Techniques for Detection of brain tumor with edema in MRI

Megha A Joshi[1], Prof. D.H.Shah[2]
[1]*PG Student, Instrumentation and Control,* [2]*Associate Professor*
[1,2]*L.D College of Engineering, Navrangpura, Ahmedabad, Gujarat 380015, INDIA.*

Abstract- **The images from the medical imaging technologies like MRI, US, CT are more complex to understand and noisy. It indicates the need of image processing to extract the important needed information. This paper discuss about an improved segmentation algorithm for detection of tumor surrounded by edema in brain MRI. The methodology used here is consists of three steps : Pre-processing, segmentation and post –processing. This will help for surgical planning, intervention and quantitative analysis such as volume measurement precise detection of tumors surrounded by edema in brain MRI is needed.**

Index Terms- **edema, image segmentation, Brain tumor detection, Magnetic resonance image**

I. INTRODUCTION

Now a days, for the human body anatomical study and for the treatment planning medical science is very much depend on the medical imaging technology and medical images[3]. Here, the area of interest is tumor surrounded by edema detection in brain MRI Images.

Brain tumor is a group of abnormal cells that grows out of control of the normal forces inside the brain or around the brain [3]. Diagnosis of brain tumors is dependent on the detection of abnormal brain structure, i.e. tumor with the exact location and orientation.Cerebral edema or cerebral oedema is excess accumulation of fluid in the intracellular or extracellular spaces of the brain[4]. It can occur in toxic or abnormal metabolic states and conditions such as systemic lupus or reduced oxygen at high altitudes. It causes drowsiness or loss of consciousness [4].

Many clinical centers maintain large databases of MR images of brain tumors and tumor surrounded by edema for various purposes, as this information may help physicians to diagnose and treat novel patient. It will help in determining the effectiveness of various treatments on previous patients with similar tumor or edema volumes.

II. LITERATURE REVIEW:

There are different tumor detection methods exist. The tumor detection is based on seeded region growing method. It works on the assumption that, the intensity values within each region/object conforms to Gaussian distribution, the mean intensity value for each region/object is different[1]. Advantage of this method is that it determine the seed points and the criteria we want to make[1]. Thresholding is the simplest method of image egmentation[3]. Thresholding can be used to create binary images from a grayscale images[3]. The morphological operations are basically based on some assumptions about the size and shape of the tumor. The final technique of image subtraction is applied to obtain the exact tumor region. The basic watershed algorithm is well recognized as an efficient morphological segmentation tool however, a major problem with the watershed transformation is that it produces a large number of segmented regions in the image around each local minima embedded in the image[4]. A solution to this problem is to use marker based watershed segmentation. Connected component analysis extracts the regions which are not separated by boundary after region boundaries have been detected. Finally tumor area is calculated using connected component analysis[4]. In CSM algorithm time complexity is linear to the size of the input data set on the brain MRI. This algorithm is the simplest method to obtain the efficient segmentation with less computational complexity compared to other methods which have been mentioned earlier as they used only two features which are locations and gray level values of every pixel for our work. The proposed method does not give efficient results for the brain MRIs where tumor is surrounded by edema (eroded image removes some portion of edema and it contains tumor and edema together). To overcome such problems the work can be extended further with evolutionary clustering approaches.

III. EDEMA DETECTION TECHNIQUE

1. Bounding Box:

This segmentaion presents an fast, automatic, and approximate technique. This technique locates a “bounding box”. It is an axis-parallel rectangle, around the tumor or edema on an MR Image. Then this bounding box is use to answer subsequent queries that ask about tumor position and size. As shown in figure 1 change (D) is detected on a test image (I), when compared with a reference image (R) [6]. In Fast Bounding Box, when the axis of symmetry will find on an axial MR slice, there are two part of image. That is the left (or the right) half serves as the test image I, and the right (or the left) half supplies as the reference image R. The region of change D here is restricted to be an axis-parallel rectangle, which essentially aims to define the abnormality. Fast Bounding Box algorithm uses a technique to detect the region of interest (ROI).

ROI stands for Region of Interest selection. ROI selection helps the user to extract the needed region [7]. Because medical images more commonly have equal regions which will have same intensity level, gray level, and same shapes. This ROI selection will helps to detect the tumor or edema region alone. It will reduce complexity and avoid the unwanted region of the medical images.

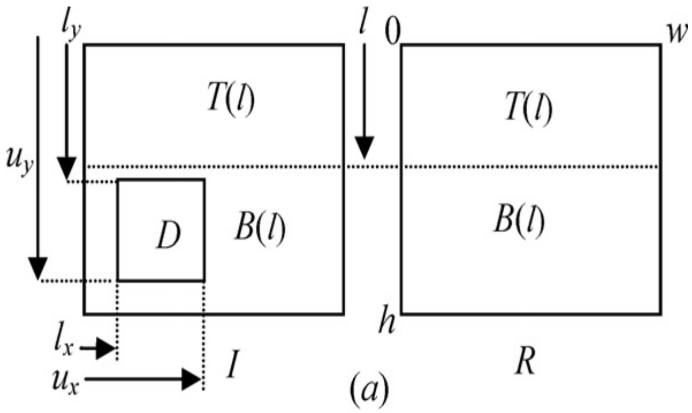

Figure1 image divided in two parts

Bounding Box approach is based on an unsupervised change detection method. That method searches for the most dissimilar region (axis- parallel bounding boxes) between the left and the right halves of a brain in an axial view MR slice [6]. Now axis of symmetry on an axial MR slice is found which divides brain in two halves left (I) and right (R) as shown in figure 1. After dividing that image in two parts Bhattacharya coefficient function is used for ROI selection figure 1 illustrates the notations [8]. I and R in figure 1 represent the test image and the reference image having same height h and same width w. The rectangular region $D = [l_x, u_x] \times [l_y, u_y]$ represents the region of change between images I and R [9]. This algorithm finds the rectangle D, i.e., the four unknown parameters l_x,u_x, l_y and u_y in two linear passes of the image. It first finds the best l_y and u_y values in a vertical sweep and then finds l_x, and u_x in a horizontal sweep over the pair of images.

In each sweep, the FBB algorithm uses a score function[8]. Let $T(l)$ is the “top” and B(l) “bottom” subrectangles of the image and, divided at a distance l from the top of the image: $T(l) = [0, w] \times [0,1]$ and $\mathrm{B(l)} = [0, \mathrm{w}] \times [\mathrm{l}, \mathrm{h}]$ (As shown in figure 1 the rectangles intersecting at the dotted line). Here, the vertical score function is:

$$\mathrm{E(l)} = \mathrm{BC}\left(P_I^{T(l)}, P_R^{T(l)}\right) - BC(P_I^{B(l)}, P_I^{B(l)}) \quad (1)$$

Where , $P_I^{T(l)}$denotes the normalized intensity histogram of image I within the region $T(l)$. $P_R^{T(l)}$, $P_I^{B(l)}$ and $P_R^{B(l)}$ are defined accordingly. BC(a,b)=$\sum_i \sqrt{\mathrm{a(i)b(i)}} \in [0,1]$ denotes the Bhattacharya coefficient[9] between two normalized histograms a(i) and b(i), with I indicating a histogram bin[9]. The Bhattacharya coefficient (BC) measures the similarity between two normalized intensity histograms[9].

BC has already been used successfully in various computer vision applications, such as object tracking , edge detection , and registration. Here, we have:

$$BC\left(P_I^{T(l)}, P_R^{T(l)}\right) = \sum_i \sqrt{(P_I^{T(l)}(i))(P_R^{T(l)}(i))} \quad (2)$$

$$BC\left(P_I^{B(l)}, P_R^{B(l)}\right) = \sum_i \sqrt{(P_I^{B(l)}(i))(P_R^{B(l)}(i))} \quad (3)$$

When two normalized histograms are identical, the BC between them is 1 and when two normalized histograms are completely dissimilar, the associated BC value is 0. Thus, the score function E(l) (from Eq. (1)) is large when the top regions T(l) in the two images are similar and the bottom regions B(l) are dissimilar. $P_I^{T(l)}$, $P_R^{T(l)}, P_I^{B(l)}$I and $P_R^{B(l)}$ R , respectively. Since the region of interest locates at bottom-right quadrant of the image shown in Figure1, value of $BC\left(P_I^{T(l)}, P_R^{T(l)}\right)$ will be high (close to one) and value of $BC\left(P_I^{B(l)}, P_R^{B(l)}\right)$R) will be low (close to zero) which leads the value of E(l) (Eq. (1)) is high.

We now prove some properties of E(l), which facilitate to fast localization of the axis-parallel rectangle D. Where we observe that the score function at first increases, then decreases, and next increases again as l increases from 0 to h. The increasing and decreasing segments meet at $l = l_y$ the lower and $l = u_y$ upper bound of D. Here the lower and the upper bounds of D can be identified from the score function plot very quickly and easily. Similarly, the left and the right bound of D, respectively, l_x andu_x, can be identified from the horizontal score function plot[9].

The following two propositions mathematically establish the increasing-decreasing-increasing nature of E(l), given some reasonable assumptions regarding I, R and D. First, Proposition 1 shows that we can obtain a lower and an upper bound for the score function (1)in terms of D[9].

Proposition1[8]:

$$U_D(l) \geq E(l) \geq L_D(l)$$

$$U_D(l) = M_D(l) + \sqrt{\frac{|T(l) \cap D|}{|T(l)|}} BC(P_I^{T(l)\cap D}, \quad (4)$$

$$L_D(l) = M_D(l) - \sqrt{\frac{|B(l)\cap D|}{|B(l)|}} BC(P_I^{B(l)\cap D}, P_R^{B(l)}) \quad (5)$$

$$M_D(l) = \sqrt{\frac{|T(l)\cap D|}{|T(l)|}} BC(P_I^{T(l)\cap D}, P_R^{T(l)}) - \sqrt{\frac{|B(l)\cap D|}{|B(l)|}} BC(P_I^{B(l)\cap D}, P_R^{B(l)}) \quad (6)$$

Proposition2[8]:

If Assumptions (i), (ii) and (iii) hold, then E(l) is (a) increasing for $0 \leq l \leq l_y$, (b) decreasing for $l_y \leq l \leq u_y$ and (c) increasing again for $u_y \leq l \leq h$, where $D = [l_x, u_x] \times [l_y, u_y]$.

Proof. Note that Assumption (i) signifies that the supports of the histograms on I inside D and on R are almost disjoint. So, $BC(P_I^{T(l)\cap D}, P_R^{T(l)}) \approx 0$ and $BC(P_I^{B(l)\cap D}, P_R^{B(l)}) \approx 0$. Thus from (2) and (3) and Proposition 1, we obtain E(l) ≈MD(l). Now applying Assumption (ii) and (iii) to (4) we obtain:

$$M_D(l) = c_1\sqrt{\frac{|T(l)\setminus D|}{|T(l)|}} - c_2\sqrt{\frac{|B(l)\setminus D|}{|B(l)|}} \quad (7)$$

It is now straightforward to verify that MD(l) in (7) is increasing when $0 \leq l \leq l_y$, decreasing when$l_y \leq l \leq u_y$ and again increasing when $u_y \leq l \leq h$. Proposition 2 suggests that we can obtain l_y, and u_y, the lower and the upper bound for D, by finding the peak and the valley in the vertical score function plot E(l).

This trend of the score function is already illustrated by figure1. Similarly, we can find the left and the right bound for the bounding box, l_x, and u_x, by a linear search on the horizontal score plot. And thus bounding box is drawn[8].

IV. RESULT ANALYSIS:

Figure 1 is the input MRI image of brain tumor surrounded by edema.

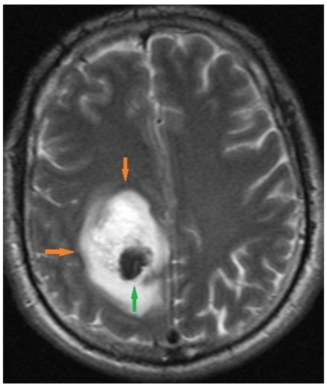

Figure 2 Input MRI image

Figure 2 shows the two points vertically one at the upper part of the image and second at the lower part. This is done by hand. The point is created by clicking on the spot where the user wants to divide the two sides. The coordinates are saved and used later in the program.

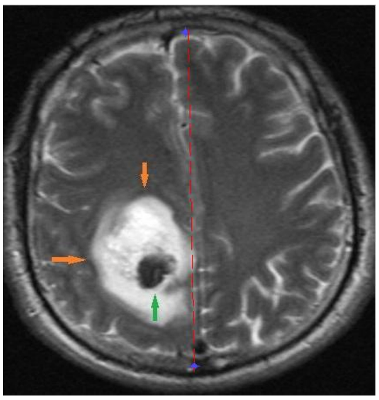

Figure 3 axis of symmetry

As shown in above figure red dotted line represents the axis of symmetry. According to the axis of symmetry input image is divided into two equal parts. Two symmetrical parts of image is shown in below figure.

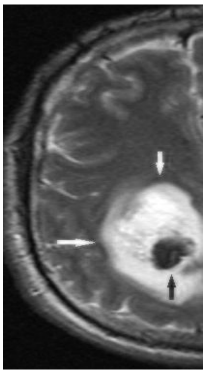

Figure 4 test image I

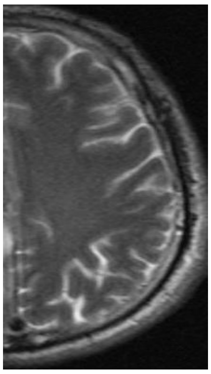

Figure 5 Reference image

Figure 4 shows a left part of an image , which is taken as an test image. Figure 5 shows a right part of an image. Which is taken as an reference image(R) .After that histogram of both the image is taken. Now, novel score function bhattacharya co-efficient is used for normalized histogram equilaization. That function measures similarity between two histogram and according to that bounding box will locate the position of tumor which is surrounded by edema.Which is shown in figure 6.

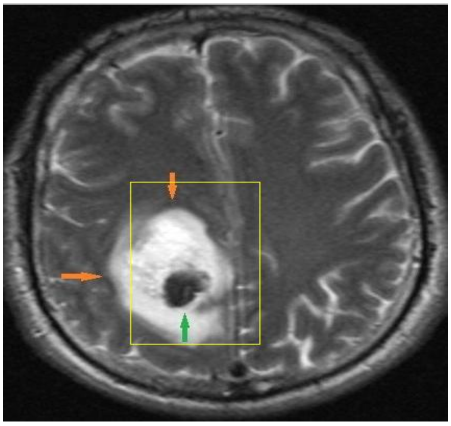

Figure 6 input image with two selection points

Following figure shows the image which is converted in to binary image by using thresholding. Here, the background(skull) is filled with zero. This operation is used to abstract the tumor surrounded by edema(as shown in figure 7). Which only shows the edema detected part.

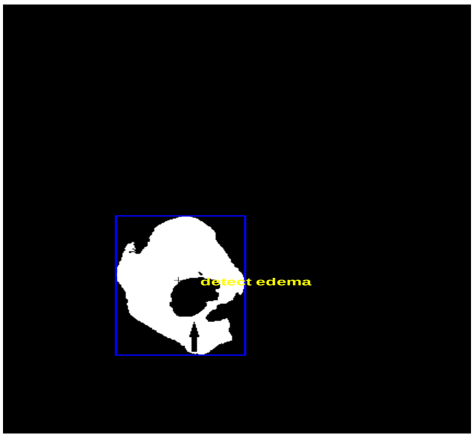

Figure 7 converted binary image

As shown in above figure white portion indicates the area, which is called edema, and the inner small part of black colour in figure is tumor.

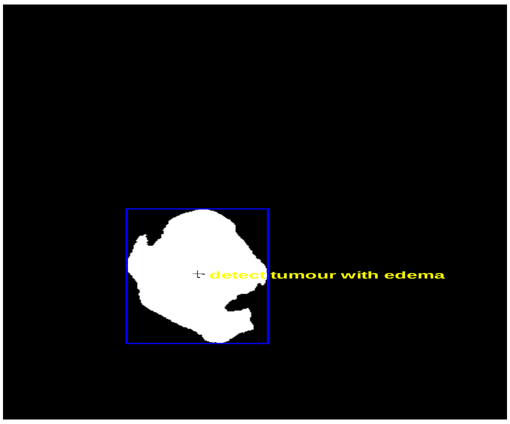

Figure 8 tumor with edema detected

Finally, figure 8 shows the white part which is the total area covered by the tumor which is surrounded by edema. Area covered by tumor is 1725 no. of pixels whereas by edema is 10415 no. of pixels.

V. CONCLUSION

For accurate diagnosis of brain tumor proper segmentation method is required for MR images to carry out an improved diagnosis and treatment. The methods referred for tumor detection gives not accurate result while tumor is surrounded by edema. The proposed algorithm of bounding box approach is used for detection of tumor surrounded by edema and it gives the result in terms of area of the tumor.

REFERENCES

[1] Praveen Kumar E Manoj kumar V Sumithra M G, Tumour Detection In Brain Mri Using Improved Segmentation Algorithm IEEE – 31661

[2] Lt Col SK Jha (Retd) "Cerebral Edema and its Management" MJAFI 2003; 59 : 326:331

[3] Natarajan P, Krishnan.N, Natasha Sandeep Kenkre, Shraiya Nancy, Bhuvanesh Pratap Singh3, Tumor Detection using threshold operation in MRI Brain Images 978-1- 4673-1344-5/12/2012 IEEE

[4] Pratik P. Singhai, Siddharth A. Ladhake, Brain Tumor Detection Using Marker Based Watershed Segmentation from Digital MR Images International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-2, Issue-5, April 2013.

[5] http:// ucbraintumorcenter.com/files/conference -2011

[6] Annelie Lindstrom "MATLAB tool for evaluating the symmetry of the forehead in patients with unicoronal synostosis before and after operation" Department Of Radiation Physics University Of Gothenburg Gothenburg, Sweden

[7] B.chanda, D.Dutta Majumdar"Digital Image Processing & Analysis"PEARSON Education

[8] Rajesh C. Patil,Dr. A. S. Bhalchandra, Brain Tumour Extraction from MRI Images MATLAB International Journal of Electronics, Communication & Soft Computing Science and Engineering ISSN:2277-9477,Volume2,Issue1

[9] Severine Dubuisson " The computation of bhattacharya between histograms without histograms" Laboratoire d'Informatique de Paris 6, Universit´e Pierre et Marie Curie.

[10] www.ajnr.org/content/27/3/475

[11] http://www.hopkinsmedicine.org

[12] Mukesh Kumar, Kamal Mehta, A Modified Method to Segment Sharp and Unsharp Edged Brain Tumors in 2 D MRI Using Automatic Seeded Region Growing Method International Journal of Soft Computing and Engineering (IJSCE)

ISSN: 2231-2307, Volume-1, Issue-2, May 2011.

[13] Subhranil Koley and Aurpan Majumder, Brain MRI Segmentation for Tumor Detection using Cohesion based Self Merging Algorithm 978-1-61284-486-2/2011 IEEE.