Automatic Detection of Brain Tumor Using Maximum Variance Standardization

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Abstract— this paper presents an automated diagnosis of brain abnormalities through the segmentation from MRI images The main objective is to find out the difference between normal and abnormal brain. Most of the abnormalities in brain are seen in the form of tumor. The tumor has different intensity value compared to the surrounding tissue. We propose a method to find out the appropriate intensity for segmentation. We apply maximum variance standardization method to find out the appropriate intensity value for segmentation. Boundary of the abnormal region is calculated by using appropriate edge detection algorithm. Here variance is calculated from the column mean value of Input MRI image.

Keywords— Brain Tumor, MRI, Column mean, Variance, Standard Deviation, Segmentation, Average Intensity

INTRODUCTION

The National Cancer Institute (NCI) estimated that 1,658,370 new cases of cancer will be diagnosed in the United States in 2015 and 589,430 people will die from the disease. Each year in the United States, more than 35,000 people are told they have a tumor that started in the brain. American Brain Tumor Association (ABTA) clarifies this statistic further by estimating that 62,930 new cases of primary brain tumors would be diagnosed in 2010[1-3] Image segmentation plays a critical role in all advanced image analysis applications, a key purpose of segmentation is to divide image into regions and objects that correspond to real world objects or areas, and the extent of subdivision depends on requirements of specific application. Complete segmentation of an image scene, where objects correlate with real world objects, cannot be usually achieved without inputs from the user or specific knowledge of the problem domain. Image feature selection is a significant prerequisite for most image processing algorithms, depending on these features the segmentation methods can be classified into three categories namely, thresholding, edge-based, region-based segmentation and classifier such as Hierarchical Self Organizing Map (HSOM)[9-10].
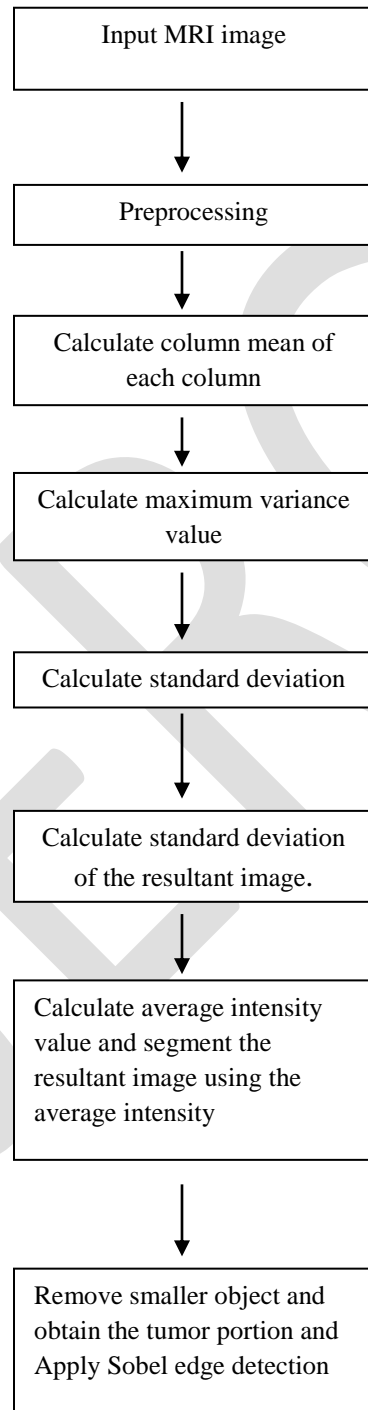
RELATED WORK

Image thresholding is the most popular segmentation method due to its intuitive properties and simple implementation [4]. Threshold selection plays a very crucial role for efficient segmentation results. Intuitively, the thresholds for multimodal histograms should be the minima between the two maxima. Some techniques sharpen the histogram peaks in image enhancement stage so as to facilitate the threshold detection. The main disadvantage of this method is the difficulty to separate object from background if the object and background are of the same intensity distribution or texture as in MRI-scans. Edge-based segmentation is described in terms of discontinuities in image attributes as Gray level, texture, color etc. These discontinuities are known as edges and are detected using edge detection operators, some of the commonly used operators are Sobel, Prewitt, Laplace, etc [5]. Segmentation resulting from edge-based method cannot be used as partial segmented output due to the presence of broken, stray, or noise edges. Advanced processing is required to obtain edges corresponding to meaningful objects. Several algorithms introduced for edge-based segmentation, the widely accepted segmentation methods are edge-image thresholding which is used to eradicate insignificant edges that occur due to factors such as noise and improper lighting conditions [5].

Edge image thresholding leads to stray edges in presence of noise where the actual edges are often missing [4]. Stray edges problem can be solved if the edge properties are determined with respect to the mutual neighbors, while presence of edge is substantiated depending on the strength of edges in local neighborhood [4]. Region-based segmentation is then used which is based on finding similarity measures to merge and split regions in an image so as to form semantic or useful division in the processed image. Self Organizing Map, SOM, as part of competitive learning neural network (CLNN) has been used to implement the vector quantization process [6-8]. The importance of SOM for vector quantization is primarily due to the similarity between the competitive learning process employed in the SOM and the vector quantization procedure. Neural units in the competitive layer need to be

approximately equal to the number of regions desired in the segmented image. It is not however, possible to determine a priori the correct number of regions in the segmented image. This is the main limitation of the conventional SOM for image segmentation.

PROPOSED WORK

In this paper we use the MRI images because the MRI images are clearer than CT images in the case of small tumor. Before the segmentation we have to prepare the image for segmentation by using some pre-processing methods.

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┌─────────────────────────┐
│     Input MRI image      │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│      Preprocessing       │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│  Calculate column mean of │
│       each column        │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│  Calculate maximum variance │
│          value           │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│ Calculate standard deviation │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│ Calculate standard deviation │
│  of the resultant image. │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│ Calculate average intensity │
│ value and segment the    │
│ resultant image using the │
│ average intensity        │
└─────────────────────────┘
             │
             ▼
┌─────────────────────────┐
│ Remove smaller object and │
│ obtain the tumor portion and │
│ Apply Sobel edge detection │
└─────────────────────────┘
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A. Pre-processing

MRI image is converted in to grayscale image in which 0 represents black and 255 represents white. The input images may contain noises. Generally, there are two types of noises impulsive noise and Gaussian noise. So we apply median filter for removing noise. Then we apply the Gaussian filter to remove the Gaussian noise and apply adaptive filter for highlighting the edges.

B. Calculation of Column mean

For calculating the columns mean convert the pre-processed image in to double. Then calculate column mean using the following formula. An image A (i,j) and the column mean intensity of the image is obtained by summing the values of all row pixels for each column and dividing it by the number of rows.

$$I_{sum}(j) = \sum_{i=1}^{M} A(i,j)$$

$$\text{Columns mean (j)} = \frac{I_{sum}(j)}{number\ of\ rows}$$

Column mean is calculated for all columns. Where M is the number of row pixels.

C. Calculation of maximum variance and standard deviation

Variance is calculated for each column mean using the following formula. Usually intensity value of the tumor is relatively high with respect to its surrounding tissues. Thus, we choose the maximum variance for calculating standard deviation. Variance is calculated by using the following formula.

$$\text{Variance} = \frac{sum\ of\ square\ of\ difference}{m-1}$$

D. Calculate standard deviation

The standard deviation calculated from variance using the following formula:

$$\text{Standard Deviation} = \sqrt{varience}$$

Standard deviation is the square root of maximum variance .Thus we get a low value for the standard deviation, which indicates that they are clustered closely around the mean. The tumor intensity pixels are far away from mean so it is impossible to segment tumor tissues from surrounding tissues using standard deviation. The intensity value greater than or equal to standard deviation is set to 255 and the intensity less than standard deviation is set to 0.

$$K(i,j) = \begin{cases} 255 & if\ A(i,j) \geq Standard\ Deviation \\ 0 & if\ A(i,j) < Standard\ Deviation \end{cases}$$

E. Calculate standard deviation of the resultant image.

The standard deviation of the resultant image is recomputed as follows

$$Standard\ Deviation_{New} = Standard\ Deviation[K(i,j)]$$

The value of $Standard\ Deviation_{new}$ is a large value, which indicate values are far from the mean. Thus the data cover large range so we choose this value for setting the threshold value.

F. Calculate average intensity value and segment the resultant image

Using the new standard deviation an average value of intensity is calculated using the following equation.

$$I_{avg} = \frac{\sum_{i=0}^{M} \sum_{j=0}^{N} (A(i,j)|A(i,j) > Standard\ Deviation_{new})}{l}$$

Where, l is the total number of pixels having intensity values greater than $Standard\ Deviation_{new}$. The I_{avg} value is taken as a threshold value to segment the tumor from the original image. The intensity value greater than or equal to I_{avg} be set to 255 and the intensity less than I_{avg} is set to 0.

$$L(i,j) = \begin{cases} 255 \; if \; A(i,j) \geq I_{avg} \\ 0 \quad if A(i,j) < I_{avg} \end{cases}$$

G. Remove smaller object and obtain the tumor portion and Apply Sobel edge detection

Label the connected component of image L (i,j) with 8 connected neighborhoods. Using regionprops function in Matlab identifies the area of the connected components. Then remove the components having an area less than the predefined value. This gives the tumor portion.

To find the boundary of the tumor Sobel edge detection is used.

$$I_x = \frac{\delta f}{\delta x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$

$$I_y = \frac{\delta f}{\delta y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

Where I_x and I_y are images of same size as the original is obtained by filtering image by Sobel mask .Compute the gradient magnitude of the image that is the value of the rate of change in the direction of the gradient vector.

$$\text{Gradient Magnitude} = \sqrt{I_x{}^2 + I_y{}^2}$$

Using the gradient magnitude tumor boundary is detected.

CONCLUSION

We propose maximum variance standardization for brain tumor Detection in this work. The proposed method uses threshold based segmentation for brain tumor detection. As appropriate values of threshold are taken, the performance of the proposed detection system is high.

REFERENCES:

[1] American Brain Tumor Association (2010). Facts and Statistics 2010 retrieved from http://www.abta.org/sitefiles/pdflibrary.

[2] Central Brain Tumor Registry of the United States. (2010). CBTRUS statistical report: Primary brain and central nervous system tumors diagnosed in the United States in 2004–2006. Retrieved from http://www.cbtrus.org/2010-NPCR-SEER/CBTRUS - WEBREPORT-Final-3-2-10.pdf

[3] Sidney Croul, Jessica Otte and Kamel Khalili, "Brain tumors and polyomaviruses", Journal of NeuroVirology, 9: 173–182, 2003

[4] D. Shevad, "Multiple object segmentation and tracking in image sequence," Lamar University -Beaumont, April 2005.

[5] R. Gonzalez and R. Woods, Digital Image Processing, 3rd Edition. Prentice Hall, 2008.

[6] Alexander Statnikov, "Automatic cancer diagnostic decision support system for gene expression domain", Thesis, August, 2005.

[7] M.M.Ibrahiem, E Emary and S. Ramakrishnan, "On the Application of Various Probabilistic Neural Networks in Solving Different Pattern Classification Problems," World Applied Sciences Journal, Vol. 4 No. 6, pp. 772-780, 2008.

[8] S.Asif Hussain and M. Praveen Raju, "Neuro-Fuzzy System for Medical Image Processing" Proceedings of the Inter. Conf. on Comm. and Computational Intellig., pp.382-385, India. Dec., 2010.

[9] D. Shevad, "Multiple object segmentation and tracking in image sequence," Lamar University -Beaumont, April 2005.

[10] T.Logeswari and M. Karnan, "An Improved Implementation of Brain Tumor Detection Using Segmentation Based on Hierarchical Self Organizing Map", International Journal of Computer Theory and Engineering, Vol. 2, No. 4, August, 2010.

[11] Dina Aboul Dahab1, Samy S. A. Ghoniemy2 , Gamal M. Selim3, International Journal of Image Processing and Visual Communication ISSN (Online)2319-1724 : Volume 1 , Issue 2 , October 2012.

[12] Pabitra Roy, Sudipta Roy, Prof. Samir Kumar Bandyopadhyay, International Journal of Advanced Research in Computer Science and Software Engineering Volume 3, Issue 11, November 2013.