

Application of Edge Detection for Brain Tumor Detection

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ABSTRACT

Brain tumors are created by abnormal and uncontrolled cell division in brain itself. If the growth becomes more than 50%, then the patient is not able to recover. So the detection of brain tumor needs to be fast and accurate. The objective of this paper is to provide an efficient algorithm for detecting the edges of brain tumor. The first step starts with the acquisition of MRI scan of brain and then digital imaging techniques are applied for getting the exact location and size of tumor. MRI images consist of gray and white matter and the region containing tumor has more intensity. So, first noise filters are used for noise removal and then enhancement techniques are applied to the given MRI scan of brain. After that the basic morphological operations are applied for extracting the region suffering from tumor. And then verification of region detected is done by using watershed segmentation.

General Term

Morphological Segmentation

Keywords

Morphological Operations, Edge detection, Noise filters

1. INTRODUCTION

Imaging technology in Medicine made the doctors to see the interior portions of the body for easy diagnosis. It also helped doctors to make keyhole surgeries for reaching the interior parts without really opening too much of the body. CT scanner, Ultrasound and Magnetic Resonance Imaging took over x-ray imaging by making the doctors to look at the body's elusive third dimension. Image processing techniques developed for analyzing remote sensing data may be modified to analyze the outputs of medical imaging systems to get best advantage to analyze symptoms of the patients with ease. There are various advantages of using digital images techniques like data is not changed when it is reproduced again and again and retains originality, enhancement of images makes work easier for physicians to interpret and quick comparison of images.

A brain tumor is an abnormal growth of cells within the brain, which can be cancerous or non-cancerous (benign). It is generally caused by abnormal and uncontrolled cell division, normally either in the brain itself (neurons, glial cells (astrocytes, oligodendrocytes, ependymal cells), lymphatic blood vessels), in the cranial nerves (myelin-producing Schwann cells), in the brain envelopes (meninges), skull, pituitary and pineal gland, or spread from cancers primarily located in other organs (metastatic tumors). Brain tumors are of two types: primary and secondary. Primary brain tumors include any tumor that starts in the brain. Primary brain

tumors can start from brain cells, the membranes around the brain (meninges), nerves, or glands. Primary brain tumors are classified as: 1) benign; 2) malignant. Benign tumors can be removed, and they seldom grow back. Benign brain tumors usually have an obvious border or edge. They don't spread to other parts of the body. However, benign tumors can press on sensitive areas of the brain and cause serious health problems. Malignant brain tumors are generally more serious and often are a threat to life. They are likely to grow rapidly and crowd or invade the nearby healthy brain tissue. Cancer cells may break away from malignant brain tumors and spread to other parts of the brain or to the spinal cord. They rarely spread to other parts of the body.

According to National Brain Tumor Society, an estimated 688,000+ people are living with primary tumors of the brain and central nervous system (CNS) in the United States, 138,000 with malignant tumors and 550,000 with nonmalignant tumors. That is up from an estimated 612,000+ people living with a primary brain and CNS tumor in the United States in 2004, 124,000 with malignant tumors and 488,000 with nonmalignant tumors. An estimated 13,700 deaths are expected to occur this year due to brain tumors, 7,720 males, and 5,980 females. About 43% of brain and CNS tumors occur in men and about 57% occur in women. So efficient and accurate techniques are required for brain tumor detection. In India, totally 80,271 people are affected by various types of tumor (2007 estimates) [2].

Magnetic resonance imaging (MRI) provides detailed information about brain tumor anatomy and acts as an essential pre processing step for tumor detection. Magnetic resonance imaging (MRI), or nuclear magnetic resonance imaging (NMRI), is primarily a medical imaging technique used in radiology to visualize detailed internal structure and limited function of the body. MRI provides much greater contrast between the different soft tissues of the body than computed tomography (CT) does [3].

This paper is divided in five parts. In the second part related work is discussed. In the third portion all the steps used in the algorithm are discussed. First step starts with the MRI scan of brain and noise disturbance is obvious in medical images, so filters are used for noise removal and then enhancement techniques are applied. Then how image segmentation is done and finally how exact size and location of tumor is obtained are discussed. The next section consists of all the experimental results and finally last section consists of conclusion and future work.

2. RELATED WORK

The ultimate purpose of applying different imaging techniques is to extract important and useful information from given image. The segmentation of brain tumor from magnetic resonance images is an important but time-consuming task performed by medical experts. The digital image processing community has developed several segmentation methods [4], many of them ad hoc. Four of the most common methods are: 1.) amplitude thresholding; 2.) texture segmentation; 3.) Template matching and 4.) Region-growing segmentation. These types of methods are used for dividing the brain images into three categories: (a) Pixel based (b) Region or Texture Based (c) Structural based. Based on the region obtained, required information is extracted.

Suchendra et al. (1997) suggested a multiscale image segmentation using a hierarchical self-organizing map. Gopal, N.N. Karnan, M. [5] suggested an algorithm which used multi-scale image segmentation. M E Jain explained a wrapper based technique for image segmentation [6]. Various techniques using fuzzy logic have also been proposed like by P.Vasuda, S.Satheesh [7] but the drawback was more computation time required, T. Logeswari, M. Karnan [8]. Ming niwu, chia-chen Lin and chin-chenchang, proposed an algorithm which uses a clustering technique (k-means) to detect the brain tumor in MR images [9].

Much research work had been carried out for detection of tumors by using image processing techniques or by using soft computing techniques. Each method is having their own advantages and disadvantages. In the next section, various image processing techniques used in our algorithm are explained.

3. PROPOSED METHODOLOGY

The different stages involved in our algorithm are shown below:

3.1 Image Acquisition:

Images are obtained by MRI scan of brain and the output of MRI provides gray level images. A gray scale image is a data matrix whose value represents shades of gray. The elements of gray scale matrix have integer values or intensity values in range [0 255]. For applying different techniques, the digital images obtained from MRI are stored in matrix form in MATLAB. Different formats of digital images like jpg, png etc. have been used in the proposed algorithm. The MRI scan of patient suffering from tumor shows some region having high intensity. The objective of the algorithm is to detect the exact the location and size of this high intensity region. MRI images can involve some noise also. So the next step is to remove this noise and get enhance image for better detection.

The following flowchart shows the various steps involved in our algorithm. Also watershed function is applied for verifying the output.

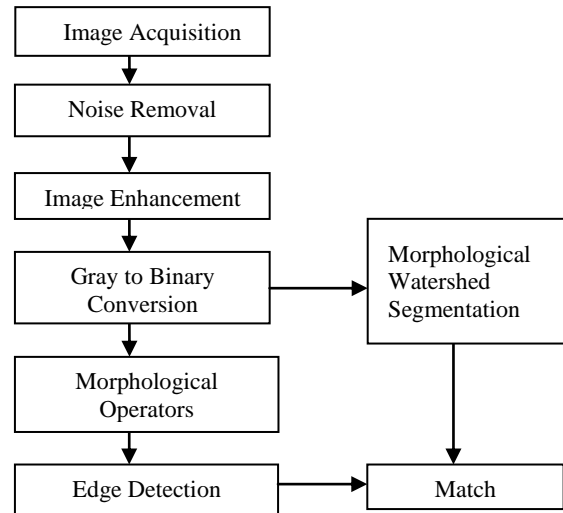


Fig 1: Stages involved

3.2 Noise Removal:

There are various kinds of filters available in image processing for removing noise and each filter is having different characteristic. In this algorithm spatial noise filters are used for noise removal. There are two types of filters: a.) linear filters; b.) non linear filters.

3.2.1 Linear Filters

Mean filters like arithmetic mean filter, geometric mean filter, harmonic mean filter, contra harmonic mean filter etc. are linear filters. The geometric filters do not blur the image as much as arithmetic filters. Arithmetic and geometric filters are suited well for random noise like Gaussian. The contra harmonic filter is well suited for impulse noise. Here geometric mean filter is used and then non linear filter is applied.

3.2.2 Non Linear Filters

The median, max and min filters are non linear, order statistic filters. Usage of median filter again and again on processed image provides much better result. The max filter removes pepper noise considerably but also removes some dark pixels from borders of dark object and since MRI image consists of more of dark object, this filter is not suitable. Median filter have been used in this algorithm. The median filter can be implemented directly by using toolbox function `medfilt2`.

The results of using linear and non linear filters are shown in next section. After noise removal, the next step is to enhance the MRI image. So the next section explains the various enhancement techniques.

3.3 Image Enhancement:

Enhancement will result in more prominent edges and a sharpened image is obtained, noise will be reduced thus reducing the blurring effect from the image. This improved and enhanced image will help in detecting edges and improving the quality of the overall image. Edge detection will lead to finding the exact location and size of tumor. For enhancing MRI images, sharpening spatial filters have to be used as these filters highlight fine details. These filters remove blurring from image and highlight edges. Sharpening filters are based on spatial differentiation. Laplacian filter is a sharpening filter. After applying Laplacian filter to the image, a new image is obtained highlighting edges and other discontinuities. The result of Laplacian filter is not an enhanced image. The Laplacian result needs to be subtracted

from original image for generating final sharpened enhanced image. Sobel filters also available for edge detection. There are also various other filters like Gaussian, Prewitt etc. Successful enhancement is achieved when range of techniques are combined in order to achieve final result and not by single operation.

In the proposed algorithm, many filters like Gaussian, Laplacian etc have been applied. The result obtained from Laplacian filter was much better than other filters. Output of using Laplacian filter is shown in next section.

After getting the enhanced image, the process of detection of exact location and size of tumor begins. For achieving this aim, first of all, the gray image has to be converted to binary image. So the next stage deals with this conversion.

3.4 Gray to binary conversion:

A binary image is a logical array of 0's (black) and 1's (white). For conversion of gray scale image to binary image, toolbox function *im2bw* is used. It scales the entire range of the input values to the range [0 1]. Thresholding concept has been used in this algorithm. The threshold concept works by choosing a threshold value, T, automatically and then extract (or separate) object from background.

The threshold function of binary image $g(x, y)$ is defined as:

$$g(x, y) = \begin{cases} a, & \text{if } f(x, y) > T \\ b, & \text{if } f(x, y) \leq T \end{cases}$$

Pixels labeled 'a' correspond to object and pixels labeled 'b' correspond to background. Usually, $a=1$ (white) and $b=0$ (black) by convention. When T is a constant applicable over an entire image, the above equation is referred to as Global thresholding. In the algorithm, global thresholding concept is used. Optimal global thresholding concept is used using Otsu's method here. Toolbox function *graythresh* computes Otsu's threshold. The syntax is:

$$[T, SM] = \text{graythresh}(f)$$

where f is input image, T is resulting threshold, normalized to range [0 1] and SM is separability measure. The image is segmented using function *im2bw*. This step is important because here the object gets separated from background and so this conversion needs to be more accurate. For this reason, different techniques were applied and found that Otsu's method provided much better results.

After segmentation process, the next step is to apply different morphological operator for finding exact size.

3.5 Morphological Operators:

Mathematical morphology is defined as a tool for extracting image components that are useful in the representation and description of region shape, such as boundaries, skeletons, etc. There are two fundamental morphological operations: a.) dilation; b.) erosion. These are defined in terms of union and intersection of an image with translated shape called a structuring element.

3.5.1 Dilation:

Dilation is operation that "grows" or "thickens" objects in image. The specific manner and extent of this thickening is controlled by a shape referred to as a structuring element. Toolbox function *imdilate* performs the dilation.

3.5.2 Erosion:

Erosion "shrinks" or "thins" object in binary image. As in dilation, the manner and extent of shrinking is controlled by structuring element. Toolbox function *imerode* performs the erosion.

Now the extent of growth and shrink is controlled by structuring element. So this choice has to be done correctly. Toolbox function *strel* constructs structuring element with variety of shapes and sizes. Its basic syntax is:

$$se = \text{strel}(\text{shape}, \text{parameters})$$

where shape is a string specifying the desired shape, and parameters is a list of parameters that specify information about the shape, such as its size. e.g. , *strel('diamond',5)* returns a diamond shaped structuring element that extends ± 5 pixels along horizontal and vertical axis. There are various shapes available like disk, line, octagon, rectangle, square etc. One can also create a matrix of zeros and ones to be used as structuring element.

In the proposed algorithm, disk has been used as structuring element and the accuracy is achieved by using disk of different radius. The output was checked by varying shape of the disk. Disk of radius 5 have been used in this algorithm. Also these operations were applied again and again to achieve more accuracy.

3.6 Edge Detection:

The last step is the detection of the edges of tumor. One may also skip this step because tumor gets detected after applying morphological operators. But by detection of edges the exact result is obtained.

3.7 Morphological Watershed Segmentation:

Image segmentation is based on three principal concepts: a.) Detection of discontinuities; b.) Thresholding; c.) Region Processing. Morphological Watershed Image Segmentation embodies many of the concepts of above three approaches. It often produces more stable segmentation including continuous segmentation boundaries. Watershed is normally used for checking output rather than using as an input segmentation technique because it usually suffers from over segmentation and under segmentation [10].

For using watershed segmentation different methods are used. Two basic principle methods are: 1) the computed local minima of the image gradient are chosen as a marker. In this method an over segmentation occurs. After choosing marker region merging is done as a second step; 2) Watershed transformation using markers utilizes the specifically defined marker positions. These positions are either defined explicitly by a user or they can be determined automatically by using morphological tools.

Watershed segmentation groups pixels of an image on the basis of their intensity. It is a good segmentation technique for dividing an image to separate tumor from image. So it was applied on gray images for grouping the region suffering from tumor from rest of brain. It was used as a method for verifying output rather than to be used as segmentation method. Toolbox operation *watershed* provides required segmentation in Matlab.

4. EXPERIMENTAL RESULTS

In this section, the results of each stage are shown and how result obtained is better and accurate. Figure 2 shows the MRI scan of brain.

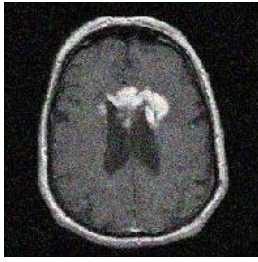


Fig 2: MRI scan of brain

As it can be seen that the image is noisy, so different noise filters are needed to be applied for noise removal and then apply enhancement techniques. The result obtained after applying step 2 and step 3 was obtained as:

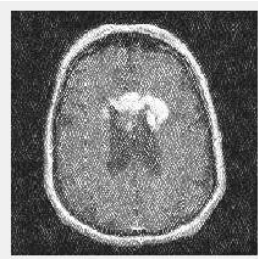


Fig 3: Enhanced Image

The output obtained after converting image to binary image using Otsu's method is shown below:

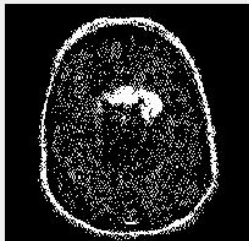


Fig 4: Binary to gray Image

Now the result obtained after applying morphological operations i.e. dilation and erosion is shown below:

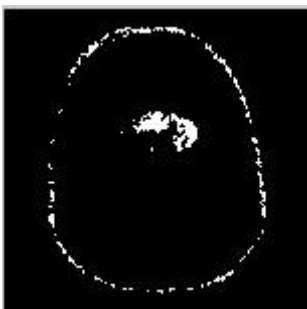


Fig 5: Result after erosion applied on image 4

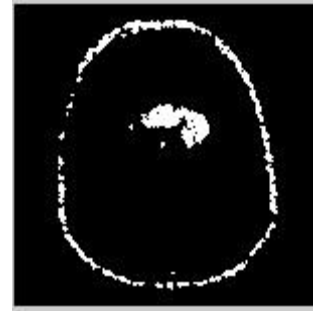


Fig 6: Result after dilation on image 5

The last step is the detection of edges of this tumor. The detected edges of the tumor was obtained as:

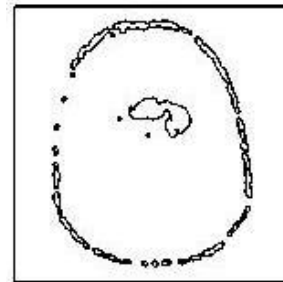


Fig 7: Final output

As explained in figure 2, we also apply watershed segmentation for grouping cells according to their intensity. The output was obtained as:

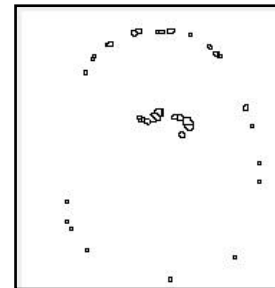


Fig 8: Watershed Segmentation

5. CONCLUSION

From the previous section it can be seen that the results obtained are much accurate and clear. Accuracy obtained in final result depends on processing of each step. For each step, there are numerous methods available and the methods providing best results were chosen. The last step is detection of edges of the tumor. For edge detection there are various classical methods but in this algorithm edge detection using 2D Cellular Automata concept was used because the detection of edges depends on neighborhood pixels. The Cellular Automata rule number 252 provides strong edge detection. The algorithm was applied on numerous images and the results obtained were very good and efficient.

Also the proposed algorithm can be applied with some modification for detection of lung cancer. The algorithm can be applied to the CT scan of the lungs and region suffering from cancerous cells can be identified.

6. REFERENCES

- [1] Oelze, M.L., Zachary, J.F. , O'Brien, W.D., Jr., Differentiation of tumor types in vivo by scatterer property estimates and parametric images using ultrasound backscatter , on page(s) :1014 - 1017 Vol.1, 5-8 Oct. 2003.
- [2] T. Logeswari and M. Karnan, An improved implementation of brain tumor detection using segmentation based on soft computing, Second International Conference on Communication Software and Networks, 2010. ICCSN'10. Page(s): 147-151.
- [3] Devos, A, Lukas, L., Does the combination of magnetic resonance imaging and spectroscopic imaging improve the classification of brain tumours?? On Page(s): 407 – 410, Engineering in Medicine and Biology Society, 2004. IEMBS '04. 26th Annual International Conference of the IEEE, 1-5 Sept. 2004.
- [4] Chunyan J, Xinhua Z, Wanjun H, Christoph M (2000). Segmentation and Quantification of Brain Tumor," IEEE International conference on Virtual Environment, Human-Computer interfaces and Measurement Systems, USA pp. 12 14.
- [5] Gopal, N.N. Karnan, M. , Diagnose brain tumor through MRI using image processing clustering algorithms such as Fuzzy C Means along with intelligent optimization techniques, Page(s): 1 – 4, Computational Intelligence and Computing Research (ICCIC), 2010 IEEE International Conference, 28-29 Dec. 2010.
- [6] Farmer, M.E, Jain, A.K. , A wrapper-based approach to image segmentation and classification, Page(s): 2060 - 2072 , Image Processing, IEEE Transactions on journals and magazines, Dec. 2005
- [7] P.Vasuda, S.Satheesh, Improved Fuzzy C-Means Algorithm for MR Brain Image Segmentation, Page(s): 1713-1715, (IJCSE) International Journal on Computer Science and Engineering, Vol. 02, 05, 2010.
- [8] T. Logeswari, M. Karnan, An improved implementation of brain tumor detection using segmentation based on soft computing, Page(s): 006-014, Journal of Cancer Research and Experimental Oncology Vol. 2(1), March 2010.
- [9] Ming niwu, chia-chen Lin and chin-chenchang, Brain Tumor Detection Using Color-Based K-Means Clustering Segmentation , Page(s): 245 – 250 , Intelligent Information Hiding and Multimedia Signal Processing, 2007. IIHMSP 2007. Third International Conference, 26-28 Nov. 2007
- [10] Gang Li , Improved watershed segmentation with optimal scale based on ordered dither halftone and mutual information, Page(s) 296 - 300, Computer Science and Information Technology (ICCSIT), 2010, 3rd IEEE International Conference, 9-11 July 2011