Brain Tumor detection using Bounding Box with Bhattacharyya coefficient

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***Abstract*—This paper introduces an proficient detection of brain tumor from cerebral MRI images. The methodology used is bounding box for segmentation of brain tumor MRI images. To get better the quality of images and bound the risk of distinct regions fusion in the segmentation phase using bounding box with Bhattacharyya coefficient. The method has positive significance in practical applications.**

***Keywords*— Brain tumor, Image segmentation, MRI, Bounding Box, Bhattacharyya coefficient.**

I. Introduction

A brain tumor is any intracranial tumor created by uneven and abandoned cell division, generally found somewhere in the brain. A tumor is a mass of tissue that develop out of control of the regular forces that regulates growth. The compound brain tumors can be divided into two common categories depending on the tumors start, their development pattern and malignancy. Primary brain tumors are tumors that occur from cells or from the top layer of the brain. A secondary or metastatic brain tumor start when cancer cells spread to the brain from a primary cancer in a different part of the body.

Magnetic Resonance Imaging (MRI) can offer better difference between dissimilar soft tissues of human brain compare to Computed Tomography (CT), it is the most ordinary image modality used in clinical observation for brain tumor diagnosis. Typically, radiologist performs manual delineation of tumor part and imparts the information to neurologist, which is very long time due to the vast quantity of images.

Image segmentation is the procedure of partition a digital image into various segments. The purpose of segmentation is to shorten or modify the representation of an image into a bit that is more meaningful and easier to analyze. Image segmentation is used to set items and limits in images. In particular, image segmentation is the process of assigning a tag to every pixel in an image such that pixels with the same label share a visual character.

In case of medical image segmentation the aim is to:

1. Study anatomical structure.
2. Identify Region of Interest i.e. locate tumor, lesion and other abnormalities.
3. Measure tissue volume to measure growth of tumor.
4. Help in treatment planning prior to radiation therapy; in radiation dose calculation.

Using segmentation in medical images is an extremely essential job for detecting the abnormalities, learning and tracking growth of diseases and surgical procedure.

Region growing based [1] tumor detection techniques are used to segment the brain tumors due to its wide range of applications but it has high time complexity. The segmented image does not give the information about the numerical parameters such as area and volume of the tumorous portion. Manual volumetric method is gold standard approach for 3D quantitative measurements. The main disadvantage of this method is that it is labor intensive and time consuming.

In this paper, an automatic, speedy, and fairly accurate segmentation technique is used that avoids these problems by locating a “bounding box” – i.e., an axis-parallel rectangle, around the tumor on an MR slice. The Bhattacharya coefficient is also used to measures the resemblance between two normalized intensity histograms. BC has already been used effectively in different computer image applications, such as object tracking, edge detection, and registration.

II. Related Work

Chen (2012) [2] proposed an integrating 3D Bayesian level set technique with volume rendering. 3D Bayesian level set method is used for previous probability judgment of the tumor and tissue and then, it is used to continuously segment the 3D targets from a sequence of brain images. Ray casting is used to make possible 3D volume image of MRI dataset, and conducted to submit the targets and construct the shell of the targets.

Li et al. (2012) [3] proposed a multi-modality framework for automatic tumor detection. The intensity, shape deformation, symmetry, and texture qualities were extracted from each MRI image. For selection of the most different kind and to segment the tumor region, AdaBoost classifier was used. For training and confirmation of the detection method, multi-modal MR images were used.

Maiti et al. (2012) [4] proposed watershed method in combination with edge detection operation. This method is color based brain tumor detection algorithm with color brain MRI images in HSV color space. The RGB image is transformed to HSV color image by which the image is separated in three parts hue, saturation, and intensity and then watershed algorithm is applied. To output image, Canny edge detector is applied. After combining the three images final brain tumor segmented image is obtained.

Parisot et al. (2012) [5] proposed a novel approach for detection, segmentation and classification of brain tumors. This method exploits past knowledge in the form of a sparse graph representing the expected spatial positions of tumor classes. Information is tied with image based arrangement techniques along with spatial efficient constraints. A two layer interconnected graph is calculated with one layer related to the low-grade glioma type and the second layer to voxel-based decisions of tumor existence. The result of the method refers to both tumor segmentation plus their classification.

Unal et al. (2012) [6] proposed a cellular automata (CA) based seeded tumor segmentation method for segmentation of brain tumors MRI images. This method standardizes the volume of interest (VOI) and seed selection. To solve the shortest path problem, the link of the CA-based segmentation to the graph-theoretic methods is done. In addition, a sensitivity parameter is used to adjust the heterogeneous tumor segmentation problem, and an embedded level set surface is evolved on a tumor probability map constructed from CA states to impress spatial smoothness. Then, an algorithm based on CA is presented to differentiate necrotic and enhancing tumor tissue content, which gains meaning for a detailed judgment of radiation therapy response. Performance of the proposed algorithm is efficient in terms of computation time.

Sreeja et al. (2011) [7] proposed anisotropic diffusion and morphological method for skull-stripping. The method can extract the brain tissue from a normal MRI quickly and accurately. There are three steps:- (1) the MRI is processed by a wiener filter (2) find the area between the skull (3) the brain tissue using thresholding methods. Using a skeletonization algorithm, the unwanted edges are removed. A sequence of morphological and connected component operator is used to make sure the region is closed. The closed region is final result.

Delon et al. (2010) [8] proposed statistical differential analysis framework of longitudinal MRI volumes. The midway-mapping was done to normalize MRI scans to a common range of values, and to handle multiplicative MRI inhomogeneity fields. Three growth indices were calculated and evaluated in terms of accuracy, comparing to manual tracing. Millimetric growth evaluation accuracy was achieved with the proposed method for the sphere-shaped radius growth index.

Guoqiang et al. (2010) [9] proposed the normalized GVF Snake model combines with traditional edge detection for the brain MRI image semiautomatic segmentation. The thinning Canny outcome is used to compute the edge map gradient of the GVF snake model. Then the normalized GVF snake model deforms with the manual initial contour. This method extracts the boundary of the tumor precisely, and can remove the problem that traditional GVF snake cannot able to converge the weak boundary.

Selvanayaki et al. (2010) [10] proposed Meta heuristic algorithms for brain tumor detection. There are three phases, namely preprocessing, enhancement, and segmentation. In first phase, film artifacts and unwanted portions of MRI Brain image are removed. Secondly, the noise and high frequency components are separated using weighted median filter. Final one is segmentation phase. It has two different approaches like block based (non algorithmic) and ACO algorithm segmentation. Finally the performance of the above two approaches are evaluated.

Dubey et al. (2009) [11] proposed Marker Controlled Watershed Segmentation method and region property functions using image processing toolbox for detection of brain tumor. The parameters extracted are area, major and minor axis length, eccentricity, direction, equivdiameter, strength and perimeter. This technique is pretty multipurpose, fast and simple to apply. It is valid to all type of 2D MR Images representing all tumors irrespective of their location in human body and their size.

III. Proposed Work

1. Brain tumor

A brain tumor is an intracranial hard neoplasm, a tumor inside the brain . Brain tumors contain all tumors within the cranium or in the central spinal canal. They are shaped by an abnormal and uncontrolled cell division, usually in the brain itself, and as well in lymphatic tissue, in blood vessels, in cranial nerves, in the brain envelopes, skull, pituitary gland, or pineal gland. Inside the brain itself, the occupied cells may be neurons cells. Brain tumors can also increase from cancers primarily positioned in other organs.

2. Bounding box

The bounding box is a name used in geometry. For a small set in N size, it indicate to the box with the minimum measure within which all the points are positioned. When other kinds of measure are used, the smallest box is generally called a view, e.g., "minimum-perimeter bounding box". The bounding box of a small set is the same as the

minimum bounding box of its convex hull, actuality which may be used heuristically to increase computation.
The term "box"/"hyperrectangle" generates from its usage in the Cartesian coordinate system, where it is visualized as a rectangle, rectangular parallelepiped etc.

3. Bhattacharya coefficient

Bhattacharyya coefficient which is to determine the amount of overlap between two statistical samples and can be used to resolve the relative closeness of the two samples being measured. It is used to compute the separability of classes in classification. Calculating the Bhattacharyya coefficient involves a simple form of combination of the overlap of the two samples.

[12] Let p(i) and p'(i) represent two multinomial populations, each consisting of N classes with respective probabilities p(i = 1), . . . , p(i = N) and p'(i = 1), . . . , p'(i = N). Since p(i) and p'(i) represent probability distributions,
$\Sigma^{N}_{i=1}$ p(i) = $\Sigma^{N}_{i=1}$ p'(i) = 1. The Bhattacharyya coefficient measure is a divergence-type measure between distributions, defined as,

$$\rho(p, p') = \Sigma^{N}_{i=1\surd}\ p(i)p'(i)$$

The choice of number of partitions depends on the quantity of members in each sample; too little partitions will drop accuracy by overestimating the overlap region, and too many partitions will lose exactness by creating individual partitions with no members regardless of surrounding populated sample space. The Bhattacharyya coefficient will be 0 if there is no overlap at all due to the growth by zero in each partition.

IV. METHODOLOGY

First step to detect brain tumor, input the MRI image. The proposed technique i.e. bounding box will select the skull/brain. After that top and down search is done using Bhattacharyya coefficient on the selected skull, so that MRI image will be divisible into two parts that is top and down, then score function is calculated from the top and down portions. Score function in Bhattacharyya coefficient measures the performance of top and down parts of MRI image. Next step is to apply vertical score function using Bhattacharyya coefficient for finding maxima and minima. The horizontal and vertical score function is combined by using Bhattacharyya coefficient equation,

$$\rho(p, p') = \Sigma^{N}_{i=1\surd}\ p(i)p'(i)\ _{[12]}$$

After measuring the sum of vertical and horizontal score function, the normalised histogram is applied. Finally, the brain tumor in MRI image detect using bounding box. The proposed process can be explained using the flowchart given in figure1.

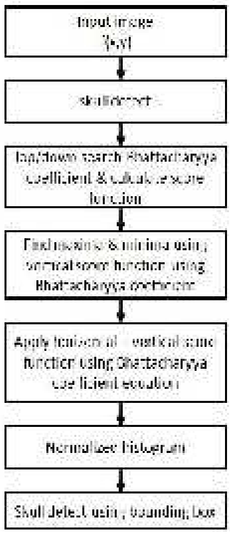

Figure 1:Flow chart of brain tumor detection.

V.CONCLUSION

Segmentation of Brain Tumor MRI images has been done with various methods. In this paper, Bounding Box technique is integrated with Bhattacharyya coefficient for detecting Brain tumor in MRI images. The proposed methodology will improve efficiency and also reduce time complexity. Technique will be implemented in MATLAB 7.10.0. Suitable performance analysis will be drawn based upon the experimental result of proposed method.

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