An Efficient Tumor Extraction Algorithm using Segmentation of Multimodal Medical Images

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Abstract

A tumor is a mass of tissue that grows out of control of the normal forces that regulates growth. The detection of tumor and its quantitative analysis allows obtaining useful key indicators of disease progression at early stages. Tumor detection using segmentation embraces a significant position in the region of image processing. It becomes more and more significant while dealing with multimodal images such as Magnetic resonance (MR), ultrasonic, Computed Tomography (CT) and X-ray images. This paper presents a well organised technique for automatic tumor segmentation for the extraction of tumor tissues using multimodal MR. The proposed method uses region based and edge based segmentation combined with morphological processing.

Keywords: tumor, segmentation, multimodal images, morphological processing, Magnetic resonance image, Computed tomography

1. Introduction

Brain tumors are abnormal and uncontrolled proliferations of cells. Some originate in the brain itself, in which case they are termed primary. Others spread to this location from somewhere else in the body through metastasis, and are termed secondary. Primary brain tumors do not spread to other body sites, and can be malignant or benign. Secondary brain tumors are always malignant. Both types are potentially disabling and life threatening. Because the space inside the skull is limited, their growth increases intracranial pressure, and may cause edema, reduced blood flow, and displacement, with consequent degeneration, of healthy tissue that controls vital functions.

Brain tumors are the second leading cause of cancer-related deaths in children and young adults. According to the Central Brain Tumor Registry of the United States (CBTRUS), there are 64,530 new cases of primary brain and central nervous system tumors diagnosed by the end of 2011. Overall, more than 600,000 people currently live with the disease. Lot of research is going on for tumor detection and diagnosis using multimodality medical images like CT scan and MRI. Computed tomography (CT) is a diagnostic procedure that uses special X-ray equipment to obtain cross-sectional pictures of the body. The CT computer displays these pictures as detailed images of organs, bones, and other tissues. This procedure is also called CT scanning, computerized tomography, or computerized axial tomography (CAT).

MRI stands for Magnetic Resonance Imaging. An MRI scanner uses a magnetic field and radio waves to build up detailed pictures of various parts of the body by picking up signals sent out by water molecules. Computer systems help with this but no X-rays are used. MRI is an advanced medical imaging technique used to produce high resolution images of the parts contained in the human body and hence MRI are often used in treatment of brain tumor.

The proposed method uses multimodal MRI images to detect and extract tumor using region based segmentation. This method is simulated in two steps 1) Pre-processing step and 2) segmentation step. In pre-processing step images are enhanced to highlight the higher intensity areas and in segmentation steps those areas are segmented and extracted from the image using thresholding and region based and edge based segmentation method.

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2. Literature review

Segmentation is the process where an image is divided into different regions on some similarity bases. Using segmentation we can easily extract different features from the images. Various techniques are developed for tumor detection using segmentation of images. Jichuanshi used Adaptive local thresholding for object segmentation [1]. Gang Li presented improved watershed segmentation with optimal scale based on ordered dither and halftone and mutual information [2]. T. Logeswari et. al. presented implementation of brain tumor detection using segmentation based on soft computing. Segmentation techniques can be combined with artificial neural network to get better results of the segmentation process[3]. P. Vasudha and S. Sathish developed improved Fuzzy C-Means algorithm for MR brain Image segmentation [4]. Hossam M. Moflah et al presented 3D brain segmentation scheme using k-means clustering and connected component labelling algorithms [5]. As all tumor do not have a clear boundary between active and necrotic parts there is need to define a clear boundary between edema and brain tissues. S. Roy and S. K. Bandopadhyay[6] recommend a common automatic scheme for detection and quantification of brain tumors using symmetry analysis. A framework of fuzzy information fusion for segmentation of brain tumor tissues on MR images is given in[7]. New techniques of tumor detection using fractal analysis are the current attraction of many researchers. Khan M. Iftekharuddin presented fractal based tumor detection in multimodal MRI [8] and discussed existing fractal based algorithm and provided improved algorithm for tumor analysis in [9]. Along with the detection of tumor lot of work is being done in the field of tumor classification. Hema Rajini. N. presented automatic classification of MR brain tumor Images using decision Tree [10]. Ahmed et al [11] has proposed a method using genetic algorithm and support vector machine for efficient classification of brain MRI with high sensitivity 98%, specificity 97% and accuracy 98%. In detecting tumors from MRI, mathematical models have been proposed in numerous works [12] that extract necessary features from the images to characterise tumor. MRI images are basically used in the biomedical to detect and visualise finer details in the internal structure of the body[13].Computed tomography is also used in several ways to detect tumor, in biopsy for deciding doses and to help plan radiation therapy[14].

3. Proposed Methodology

Proposed method works in two main steps:
1. Pre-processing
2. Segmentation

Figure 1 shows the flow graph of the proposed method. Each step is described in detail as follows.

3.1. Input Images

Different types of medical images are available for tumor detection and diagnosis. We have applied this algorithm on Multimodality MRI and CT scan images. Image size is restricted to 200 X 200 for making the processing simple. MATLAB is used for simulation of the process.

3.2 Preprocessing

Pre-processing images commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images. Image pre-processing is
3.2.1. Greyscale conversion

In this step acquired colour image is converted to greyscale image by weighted sum of each three (RGB) components, eliminating saturation and retaining luminance. This is achieved by luminosity method of greyscale conversion. The luminosity method is a more sophisticated version of the average method. It also averages the values, but it forms a weighted average to account for human perception. Human eyes more sensitive to green than other colors, so green is weighted most heavily. The formula for luminosity is

\[ I_{\text{grey}} = 0.21 \text{R} + 0.71 \text{G} + 0.07 \text{B}. \]

As the acquired images vary in size, all the images are resized to size 200 x 200 pixels. This makes processing and analysis simpler and takes less time.

3.2.2. Noise removal by filtering

The median filter has been proven to be very useful in many image processing applications. In a median filter, a window slides across the data and the median value of the samples inside the window is chosen to be the output of the filter. This nonlinear filter, compared to linear ones, shows certain advantages: edge preservation and efficient noise attenuation with robustness against impulsive-type noise. Here we used relaxed median filter for the suppression of noise and preserving details of the image. Relaxed median filter works as follows:

Let \( \{X_i\} \) be a M dimensional array, \( i \in \mathbb{Z}^n \). Sliding window \( W \) is a subset of \( \mathbb{Z}^n \) of an odd size \( 2N+1 \).

\( W_i = \{ X_{kn}, r \in W \} \) to be the window located at position \( i \). Let \( X_i \) be input and \( Y_i \) be output at location \( i \). Then \( Y_i = \text{med}\{ W_i \} = \text{med}\{ X_{kn} : r \in W \} \), \text{med}\{\} denotes the median operator. This works as follows: two bounds \( l \) and \( u \) that is lower and upper bound respectively define a sublist inside the [Wi], which contains the grey levels that we assume to be good enough not to be filtered. If the input belongs to the sublist, then it remains unfiltered, otherwise the standard median filter is the output. Relaxed median filter can be defined as follows:

\[
Y_i = \text{med}_{[W]}(X_i) = \begin{cases} 
X_i & \text{if } X_i \in [MDr, MDr] \\
\text{otherwise} & \end{cases}
\]

Where \([W]_{[0]}\) is the median value of the samples inside the window \( W_i \). This filter is very effective in suppressing noise and preserving required details of the image.

3.2.3. Image Enhancement

This step is used to enhance the intensities of the other objects like white matter, gray matter and pathological tissues like tumor after removal of noise. In this step Resized image and Filtered image is added with some grey level value. This grey level value is computed as average of grey level values present in the filtered image. This value may come different for different images based on range of grey level values present in that image. After this Gaussian high pass filter is applied to enhance the boundaries of the objects in the image. This helps to display the finer details of different objects present in the image and separate the tumor from other objects.

3.2.4. Segmentation

Segmentation of MRI image for tumor extraction is achieved in three steps as follows:

1. Thresholding:

   Thresholding is used to convert greyscale image into binary image. The main logic is the selection of threshold value. Threshold computation follows the following steps.

   Make an initial guess at \( t \): set it equal to the median pixel value, that the value for which

   \[
   \sum_{k=0}^{t-1} h_k \geq \frac{n^2}{2} > \sum_{k=0}^{t} h_k
   \]

   Where \( n^2 \) is the number of pixels in the \( n \times n \) image.

   - Calculate the mean pixel value in each category. For values less than \( t \)

   \[
   \mu_1 = \frac{\sum_{k=0}^{t-1} kh_k}{\sum_{k=0}^{t-1} h_k}
   \]

   For values greater than \( t \)

   \[
   \mu_2 = \frac{\sum_{k=t}^{n^2} kh_k}{\sum_{k=t}^{n^2} h_k}
   \]

   - Re-estimate \( t \) using

   \[
   t = \frac{\mu_1 - \mu_2}{2}
   \]

   - Repeat steps 2 and 3 until \( t \) stops changing value between consecutive evaluations.

2. Watershed Transformation:

   Watershed transformation is used to group pixels of an image on the basis of their intensities. Pixels falling under similar intensities are grouped together. This can be achieved by computing local minima of the image gradient or watershed transformation using markers. But these methods may result in over segmentation. Therefore we have used Otsu segmentation.

3. Contour detection and tumor extraction:

   After segmentation is over, tumor tissues are separated and extracted using morphological operators like erosion and dilation. This helps to display only tumor separated from other objects in the image.

4. Experimental Results

   All the simulations are implemented in Matlab 7.0. Multimodality Medical images like MRI (T1 weighted, T2 weighted), CT scan images are used for simulation. Step by step results are obtained and analysed.

   Figure 2 is the input image showing presence of tumor in a paediatric patient. Tumor can be visualised in the image as a high intensity portion. But there are other tissues present in the image.
like white matter, grey matter which can be separated from tumor. Tumor is termed as a pathological tissue.

Figure 3. Pre-processed Image

Figure 3 shows the preprocessed image. Preprocessing follows steps given in block diagram. After preprocessing edges, white matter, grey matter, skull boundaries can be visualised easily. This makes exraction of the tumor simple and easy to analyse.

Figure 4. Histogram of Pre-processed Image

Figure 4 Shows histogram of the pre-processed image. This histogram is required to set the threshold for segmentation process. Histogram represents pixel value of the individual pixel in an image. Above histogram represents pixels representing tumor has values from 205 to 255. With the help of thresholding we can separate background and different objects. This helps us in tumor extraction process. Threshold value can differ for different type’s images.

Figure 5(a). Threshold segmentation, Figure 5(b). Watershed Transformation

Figure 5(a) shows the results of threshold segmentation. From the image we can easily interprete different objects of the image. Tumor is also shown with sharp edges. Background is separated from the objects.

Figure 5(b) shows the watershed transformed image. Here high intensity portion, which we refer as tumor is highlighted clearly. Comparison of thresholding image and watershed transformed image, we can analyse that same portion is highlighted which we have interpreted as tumor from histogram processing. This step is very useful to extract pixels representing tumor.

Figure 6. Extracted tumor shown as white portion

Figure 6 shows the extracted tumor. Background and other objects are suppressed using morphological operators like erosion and dilation and only tumor is highlighted as white portion. Comparison of figure 4(a), figure 4(b) and figure 5 proves that same portion is extracted as tumor. This helps in proper diagnosis and treatment of cancer patients.

5. Conclusions and Future Work

Proposed segmentation technique was experimented with multimodal MRI images and it is observed that it works well for all types of MRI images. This method gives efficient results of tumor extraction. We can visualise exact location and size of the tumor in very less time and this will be helpful for the detection and diagnosis of tumor. Our future work is to extend the proposed method for 3D images and also other medical imaging modalities. After extraction of tumor, faster methods can be developed to evaluate tumor size, distance from skull boundaries, classification of tumor, area occupied by the tumor inside skull which will be helpful for the complete treatment of the cancer caused by brain tumor.

References