American Journal of Engineering Research (AJER)	2016
American Journal of Engineering Res	earch (AJER)
e-ISSN: 2320-0847 p-ISS	N:2320-0936
Volume-5, Issue-1	12, pp-218-223
	www.ajer.org
Research Paper	Open Access

# Brain TumourDetection by Using Bounding Box Methodology Based on Bhattacharyya Coefficient

A.H.M.Zadidul Karim<sup>1</sup>, Md. Abdullah Al Mahmud<sup>2\*</sup>, M. Abdullah Al Amin<sup>3</sup>, Mr.Muhammad Towhidur Rahman<sup>4</sup>

<sup>1,2\*,3,4</sup>Department of EEE (University of Asia Pacific)

**ABSTRACT:** Braintumour, a severe disease that has devastated many human lives. Day by day the numbers of affected people are increasing and researchers are becoming more concerned to detect these types of severe disease with accuracy. They are now combining their knowledge from medical to mathematical science to detect this disease with an appropriate way. The main objective of this paper is to form an algorithm to detect tumour in an appropriate way. For this process of detection an MRI image should be considered as an input. After that it will be normalized to a standard intensity level. Then skull will be detected for creating mask of MRI image. After the creation of mask, MRI image will be scanned horizontally and vertically on the basis of Bhattacharyya coefficient based score function. Finally tumour will be detected by making a rectangle around the tumour affected area. At the end of this task a graphical interpretation is plotted against the rectangle so that anybody can easily identify the size of tumour.

Keywords: Brain tumor, MRI, MATLAB, Bhattacharyya coefficient, Mask, Pixel intensity.

### I. INTRODUCTION

There have a lot of diseases in human body. Diseases of brain are very common in human body. It takes place in different forms. Some of the major classes of brain diseases are tumours, infections, stroke, trauma and seizures [1]. An infamous disease has affected and devastated many lives which is brain tumour. This type of disease has been the intermediate of outlook of thousands of researchers over many years around the world.

Brain Tumour: There are predominantly two types of brain tumour. Those are start in the brain (primary) and those are spread from cancer somewhere else in the body (metastasis). Primary brain tumours such as glioma happen very rare and when they do, they are commonly malignant (cancerous). A malignant tumour is a clump of cancer cells that stands growing; except feed off the body it doesn't do anything [2-3].

MRI: Magnetic resonance imaging (MRI) of brain is a safe and smooth test that uses a radio waves and magnetic field to produce manifest images of the brain and the brain stem [4]. An MRI scanner build with a large doughnut-shaped magnet that mostly has a tunnel in the centre. Patients are lying on a table that slides into the tunnel. During the experiment, radiowaves manipulate the magnetic position of the atoms of the body, which are collected by a powerful antenna and then sent to a computer. The computer carry out millions of calculations for resulting in clear cross-sectional black and white images of the body [5]. These images can be modified by three-dimensional (3-D) pictures of the scanned area. This helps identify the problems in the brain when the scan focuses on a specific areas.

In this paper an automatic brain tumour detection algorithm is proposed. This proposed algorithm will detect tumour and finally tumour area will be interpreted by the designed system.

# II. METHODS

To detect brain tumour in an accurate way an algorithm of bounding box method based on Bhattacharyya coefficient has been proposed in this paper [6-7]. Steps of design has been shown as following- $\Box$  As an input taking a MRI image

- Normalize the image
- □ Skull Detection
- □ Mask creation
- $\hfill\square$  Vertical and Horizontal Scanning For computing BC based score function
- $\Box$  Detecting tumour by bounding a box around the tumour cell and plotting graphical interpretation.

www.ajer.org

# A. As an input taking a MRI image:

For processing the 'imread' command have been used to read an input image. 'imread' command reads a Grayscale or Color image from the specified filename. If the imread can't find a file named 'filename', it looks for a file named 'filename.fmt'. Filename must be a string and .fmt is a string that specifies the format of the file. If the file is not in the current path, specify the full pathname of the location on the system. The output of 'imread' is an array containing the image data, when the file contains a grayscale image, it will be an M-N array. Again when the file contains a color images, it will be an M-N-4 array. This is read the sample images 't.bmp' and it stored in an array named I.

# I=imread('t.bmp');

By its standard file extension, the text string '.bmp' specifies the format of the file. The format files can bespecified by 'bmp' for windows bitmap. As it is already mentioned that the return value of I is an array containing the images data. It will be an M-N array, if the file contains a grayscale image I. I is an M-N-3 dimensional array, if the file contains a true color image. I is an M-N-4 dimensional array, if TIFF files taking on color images that use the CMYK color space. On bit-per-sample of the image data, the class of 'A' depends. Which is rounded to the next byte boundary. Fig-2 is the representation of MRI image as an input.

#### B. Normalize the image:

Normalization is an important pre-processing step especially for the analysis of Magnetic Resonance Images (MRI) of human brains. Intensity normalization takes a very significant role for automatic image segmentation and classification is done on the basis of their assumptions regarding the intensity distributions on a standardized intensity range. There are many approaches for intensity normalization. Nyul and Colleagues invented one of the fast and accurate approach. A comprehensive validation of this procedure in real clinical domain is used for intensity dissimilarity correction that is responsible for scanner-specific antiquities. MRI volumes can be affected from various causes such as data dissimilarity resulting from multi-site and multiscanner antiquities. The presence of multiple sclerosis lesions and the stage of disease movement in the brain can also affect MRI volume. The usefulness of the normalization in rendering under the distributional presumption of segmentation approaches have been estimated. Again intensities, that are more homogenous for the same types of tissue while simultaneously resulting in the better tissue type separation by using the distributional divergence criteria have been done. The convenience of the piece-wise linear method have been demonstrated on the task of multiple sclerosis lesion segmentation against a linear normalization method over three image segmentation algorithms:

i. A standard Bayesian classifier

- ii. An outlier detection based approach
- iii. A Bayesian classifier with Markov Random field (MRF) based on post-processing.

### Fig-3 is the representation of normalize image.

#### C. Skull Detection:

In order to detect Skull a loop is constructed to find out the identity matrix of the image. For this purpose image is converted to binary and a threshold level is fixed. Converting this level to a matrix a special type of loop (i.e. for loop) is used to calculate the total number of pixels. After that using "double" command image is filtered to double precision. Performing that image is scaled by using graycolor map. Then aspect ratio of image specially x-y and z axis are automatically adjusted and plotted in a box to fit lightly.

Defuzzify membership function "centroid" is used to detect the center of the images. Image registration technique is applied to rotate the image and finally Skull is detected.Fig-4 is the representation of skull detected image.

#### D. Mask creation:

For creating mask new variable "STATS" and "Midx" have been declared. Under STATS variable a new command "regionpnp" have been used. Which determine the property of image region. All pixels should be considered as non-zero matrix. Then the result of "STATS" variable is rounded to the nearest integer. For the purpose of filtering in an accurate way image was rotated to 900 either clock wise or anti clock wise direction. For masking clearly "Midx" variable have been selected. Its range is fixed from -1 to 1. Then the value is plotted to rotated or registrated image. After that Left part is masked. Again for masking Right part, "Midx" variable has again selected. But the range is up to end. It is also plotted to rotated/registrated image. Finally brain tumour part has been masked to cross match the similarity between two parts.Fig-5 is the representation of creation mask.

#### Vertical and Horizontal Scanning For computing BC based score function: Е.

The Bhattacharyya coefficient (BC) is an estimate measurement of the amount of overlap between two samples. To determine the relative closeness of this two samples being considered, this coefficient can be used.

Calculating the Bhattacharyya coefficient involves a basic fundamental form of integration of the overlap of this two samples. The interval of the values of this two samples is split into chosen number of partition and the number of members of each samples in each partition is used in the following formula,

$$BC(p,q) = \sum_{i=1}^{n} \sqrt{piqi}$$

Where. Samples are p and q, Number of partitions is n and The numbers of members of samples p and q in the i<sup>th</sup> partition are  $p_i$  and  $q_i$ 

Fig.1 explains the notations. In Fig.1 I and R represent the object and the source images respectively, which have same height hand same width w. The rectangular area  $D = [l_x, u_x] \times [l_y, u_y]$  illustrates the area of tumour or edema that are looking for tumor between these images I and R. FBB algorithm finds the rectangle area D, which have four parameters have to know i.e. l<sub>x</sub>, u<sub>x</sub>, l<sub>y</sub> and u<sub>y</sub> in two linear passes of the source and object image. In a vertical sweep first it finds the  $l_v$  and  $u_v$  values and then finds  $l_x$  and  $u_x$  in a



**Fig.1** (a) Finding violation D from test image I using reference image R. (b) Energy function plot.

horizontal sweep over the object and source images. A score function is used to the FBB algorithm in each sweep. Here the vertical score function is described here because of the horizontal score function coincides with the vertical score function which applied to the interchange of the images.

Let T(l) is the "top" sub-rectangles of the image and B(l) is the "bottom" sub-rectangles of the image, separated at a distance 1 from the top to bottom of the image:-

According to the figure-1 (a)

 $T(l)=[0, w]\times[0, l]$  and  $B(l)=[0, w]\times[l, h]$ vertical score function can be defined as:  $E(l) = BC(P_{I}^{T(l)}, P_{R}^{T(l)}) - BC(P_{I}^{B(l)}, P_{R}^{B(l)})$ (1)Where,  $P_I^{T(l)}$  is the normalized intensity histogram of the image I within the area T(1).

 $P_R^{T(l)}$ ,  $P_I^{B(l)}$  and  $P_R^{B(l)}$  are defined respectively.  $P_R^{T(l)}$ ,  $P_I^{B(l)}$  and  $P_R^{B(l)}$  are defined respectively.

www.ajer.org

BC(a, b)=  $\sum_{i} \sqrt{\{a(i) \ b(i)\} \in [0, 1]}$  denotes the Bhattacharya coefficient between two normalized histograms a(i) and b(i) by indicating a histogram bin.

The Bhattacharya coefficient calculates the affinity in the midst of two normalized intensity histograms. BC has already used very successfully in different computer perspective applications, such as edge detection [8], object tracking [9], registration [10].

Here 
$$-$$
 BC(P<sub>I</sub><sup>T( $l$ )</sup>,

and

$$BC(P_{I}^{T(l)}, P_{R}^{T(l)}) = \sum_{i} \sqrt{\{(P_{I}^{T(l)}(i))(P_{R}^{T(l)}(i))\}}$$
and
$$BC(P_{I}^{B(l)}, P_{R}^{B(l)}) = \sum_{i} \sqrt{\{(P_{I}^{B(l)}(i))(P_{R}^{B(l)}(i))\}}$$
[3]

When the established scatter diagram are the same, then BC = 1 and when two established scatter diagram are completely different from each other, then BC = 0. Thus the scoring rule E(l) (from equation -(1)) is broad when the domain region T(1) in two images are akin and the base regions B(1) are totally contrasting.

#### F. Detecting tumor by bounding box around the tumor cell and plotting graphical interpretation:

The step by step tasks associated with automated localization of a square box on an MRI slice which is shown in Fig-6. Fig-6(a, a') shows that a tumor on the left side and right side of the brain on two TIC MRI slices respectively. After automated global thresholding and subsequent post-processing Fig-6(b, b') shows that the cranium border is detected. Now the cranium border is rounded by an allegory. By computing angle between the main axis of allegory, cranium border and vertical axis is detected and the angle of the skull is founded. Then the cranium is revolved by a precise angle that's why the major axis becomes vertical. After that a vertical line is drawn (i.e. consider an approximate line of symmetry) through the centered of the cranium mask (as Fig-6(b, b')) that splits the whole image into two pieces: the true side of ALOS is considered as the mentioned image R and the left side of ALOS is viewed as the trial image I. Fig-6(c, c') the steep account function plots against the distances from the top of the image. Both plotting figures show the rising-dropping- rising nature of the score plots. The positive peak and the negative peak corresponding to the major, minor, true and left bounds of the bounding box are superimposed in Fig.6(a, a') and are also displayed by burnet dots in Fig.6(c, c') and 6(d, d'). To estimate whether the true half image or the left half contains the tumor, the moderate severity within the bounding boxes have been placed on left and right sides. Finally the tumor is disclosed where the bounding box is displayed. Fig-6 is the representation of tumor detected image by a box and a graphical interpretation is plotted in the figure.

# **III. SIMULATION RESULTS**



Fig.2:- MRI image as an input



Fig.3:- Normalize the image



Fig.4:- Skull Detection





Fig.5:- Mask creation









2016



**Fig. 6**(a, a') Output of MR image (b, b') Line of symmetry (c, c') Score plot for vertical direction (d, d') Score plot for horizontal direction

# **IV. CONCLUSIONS AND FUTURE WORK**

In this paper an efficient and fully automated tumour detection method is designed. This detection algorithm is better than previous detection techniques. In previous time watershed segmentation and pixel intensity based methodologies were used. The shortcomings of water shed segmentation method was that it was only applicable for low resolution MRI Image. This problem was overcome in pixel intensity based method. Any high resolution MRI image is readable in pixel intensity based method. But the main shortcomings of those methods were they were applicable only for top view of the images. They weren't applicable for any other view (i.e. left view, right view, front view) of an MRI image. The main superiority of the proposed algorithm of this paper is it can detect tumour from any side of an MRI image and it is also applicable for any high resolution MRI image. Finally a graphical interpretation is plotted against tumour affected area so that anybody can easily identify the growth of tumour.

#### REFERENCES

- [1]. http://www.webmd.com/brain/brain-diseases#1
- [2]. http://www.webmd.com/cancer/brain-cancer/brain-tumors-in-adults
- [3]. http://www.nhs.uk/Conditions/brain-tumours/Pages/Introduction.aspx
- [4]. http://www.radiologyinfo.org/en/info.cfm?pg=bodymr
- [5]. https://medlineplus.gov/ency/article/003791.htm
- [6]. BaidyaNathSaha, Nilanjan Ray, Russell Greiner, Albert Murtha, Hong Zhang, "Quick detection of brain tumors and edemas: A bounding box method using symmetry", Computerized Medical Imaging and Graphics 36 (2012) 95-107
- [7]. Brummer ME, Mersereau RM, Eisner RL, Lewine RJ. Automatic detection of brain contours in MRI data sets. IEEE Transactions on Medical Imaging 1993;12(2):153–66
- [8]. Comaniciu D, Ramesh V, Meer P. Real-time tracking of non-rigid objects using mean shift. Proceeding of CVPR 2000;2:142-9
- [9]. Konishi S, Yuille A, Coughlan J, Zhu S." Fundamental bounds on edge detection: an information theoretic evaluation of different edge cues." IEEE CVPR 1999:573–9
- [10]. Viola P, Wells W. "Alignment by maximization of mutual information". International Journal of Computer Vision 1997;24(2):137-54

2016