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Brain Tumor Boundary Detection in MR Image by Homogeneity Enhancement Process

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Abstract

Brain cancer can be counted among the most deadly and intractable diseases. Tumors may be embedded in regions of the brain that are critical to orchestrating the body's vital functions, while they shed cells to invade other parts of the brain, forming more tumors too small to detect using conventional imaging techniques. Brain cancer's location and ability to spread quickly makes treatment with surgery or radiation like fighting an enemy hiding out among minefields and caves.

Boundary detection in MRI with brain tumor is an important image processing technique applied in Radiology. The non-homogeneities density tissue of the brain with tumor can result in achieving the inaccurate location in any boundary detection algorithms. In this paper, we propose a new approach to detect the boundary of brain tumor based on the

In this research paper we have proposed homogeneity enhancement process for brain image. This is followed by edge detection and finally obtaining the boundary by using Border Boundary Enhancement Algorithm. This composite method have been implemented and applied to brain database. The experimental results indicate that the boundary regions were extracted accurately characterize the corresponding ground truth images.

Key Words- MRI, ROI, Homogeneity, Enhancement, and Contextual Regions

1. Introduction

Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and other imaging modalities provide an effective means for noninvasively mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and are a critical component in diagnosis and treatment planning.

The properties of MR images have a strong influence on the usefulness of specific segmentation methods. Classical segmentation methods attempt to partition an image optimally into a number of regions that each satisfies some intensity uniformity constraint. In the ideal case, the resulting regions are meaningful and contain distinct sets of pixels.

Medical CT image has been applied in clinical diagnosis widely. It can assist physicians to detect and locate pathological changes, and determine the property of them. But the diagnosis result is often subjective, different physicians may get different diagnosis result at different time [1]. Computer Aided Diagnosis (CAD) aims to provide a computer output as a second opinion in order to assist physicians in the detection of abnormalities, quantification of disease progress and differential diagnosis of lesions [2].

The typical architecture of a CAD system includes four main modules: image pre-processing, definition of region(s) of interest (ROI), extraction and se-lection of features and classification of the selected ROI [3].

Two fields closely related to segmentation that we discuss here are feature detection and motion estimation. The distinction we make between segmentation and feature detection is that feature detection is concerned with determining the presence of some image property while segmentation generally assumes that the property is already present and attempts to precisely localize areas that possess the property. For example, edge detection methods can find out the location of edges in an image but without further processing, do not necessarily extract any region of interest. Motion estimation methods often consist of applying segmentation algorithms to time sequences of images.

Texture analysis is an important task in many computer applications of Computer image for classification, detection or segmentation of images based on local spatial patterns of intensity. Textures are replications, symmetries and combinations of various basic patterns, usually with some random variation.

The major task in texture analysis is the texture segmentation of an image, that is, to partition the image space into a set of sub regions each of which is homogeneously textured. Automated MRI brain tumor segmentation provides useful information for medical diagnosis and surgical planning. However, it is a difficult task due to the large variance and complexity of tumor characteristics in images, such as sizes, shapes, locations and intensities. So in practice, segmentation of brain tumor continues to depend on manual tracing and delineating. Many image processing techniques have been proposed for MRI brain tumor segmentation.

Feature extraction refers to various quantitative measurements of medical images typically used for decision making related to the pathology of a structure or tissue. When the features have been extracted, selection of a subset of the most robust features is essential, aiming at improving classification accuracy and reducing the overall complexity.

Brain boundary detection as well as segmentation is a very important feature in image analysis. This process can improve clinical diagnosis of different types of brain diseases. The accurate segmentation of the brain region in MRI is an essential step in the computerized analysis of images. It allows the search for abnormalities to be limited to the region of the brain. It also facilitates enhancements for techniques such as comparative analysis, which includes the automated comparison of corresponding MRI.

The brain boundary contains significant information relating to the symmetry and deformation between two halves of mage. Hence in this work, we have proposed step-by-step algorithms for segmentation, determine the edge of segmented region, extract the boundary and improve the boundary using boundary enhancement.

2. Review Works

One of the most difficulties in tumor excisions and tissue differentiation is the border and cells overlapping between normal and abnormal tissues in gray level of the medical images and that are the challenge of the surgeon or physician to distinguish that.

The difficulties are summarized by image gray level overlapping between two or more different parts in the same image. And that very clear when the image of MRI and CT scan were taken to a patient.

MR imaging technique, because of good ability in showing difference between soft tissues, high resolution, good contrast and non-invasive technique for using no ionization rays is very appropriate. Segmentation is the first step at quantitative analysis of medical images. Medical images analysis field [4, 5, 6], because of indirect and Sophisticate structures are very complicated but interesting. Segmentation methods are very successful on normal tissues [4, 7-12] but it has not been done good theoretical and practical segmentation on abnormal tissues yet [4]. Computer aided tumor detection is one of the hardest index in field of abnormal tissue segmentations. There are two important problems. First, automatic tissue measurement is not very easy because of variations in the structures. Intensity distribution of normal tissues is very complicated and exist some overlaps between different types of tissues. Moreover it is probable to have some variations in the size, location and form of the brain tumor tissues and usually contains any dropsy. Other tissues that contain any dead, bloodshed or shrinkage, can be as abnormality and so abnormal tissues boundaries can be blurred.

Second problem is the MR images have formed from high number of pixels (for example 256*256*128), so segmentation problem, has a high computational complexity and needs much memory.

This problem can be solve by using 2D repetitive methods or semi-automatic segmentation helping human knowledge, but will lose much information such as geometry and etc [4].

MRI for patient with brain tumor; there is an overlapping between the boundaries of tumor in the cerebellum part and tissue surrounded; the surgeon must be very accurate and carful to remove that tumor without cause a damage for the surrounding tissue. If the surgeon has the accurate dimensions of the involved tissue he can do his job with more flexibility; there are a new medical instrument used to remove the tumor specially in the brain without opening a large area in the scalp depending on the image only, like Brain lab instrument (Navigator) [11], as well as Linear accelerator (LINAC) [12] these devices need well defined dimensions of abnormal tissue for extraction.

There are many methods used in many researches to differentiate biological tissue boundaries in the images like Matei Mancas et al, they used a novel method called iterative watersheds is then used inorder to segment the tumors for CT image of the neck [13] and then they used Fuzzy logic for tumor segmentation in another research [14]. Fuhui Long et al [15] they present a method based on 3D watershed algorithm of segmentation using both the intensity information of the image and the geometry information of the appropriately detected foreground mask of biological nuclei images. Regina Pohle et al [16] they developed a region growing algorithm that learns its homogeneity criterion automatically from characteristics of the region to be segmented for MRI and CT images. Rune Petter Sørlie [17] used the watershed with snake method to study the speckle noise and edge detection of the liver tumor image. Kathleen Marty [18] used watershed algorithm for brain cortical surface meshes. The function used is curvature measures inherent in the geometry of the mesh with four different curvature measures are compared: mean, Gaussian, absolute, and root mean square.

3. Proposed Approach

A feature is a significant part of information extracted from an image which provides more detailed understanding of the image. Common features include corresponding points, edges, contours or surfaces. The extraction of features constitutes a preliminary stage in many processes in computer vision. The used methods could be either worked interactively with an expert or automatically. The choice of a suitable detector method is closely linked to the situation. The detection methods should have good localization accuracy and should not be sensitive to the assumed image degradation.

There are different types of noises, which appear in MR images. The algorithm should estimate these regions and exclude them from the remaining process.

High intensity noise is characterized by high values of optical densities, such as labels or scanning artifacts. Tape artifacts are markings left by tapes, or other shadows presenting themselves as horizontal running strips. Such noise is replaced by black pixels.

Our method operates on small regions in the image called tiles rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the uniform distribution or Rayleigh distribution or exponential distribution. Distribution is the desired histogram shape for the image tiles. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise and reduce edge-shadowing effect that might be present in the image; the technique is described below:

Step 1. MRI was divided into a number of non-overlapping contextual regions of equal sizes, experimentally set to be 8x8, which corresponds to approximately 64 pixels.

Step 2. The histogram of each contextual region was calculated.

Step 3. A clip limit, for clipping histograms, was set (t=0.001). The clip limit was a threshold parameter by which the contrast of the image could be effectively altered; a higher clip limit increased mammogram contrast.

Step 4. Each histogram was redistributed in such a way that its height did not exceed the clip limit.

Step 5. All histograms were modified by the transformation function

$$T(r_k) = \sum_{j=0}^{k} p_r(r_j) \quad (1)$$

Where $$p_r(r_j) = \frac{n_j}{n} \quad (2)$$

is the probability density function of the input image gray scale value j, n is the total number of pixels in the input image and nj is the input pixel number of gray scale value j.

Step 6. The neighboring tiles were combined using bilinear interpolation and the image gray scale values were altered according to the modified histograms.

In our experiment, we defined tiles size i.e. the rectangular contextual regions to 8X8, which is chosen from best result from trial. Contrast factor that prevents over-saturation of the image specifically in homogeneous areas is restricted to 0.01 here to get the optimized output. The number of Bins for the histogram building for contrast enhancing transformation is restricted to 64 and the distribution of histogram is 'Rayleigh' i.e. Bell-shaped for our experimentation. The range is not specified in the experiment to get the full range of output image. Output of the algorithm is shown below:

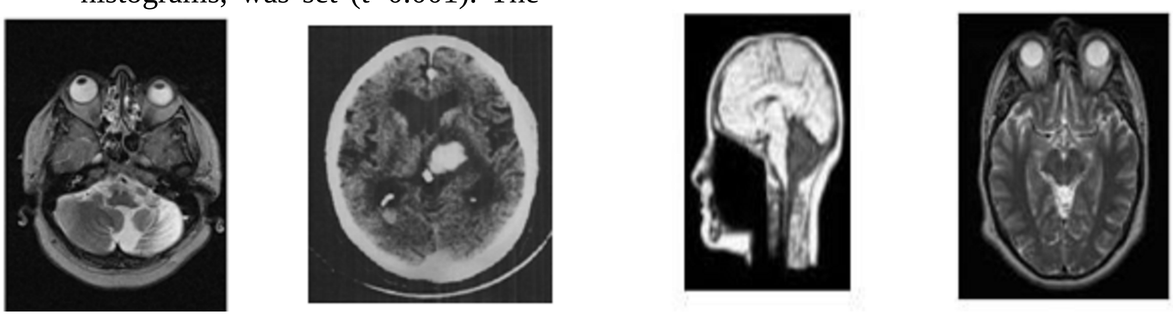

Figure 1 Input Image

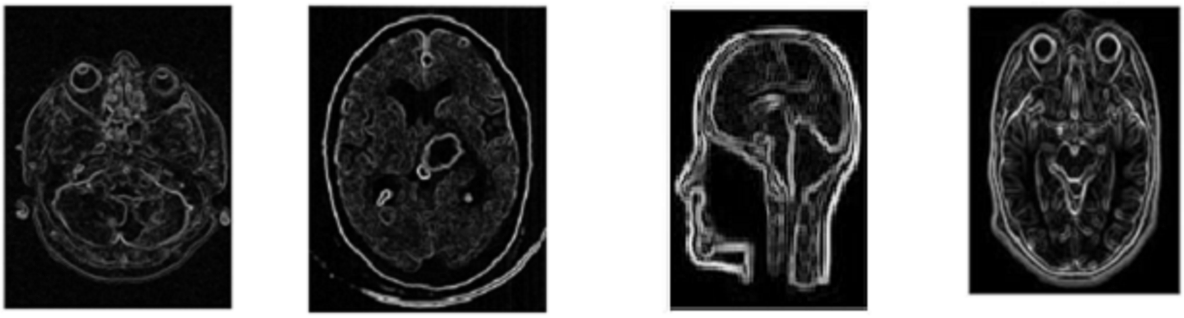

Figure 2 Computing magnitude and edge detection using technique

Segmentation divides image into its constituent regions or objects. Image segmentation techniques can be broadly classified as into five main classes threshold based, Cluster based, Edge based, Region based, Watershed based segmentation.

Segmentation plays an important role in image analysis. The goal of segmentation is to isolate the regions of interest (ROI) depending on the problem and its characters. Many applications of image analysis need to obtain the regions of interest before the analysis can start. Therefore, the need of an efficient segmentation method has always been there. A gray level image consists of two main features, namely region and edge. Segmentation algorithms for gray images are generally based on two basic properties of image intensity values, discontinuity and similarity. In the first category, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principle approaches in the second category are based on partitioning image into regions that are similar according to a set of predefined criteria. Thresholding, region growing and region splitting and merging are examples of the methods in this category.

In this process, the Mammogram image is treated as an array of pixel data. First step of the process is to determine the dimension of the image and determine the middle position of image array. We then take a maximum difference threshold (MDT) value, which is constant threshold determine by observation. We start checking this value with the image data by horizontally scanning from left of the array to the right. If result of any subtraction is greater than the MDT, the array will be divided into two equal subsets along middle position and the first and last positions of the two subsets will be pushed to stack. Otherwise, the mode value of subset will be propagated to all other position after modifying value using uniform colour quantization technique in colour space breaking in sixteen level scales. The process will be continued recursively, popping the start and end position subset array from the stack and repeat the aforesaid process. The process will be continued until the stack is empty. Outputs obtained from the process are shown in Figure 3 (a-g).

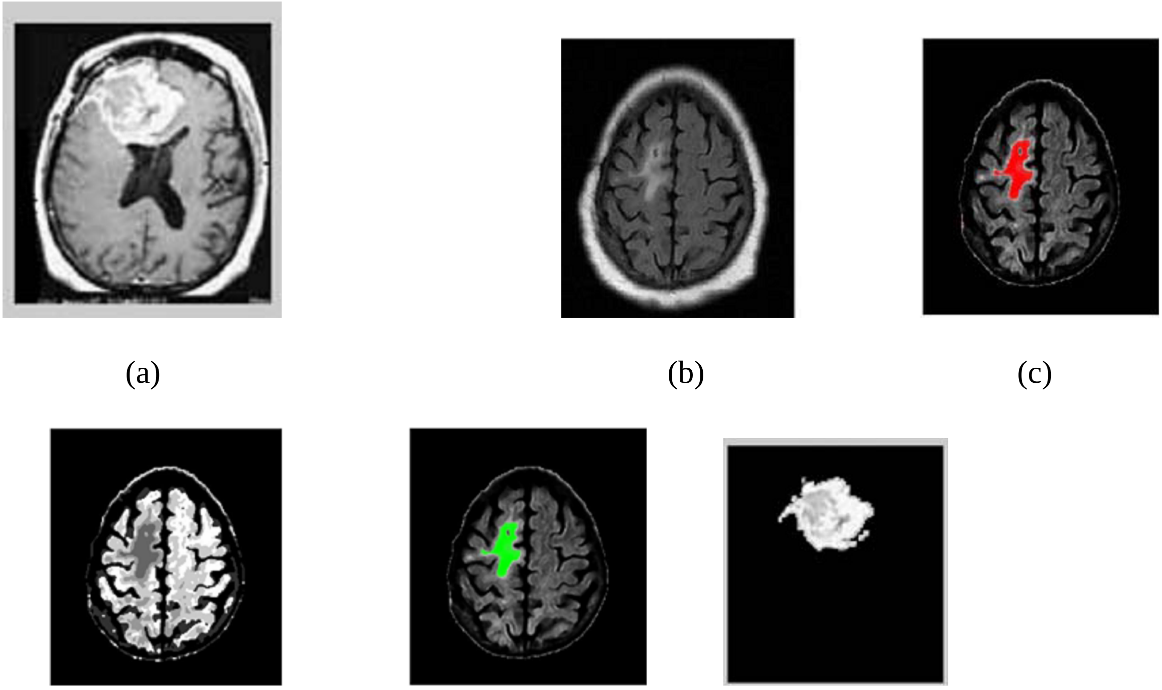

Figure 3(a) Input Image with Noise (b) Segmented Image (c)-(f) Isolated region of Interest

(g) Isolated Tumor

4. Conclusions

In this research paper we have proposed homogeneity enhancement process for brain image. This is followed by edge detection and finally obtaining the boundary by using Border Boundary Enhancement Algorithm. This composite method have been implemented and applied to brain database.

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