Brain Tumor Detection using Image Segmentation

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Abstract-- **Now-a-days Brain Tumor Detection and Segmentation is a developing issue.There are many research teams which are working on this and producing different results using various techniques and algorithms.**

This article is basically based on focusing on detection of Brain Tumor location in Magnetic Resonance image. In this paper we have used symmetry analysis technique to detect the location of tumor. In this, detection is based on locating the area of tumor which breaks the area of brain into two parts i.e left and right symmetry respectively.

Here we have used the concept of Maxima and Minima as well as BC coefficient which has been implemented in this paper.

Keyword-- **Symmetry, BC coefficient, Brain Feature extraction, Maxima Transform**.

I. INTRODUCTION

The detection of brain tumors is generally a more complex task than the detection of any other image object. Pattern recognition usually relies on the shape of the required objects. But the tumor shape varies in each case so other properties have to be used. The general properties of healthy brain arewidely used as a prior-knowledge.. Another widely used knowledge, which is used in this article, is the approximate left-right symmetry of healthy brain. Areas that break this symmetry are most likely parts of a tumor. There are also many other methods used for tumor extraction, but they usually rely on machine learning algorithms such as SVM used e.g. in [6]. For this purpose, many algorithms need to have patient specific training dataset. This makes the method more demanding for the experts. These methods usually rely on other contrast images, such as T1-weighted contrast enhanced images [10]. Fully automatic exact segmentation of the tumor is still an unsolved problem, as the accurate image segmentation itself. The method proposed in this work is less accurate than many other methods used nowadays, but it is fully automatic and it is used only for the detection of the brain tumor location for subsequent segmentation, which will be the aim of future work.

In this paper we propose a fully automatic method to detect brain tumor. We make use of bilateral symmetry property of human brain to detect the abnormality and maxima transform to locate the tumor region. The structural arrangement of the whole brain is similar on the both side of hemisphere and is symmetrical about the vertical axis through the brain centre. The big advantage of the symmetry approach is that the process does not need any intensity normalization, human work etc. The only step that needs to be done is the symmetry axis detection. Another advantage is its independence on the type of the tumor. It can correctly detect anomalies in images containing a tumor, a tumor with edema or only an edema, which is an abnormal accumulation of the fluid around the tumor and is present only with particular types of tumors.

II. RELATED WORK

Sometimes, tumors have similar intensity characteristics of non-brain tissues like fat, muscles and background clutters. Hence the brain portion should be extracted first to eliminate these overlapping intensity arte facts. Our method then checks whether any abnormality is present within the slice and separate the abnormal slices from normal ones. The tumor detection process consists of several steps. The first step is the brain extraction followed by cutting the image. In this cut image, the asymmetric parts are detected and then the decision which half contains the tumor is made. The detection of the symmetry axis is skipped because the input data were aligned in previous processing. The only assumption of proposed method is a vertically aligned head. For the purpose of detecting the symmetry axis, the well performed algorithm works and is described in [8].Addition of this method as a preprocessing step will be one of the aims of the future work.

III. CLASSIFICATION TECHNIQUES

Segmentation of Brain Tumor is an important concept. For extracting the tumor region from MRI Brain Scans we are going to follow three steps:

1) Brain portion extraction,
2) Abnormality detection
3) Tumor segmentation.

The following flowchart illustrates the different stages implemented in our method.

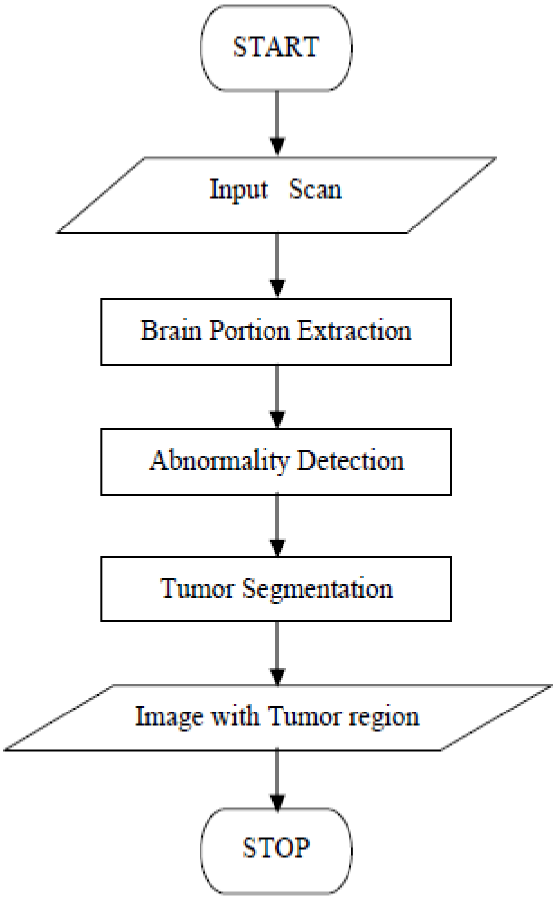


Fig. 1: Flowchart of Proposed Method

3.1. Brain Extraction

The extraction of skull is based on technique mentioned in and is done by the well-known method called Active contour, or Snakes. At first, the smallest rectangle, whose sides are parallel to the image sides, surrounding the skull are detected. The initial mask is set to this rectangle to be sure that the whole skull is inside the mask. Then the algorithm is executed. Assuming that the head is approximately symmetric ,the symmetry axes is set to be parallel to the vertical axis and to divide the detected rectangle into two parts of the same size. The results of the segmentation algorithm is not only the border of the skull, but also the border of the brain. This border is used to extract only the brain instead of the whole skull . Only the segment that is located in the center is extracted. Because in some cases the brain segment can be joined to the skull segment but not symmetrically, another processing has to be done. The operation of logical conjunction is performed with this segment and its symmetric flipped image. This causes that points that are not on one side will not be considered also on the other side. The resulting mask is applied to the input image. The result of the brain extraction is shown in Figure 1.

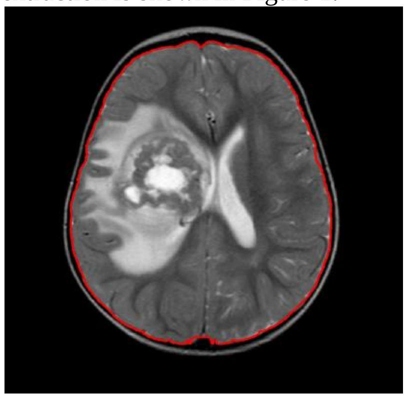


Fig 2: Extraction of brain.

3.2. Asymmetry detection

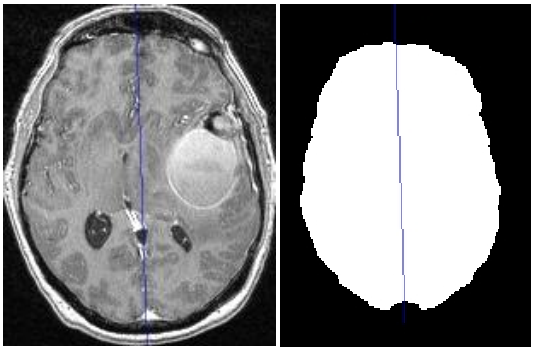
The main part of this work is the detection of symmetric anomalies, which are usually caused by brain tumor, whose detection is the main purpose of this article. The first step of this process is dividing of the input image into two approximately symmetric halves. The algorithm goes through both halves symmetrically by a square block. The size of the block is computed from the size of the image. The step size is smaller than the block size to ensure the overlapping of particular areas. These areas are compared with its opposite symmetric part using by **Bhattacharya coefficient**. Normalized histograms with the same range are computed from both parts and the Bhattacharya coefficient (BC) is computed from these histograms as follows:

$$BC = \sum_{i=1}^{N} \sqrt{l(i).r(i)}$$

BC =XN i=1p

l (i) ¢ r (i); (1)

where N denotes the number of bins in the histogram, l and r denote histograms of blocks in left and right half, respectively. The range of values of Bhattacharya coefficient is h0; 1i, where the smaller value, the bigger difference between histograms. For the next computation, the asymmetry is computed as:
A = 1 – BC



(a) (b)

Fig 3: (a) One axial slice of the original 3D image. (b) Brain mask and symmetry plane.

3.3. Locating the tumor

Tumor segmentation is the main contribution of our work. Here we make use of extended maxima transform to detect the tumor locations. It is the regional maxima of the H-maxima transform [19]. It finds the peaks which are n intensity values higher than the background in regions. It is a robust peak finder, depends only on contrast. It performs first H-maxima transform followed by recognition of regional maxima. H-maxima transform is based on morphological reconstruction, repeated dilations of image followed by masking. The H-maxima transform is given by Koh :

$$HMAX_h(f) = R_f(f - h)$$

where *Rf (f-h)* is the morphological reconstruction by dilation of image f with respect to *(f - h)* . This morphological operation suppresses all points whose value with respect to their neighbors is smaller than a threshold level h. This H-maxima transform belongs to the class of connected operators. The transform is then followed by an extended maxima operation to identify all regional maxima. Regional maxima are connected components of pixels with a constant intensity value, and whose external boundary pixels
all have a lower value. The extended maxima operation is defined by:

$$EMAX_h(f) = RMAX[HMAX_h(f)]$$

It removes local peaks which are lower than h intensity values from the background. Based on the analysis done during our experiments, h is set to 10. The tumor regions extracted by using extended maxima transform.

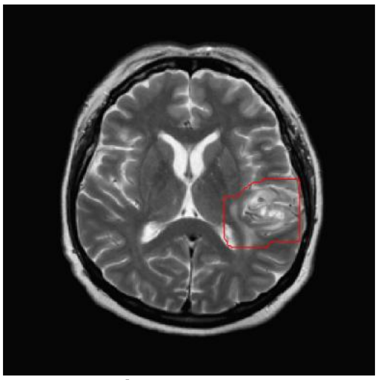
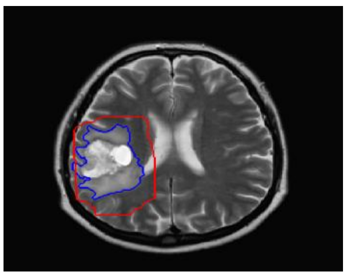


Fig 4: Extracted tumor region.

IV. EXPERIMENTAL RESULT

We have applied the method to 10 different real 3D T1-weighted MRI (of size 256 * 256 *124). A few results can be seen in the Figur [5] and [6].The area of the tumor location is surrounded by a red line. One can see that the detected area is a little bit larger than the pathological area itself. One reason is the use of dilation at the end of asymmetry detection. This is done to locate the whole tumor and not only a part of it. Another reason could be explained by influence of the tumor in the neighbor parts of the brain. Because the tumor is a tissue which is growing during the time, it presses the other parts of the brain. This creates the deformation and asymmetry not only in the tumor location but also in the adjacent parts and gradually in the whole brain. Since the method is based on asymmetry detection ,the problem appears when the tumor is located in both halves or on the symmetry axis. In this case, some parts of the tumor could be outside of the extracted area even if they are located in the half in which the tumor was detected. The reason is that the tumor located in both sides causes symmetry in these parts, so for the algorithm it seems to be a healthy tissue. The part of the tumor located in the other half of the brain is also outside the detected area. The example of that problematic type of tumors is shown in the Figure 6(a). This problem could be prevented by an additional step that consists of checking whether the border of the asymmetric area matching the symmetry axis border, in other words if the both-sided mask creates only one homogeneous region.



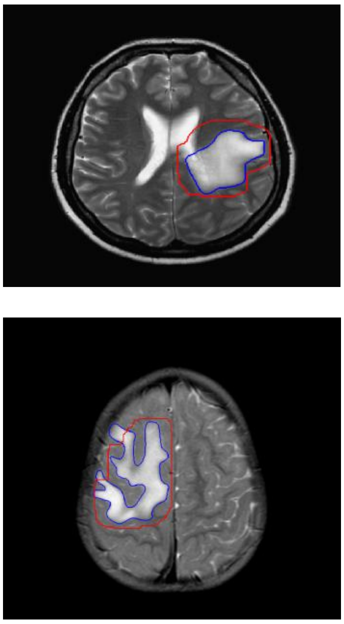


Fig 5: Examples of results (red area) compared to the ground truth (blue area).

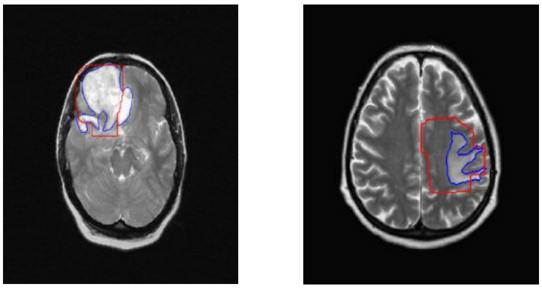


Fig 6:. Less precise results (red area) compared to the ground truth (blue area): (a) Problematic type of tumor located in both halves, (b) Result evaluated as a large area

V. CONCLUSION

The aim of this work was not the precise segmentation of the brain tumor but only detection of approximate location of the tumor. This location could be then used for more precise tumor extraction and could make this task easier.The future work will consist of the automatic symmetry axis detection and the more precise extraction of the tumor based on current results. The attention in the future work will also be paid on automatic detection of the image containing the brain tumor and searching for the relations between neighbor slices. After that, the work will continue with extending the method to 3D MR images

VI. REFERENCES

[1] Bhattacharyya, A., "On a measure of divergence between two statistical populations defined by their probability distribution," Bulletin of the Calcutta Mathematical Society, vol. 35, pp. 99–110, 1943. 3

[2] Ray, N. and Saha, B.N. and Graham Brown, M.R., "Locating Brain Tumors from MR Imagery Using Symmetry," Signals, Systems and Computers, 2007.ACSSC 2007. Conference Record of the Forty-First Asilomar Conference on, pp. 224–228, November 2007. 2, 5

3. Dvorak, P., W. G. Kropatsch, and K. Bartusek, \Automatic detection of brain tumors in MR images," 36th International Conference on Telecommunications and Signal Processing (TSP), July 2013.

4. Cuadra, M. B., C. Pollo, A. Bardera, O. Cuisenaire, J. G. Villemure, and J. P. Thiran, \Atlas-based segmentation of pathological MR brain images using a model of lesion growth," IEEE Trans. on Med. Imaging., Vol. 23, No. 1, 1301{1314, 2004.

5. Cap, M., P. Marcon, E. Gescheidtova, and K. Bartusek, \Automatic detection and segmentation of the tumor tissue," PIERS Proceedings, 53{56, Taipei, March 25{28, 2013.

6. Pedoia, V., E. Binaghi, S. Balbi, A. De Benedictis, E. Monti, et al., \Glial brain tumor detection by using symmetry analysis," Proc. SPIE 8314, Medical Imaging 2012: Image Processing, 831445, February 23, 2012.

7. Mikulka, J. and E. Gescheidtova, \An improved segmentation of brain tumor, edema and necrosis," PIERS Proceedings, 25{28, Taipei, March 25{28, 2013.

8. Dvorak, P., W. G. Kropatsch, and K. Bartusek, \Pathological area detection in MR images of brain," Elektrorevue, Vol. 4, No. 1, 17{21, April 2013.

9. Kropatsch, W. G., Y. Haxhimusa, and A. Ion, \Multiresolution image segmentations in graph pyramids," Applied Graph Theory in Computer Vision and Pattern Recognition Studies in Computational Intelligence, Vol. 52, 3{41, 2007.

10. Lim, J. S., Two-dimensional Signal and Image Processing, Englewood Cli®s, NJ, Prentice Hall, 1990.

