MEDICAL IMAGE SEGMENTATION METHODS FOR SKULL STRIPPING FROM MRI OF HUMAN BRAIN SCANS

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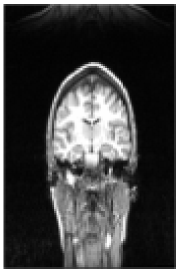
ABSTRACT

Human brain plays an important role in the functions of human body. Any defects and abnormalities in the human brain lead to major problems in the functions of the human body. Such defects can be identified by taking images of the affected tissues using different imaging modalities. In this paper, we present the image processing techniques which are used to remove skull from the MRI of human brain scans. When the skull is removed, the physicians can easily interpret the brain tissues and identify defects. It is helpful to diagnose a disease and control its progression.

Keywords - Human brain; MRI; image processing; diagnosis;

I. INTRODUCTION

Medical image processing comprises image capturing, filtering, enhancement, registration, segmentation, compression etc. The aim of medical image processing is to help the physician take a decision about the nature of the disease that affects human organs. So, the identification of affected locations called region of interest (ROI) is needed for all the MR images. The imaging technique called magnetic resonance imaging (MRI) is recommended for brain related disorders. This is because the MRI of brain and other tissue structures are clearer, accurate and more detailed when compared to all other imaging methods. This detailed information makes MRI an efficient tool in early diagnosis and evaluation of many conditions like Alzheimer's disease and tumors. Fig. 1 shows the sample MRI of human brain scans.



(a) T1W coronal

(b) T2W axial and

(c) T2W sagittal images

Fig. 1. MRI of human brain scans .

In MRI technique, the image is captured in three orientations such as coronal, axial and sagittal as shown in Fig.1. In coronal type the image is scanned from back head to fore head. For sagittal, the image is obtained by scanning from one ear moving to the second ear. The axial type of image is produced by scanning from the chin moving to the top of head.

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II. NEEDS OF BRAIN SEGMENTATION

The segmentation of brain image is a major clinical image processing technique for rapid diagnosis. When the image of the human brain is produced by the imaging technique, the doctors try to analyze the features of an image like the intensity of a tissue, sub-images, edges of a particular structure and the shapes. From this information, the physician finds the location of defects/abnormality/injury/tumor etc. made to the brain tissues. In such cases, the images produced by the MRI are more detailed and accurate compared to the images generated by x-rays. Sometimes, there is a situation where the brain images need to be stored and made available in the same machine or a remote machine through a network. So, image segmentation of human brain is needed.

A. Manual Segmentation

The segmentation of human brain is performed manually [1] by the doctors. The manual segmentation is done by drawing a boundary on a ROI by hand. But it leads to segmentation errors most of the time and becomes slow [2] and is operator-biased. Also, it is labor intensive because of the huge number of images generated while scanning. To overcome the drawback of manual segmentation, semi-automatic techniques are developed.

B. Semi-automatic segmentation

The physicians are in need of accurate segmentation of anatomical structures of brain for an early diagnosis. In order to increase the speed of brain segmentation from the magnetic resonance images, semi-automatic techniques are proposed. For the semi-automatic methods, the input is given manually such as selection of seed point in the image, region of interest (ROI) and initial parameters like the co-ordinate values of the image. Using these inputs, the method starts processing. The semi-automatic segmentation methods are the conventionally used techniques in the field of medical image segmentation, since they reduce the processing time.

In [3], Dubey proposed a technique to segment tumor-affected tissues from MRI. In this method, the intensity based classification of voxel is used to separate the image into two classes such as tumor and background.

The segmentation is done by using morphological operations such as erosion in [4]. In this method, a disk shaped structuring element (SE) is applied. This SE differentiates between brain and non-brain tissues. Then the binary image is produced using intensity adjustment. The connected component analysis is used to get a labeled image.

The drawbacks of semi-automatic methods are that this technique needs human intervention. Also, the seed selection should be accurate; otherwise, it produces unexpected outputs.

C. Fully-automatic segmentation

To eliminate the human intervention, the fully automatic techniques have been developed.

The fully automatic method is proposed by Badran [5] in which basic image processing techniques such as morphological operations and region filling are applied. The ROI feature is generated before the techniques are applied. For experimentation, T1W sagittal images are used. This technique extracts the cerebellum, corpus callosum as well as brain portion.

Another automatic method developed has been by Brummer [6] using histogram based thresholding. The morphological operation is applied to refine the edges of an input image. After the refinement, the wanted and unwanted portions are highlighted. This method is implemented for two-dimensional and three-dimensional morphological operations.

The level set method is used by Baillard [7] to segment brain from MRI of human brain scans. The level set is integrated with 3D registration process. The adaptive parameters are set for level set propagation.

III. BASIC IMAGE PROCESSING TECHNIQUES

A. K-Means (KM) algorithm

Segmentation can also be done using clustering technique. Clustering techniques are divided into two types, namely supervised and unsupervised [8]. Supervised methods require user interaction and thus known as semi-automatic. Unsupervised techniques are completely automatic. The popular unsupervised classification techniques are K-Mean (KM), fuzzy C-means (FCM) and expectation maximization (EM) methods. The K-Mean clustering is a hard segmentation and also an unsupervised algorithm that generates a sharp classification. It may or may not assign each pixel to a class.

This algorithm consists of the following steps with a data set xi, i=1,2,..n.

Step 1: Input the number of clusters required (k)

Step 2: Initialize the centroids cj, j=1,2,..k

Step 3 : Assign each data point to the group that has the closest Centroid, using the objective function

$$J = \sum_{j=1}^{k} \sum_{i-1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (1)$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is a measure of intensity distance between a data point xi and the cluster center cj. For simplicity, the Euclidean distance is used as the dissimilarity measure.

Step 4: When all points have been assigned, calculate the positions of the k centroids.

Step 5: Repeat Steps 2 and 3 until the centroids no longer move. This produces a separation of the data points into k groups from which the metric to be minimized can be calculated.

B. Conservative Smoothing

Conservative smoothing is a simple, fast filtering algorithm that suppresses noise in an image [9]. The conservative smoothing (CS) finds the minimum and maximum intensity values of pixels in a windowed region (3x3). If the intensity of a central pixel is greater than the maximum value, it is set to the maximum value, and if the central pixel intensity is less than the minimum value, it is set to the minimum value. The output pixel will remain unchanged if the central pixel lies within the intensity range (minimum < xc < maximum). The algorithm of CS is given as:

Step 1: Consider a mask of size 3x3

Step 2: Arrange the pixel values (excluding center pixel) in the mask in ascending order.

Step 3: Find the maximum (max) and minimum (min) values from the list.

Step 4: Apply smoothing as:

$$xc = \begin{cases} \text{max, if } x_c > \text{max} \\ \text{min, if } x_c < \text{min} \\ xc \quad \text{otherwise.} \end{cases} \qquad (2)$$

where, xc is the center pixel in the mask.

C. Largest Connected Component (LCC)

The run length identification scheme for region labeling described by Sonka et al. [10] is used to find the LCC among the regions as:

RLCC=R(arg MAX RA(i)) (3)

where, the area RA(i) of ith region R(i) is the total number of pixels in that region.

IV. CONCLUSION

In this paper, we have discussed the importance of medical image segmentation. The segmentation can be done in three ways such as manual, semi-automatic and fully automatic methods. Every method has its own advantages and drawbacks. The method that works well for the particular dataset may not provide good results for another type of images. This is one of the drawbacks of the fully automatic method. The clustering technique is the commonly used technique for medical image segmentation. This method plays an important role in differentiating between tissues of various organs.

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