial segmentation, which is not accurate enough, we use edge information. A deformable model constrained by spatial relations is applied for this purpose. Volume of severe block of image is also calculated.

III. METHODOLOGY AND MATERIALS

A. Materials

The required dataset is collected from the MRI scan images of a person. Each technique has 25 slices for each plane. Dimensions of tumor images are 256x256. The method is tested on Microsoft windows XP (Professional), Windows 7, Windows 8 version with 1GB of RAM.

B. Proposed Methodology

The algorithm has two stages, first is preprocessing of given MRI Image and second is Tumor Detection and 3D visualization after calculating volume of detected portion of tumor. Then perform morphological operations on them. Algorithm steps are as follows:-

I. Give MRI images as input (this is images of tumor).
II. Convert this image into gray scale.
III.Compute threshold segmentation.
IV.Calculate the boundaries using edge detection sobel algorithm and Canny Edge detection is used. Result also compared.
V. Tumor Detection.
VI. Tumor Comparisons
VII.2D visualization of Tumor
VIII.3D visualization of tumor and volume calculation.
IX. Finally we will get a final output a tumor region.

All above steps are explained in detail.

Block Diagram of System

1. *Preprocessing of tumor image:* Preprocessing includes some more operations like gray-scaling of image, Threshoulding and edge detection of image. The result of preprocessing phase is noise free, image is normalized so that it can proceed for further tumor detection phage.

A: Gray-scaling of tumor image: In photography and computing, a grayscale or greyscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called *bilevel* or *binary images*). Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the absence of any chromatic variation (i.e., one color). Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured. But also they can be synthesized from a full color image. The intensity of a pixel is expressed within a given range between a minimum and a maximum, inclusive. This range is represented in an abstract way as a range from 0 (total absence, black) and 1 (total presence, white), with any fractional values in between. This notation is used in academic papers, but it must be noted that this does not define what "black “or "white" is in terms of calorimetry.

B: Threshoulding of tumor image: Threshoulding is the simplest method of image segmentation.

• From a grayscale image, Threshoulding can be used to create binary images i.e. image with only black or white colors.

• It is usually used for feature extraction where required features of image are converted to white and everything else to black. (Or vice-versa) Threshoulding is the simplest method of image segmentation. From a grayscale image, Threshoulding can be used to create binary images. During the Threshoulding process, individual pixels in an image are marked as "object" pixels if their value is greater than some threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. This convention is known as threshold above. Variants include threshold below, which is opposite of threshold above; threshold inside, where a pixel is labeled "object" if its value is between two thresholds; and threshold outside, which is the opposite of threshold inside .Typically, an object pixel is given a value of"1" while a background pixel is given a value of "0." Finally, a binary image is created by coloring each pixel white or black, depending on a pixel's labels.

C: Edge Detection: For the detection of edges two methods are used sobel and canny. Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There is an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. Variables involved in the selection of an edge detection operator include:

- Edge orientation: The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edges.

- Noise environment: Edge detection is difficult in noisy images, since both the noise and the edges contain high-frequency content. Attempts to reduce the noise result in blurred and distorted edges. Operators used on noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. This results in less accurate localization of the detected edges.

- Edge structure: Not all edges involve a step change in intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity. The operator needs to be chosen to be responsive to such a gradual change in those cases. Newer wavelet-based techniques actually characterize the nature of the transition for each edge in order to distinguish, for example, edges associated with hair from edges associated with a face.

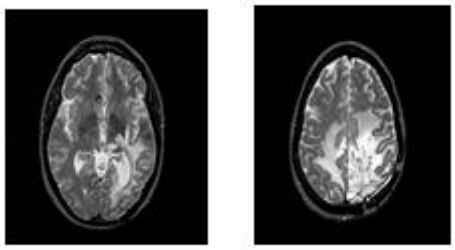


Fig.1. Sample tumor images

2. *Tumor Detection*: In this phase to load any tumor images and tumor detection is done.

A)Feature Block: In most medical images, the structures of interest such as tumors, lesions and arteries, occupy a percentage that is often well below 10% of the total number of pixels .Conventional medical imaging involves visually comparing images side-by-side to discern differences from normal oremergence of changes with time. Detecting minute differences between two pictures however can be nearly impossible. For the analysis of such small tissues or structures, we devised a block system that divides the region of interest (*ROI*), which is highly dependent on imaging modalities, into block size (*B*). A block (*B*) is denoted as a part of the whole image (*ROI*), divided evenly by a factor of eight, as shown in Fig. 3.This supervised block is further divided into tumor blocks that are categorized from low-density tumor blocks to high-density tumor blocks. The different levels of the *EGT* value of the feature block are represented as different colors, and the color code is shown below:

a) Severe Block:-Red Color

b) Less Severe Block:-Yellow Color

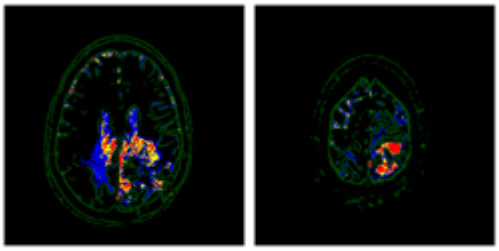


Fig.2 Tumor detected images

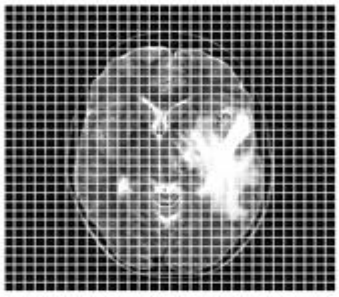


Fig.3 ROI of an input image (256 x 256) with block size B (8 x 8 pixels)

B. Multipara meter

Recent advances in medical image analysis often include processes for an image to be segmented in terms of a few parameters and into smaller sizes or regions, to address the different aspects of analyzing images into anatomically and pathologically meaningful regions. Classifying regions using their multipara meter values makes the study of the regions of physiological and pathological interest easier and more definable. Here, multipara meter features refer to the following three specific values for the edges (*E*), gray values (*G*), and Threshold Value (T) of the pixels.

i)Gray-Scale: In this technique, the gray value parameter (G) for each block of the is calculated as below

– Read individual pixel color value (24-bit).
– Split the color value into individual R, G and B 8-bit values.
– Calculate the grayscale component (8-bit) for given R, G and B pixels using a conversion formula.
– Compose a 24-bit pixel value from 8-bit grayscale value.
– Store the new value at same location in output image.

Traverse Through Entire Image
for(y=0;y<height;y++) {
for(x=0;x<width;x++) {
pix = input[y][x];
Extract 8-bit R, G and B values from
24-bit Color Value
b = pix & 0xff;
g = (pix >> 8) & 0xff;
r = (pix >> 16) & 0xff;

E.g. Assume PIXEL value is 0x435A56 where 0x43 is red, 0x5A is green and 0x56 is blue component. Now to separate blue we can use the

LOGICAL AND operator to mask or filter the blue component from the rest. Since AND'ing with 1 makes no difference where as AND'ing with 0 will force the bit to 0.

435A56
AND 0000FF

0x000056 - blue separated

For Green we shall first right shift the pixel value by 8 bits so that green component is now at LSB position. And then repeat the masking process.

435A56 >> 8 = 435A
0x435A
AND 0x00FF

0x005A - green separated

Similarly we shall right shift by 16 bits so that red component will be at the LSB position and then do the masking.

Calculate grayscale component
gs = (r + g + b) / 3;

There are various ways to convert color values to grayscale. Any one can be used depending on the user's needs.

RGB Averaging Formula
gs = (r+g+b) / 3;

Here average of all three colors is calculated and saved in output image.

Above formula can also be written as
gs = r * 0.33 + g * 0.33 + b * 0.33;

i.e. 33% of all colors is used to compose final 100% grayscale component.

ii) Threshoulding: In this Image segmentation the image is divided into multiple parts. By doing this we can identify objects or other related information in the given digital image. We can say that this also refers to the partitioning of an image into multiple sets of pixels (that share some common characteristics such as color or intensity).

a:first calculate the portion of proceed image which is detected.(sumall value)

b:calculate threshold value. And assign th=sumall (threshold value).

c: find maximum and minimum intensity value.Tmin and Tmax

d:Range r=Tmax-Tmin,also find range1,range2 and range3.

range1 = (int) ((maxCol - minCol) / 4.0) + minCol;
range2 = (int) ((maxCol - minCol) / 2.0) + minCol;
range3 = (int) ((maxCol - minCol) * 3.0 / 4) + minCol;

e:Tsevere=(R3/4)+Tmin , T_less_severe=(R(1/2))+Tmin.

f: calculate blockwise score. If blockscore >th then redcount increase otherwise yellow count increase.

g:Fill severe block with red color and less severe block with yellow color.

i:Display the result of count of block having severe and less severe block.

iii) Edge Detection:

a) Sobel Edge detection method is used

Sobel Operator as below: The operator consists of a pair of 3×3 convolution kernels as shown in Figure 1. One kernel is simply the other rotated by 90°.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these *Gx* and *Gy*). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

Typically, an approximate magnitude is computed using:

$$|G| = |Gx| + |Gy|$$

Which is much faster to compute.

The angle of orientation of the edge (relative to the pixel grid) giving rise to the spatial gradient is given by:

$$\theta = \arctan(Gy/Gx)$$

Figure 4.13 Tumor Detection using sobel edge detection methods.

b) Canny Edge detection

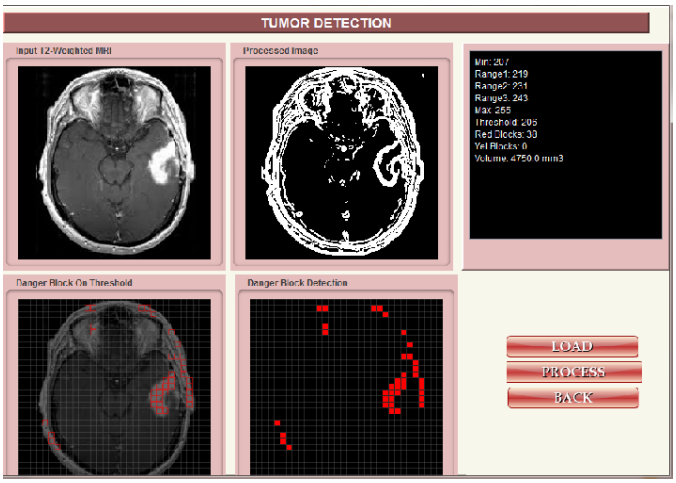


Figure 4.13 Tumor Detection using sobel edge detection methods.

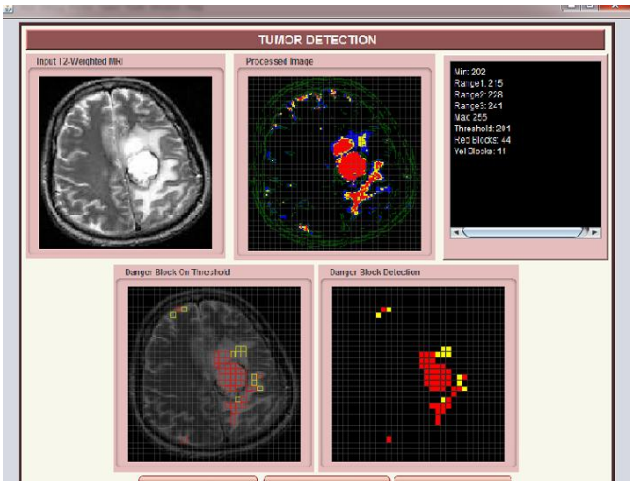
3. *Tumor Comparisons*: The objective of this phase is to extract the features of the test image that will be compared to the features of other tumor image for verification purpose.

4.*2D visualization of Tumor*: In this two dimensional view of image of tumor is generated.

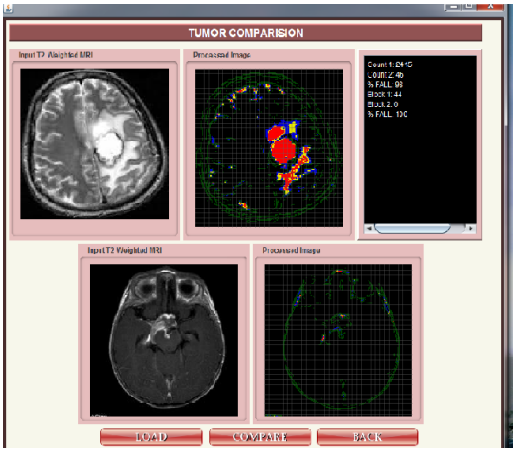
5.*3D visualization of Tumor with volume calculations:* Interactive 3D view of 25 images is generated. And shows the severe and less severe block from the images with calculated volume in mm3.

IV. EXPERIMENTAL RESULTS

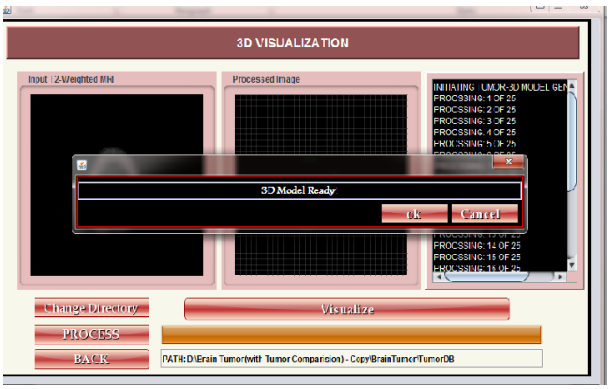
1. Detection results on single slice



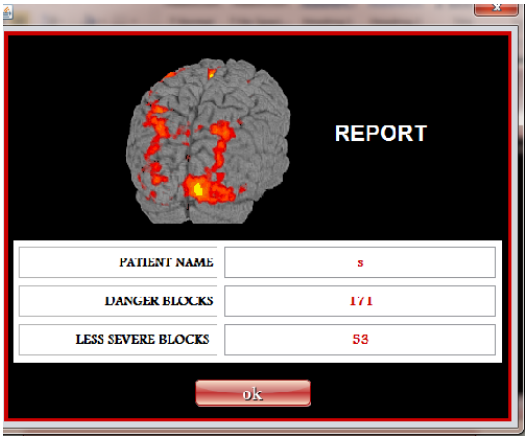
2.Detection results on two slice comparison



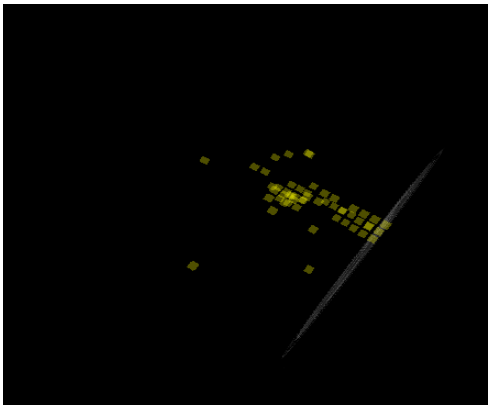
3. Construct 3D model of multiple 25 images



4. GUI design of application to show processing of 3D model.



5. Show the Yellow(less severe) block (press 2)



6. Show the Red (danger) block (press 1)

V. ACKNOWLEDGMENT

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VI. CONCLUSION

In this paper, we introduced a conceptually simple classification method using multiparameter features on supervised block to computationally classify brain images. Our conclusion is that the proposed method is effectively capable of identifying tumor areas in T2-weighted medical brain images taken under different clinical circumstances and technical conditions, which were able to show high deviations that clearly indicated abnormalities in areas with brain disease. The response time for processing system is 176 milliseconds for each image analysis. Currently we are working towards improving the brain model to include more cases. This method gives 99.9% efficiency in segmenting out tumor. After which the 3D volume representation of the tumor can be obtained within few seconds as mentioned above. This will save a lot of time of the surgeons and radiologist providing a much modern technique for brain tumor surgery. As the future work, the validity of procedure can be observed by applying to more cases of same type as well as on other types of tumor. In order to match the results of volume with the original data we need to have such cases in which the whole tumor is sent for biopsy. The 3D analysis and volume calculations can be done by any other software such as SPM and MATLAB. The results can be compared. This will allow error calculations to be done. By 3D modeling of different types of tumors we can see the similarities and differences between them regarding their shapes and structures which will be helpful for the physicians. This can be done with in depth study of different cases of tumor which in turn help the medical professionals in classifying the tumors types on the basis of their volume.

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