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Brain Tumour Detection for Digital Images

Rahil Malhotra[1]
Research Scholar,
Department of Computer Science,
Chandigarh Engineering College, Landran, India

Madhu Bahl[2], **Harsimran Kaur**[3]
Assistant Professor,
Department of Computer Science,
Chandigarh Engineering College, Landran, India

Abstract— ***Segmentation is the process to segregate the portion in digital image process. Brain tumor is one of the common diseases which are treated in medical science. Detection of brain tumor in early stages can enhance the prevention mechanism to stronger level. Detection of brain tumor from digital image processing techniques is one of the most essential parts for work. In our research we will work on segmentation of brain tumor area for digital images. The detection of brain tumor has been done with Magnetic resonance imaging (MRI) process by doctors. We will proceed with quantization process for images and will focus on clustering process of different detecting areas of the brain and finally with ROI technique we will detect the brain tumor and image will reflect the segregated portion of brain tumor.***

Keywords— ***Segmentation, Image Processing, Tumor Detection, Quantization Process, Magnetic Resonance Imaging, Clustering, Noise Removal, Edge Detection***

I. INTRODUCTION

In image analysis, segmentation is the partitioning of a digital image into multiple regions (sets of pixels), according to some homogeneity criterion. The problem of segmentation is a well-studied one in literature and there are a wide variety of approaches that are used. Different approaches are suited to different types of images and the quality of output of a particular algorithm is difficult to measure quantitatively due to the fact that there may be much "correct" segmentation for a single image. The segmentation of brain tumor from magnetic resonance (MR) images is a vital process for treatment planning, monitoring of therapy, examining efficacy of radiation and drug treatments, and studying the differences of healthy subjects and subjects with tumor [6]. The process of automatically extracting tumors from MR images is a challenging process. This leads to many different approaches for automatic tumor segmentation. The usual standard used for validating segmentation results of the automatic methods is the manual segmentation results done by human experts. However, different investigators are likely to employ different image acquisition parameters and different manual segmentation techniques. A compounding issue is that any manual segmentation method suffers from lack of reliability and reproducibility [11]. Even if a rich set of manual segmentations are available, they may not reflect the ground truth and the true gold standard may need to be estimated. Furthermore, validation is typically not performed for the segmentations of non-tumor structures since manual segmentations of edema and the healthy brain tissue are very challenging tasks and have a high degree of variability. In order to provide objective assessments of segmentation performance, there is a need for an objective 3D ground truth with associated MR images that exhibit the same major segmentation challenges as that of common, realistic scans of a tumor patient. A database of real brain tumor MR images, along with their segmentations, may provide the means to measure the performance of an algorithm by comparing the results against the variability of the expert raters' judgments. However, an objective evaluation to systematically compare different methodologies also needs a ground truth with little or no variability [12]. An example of such a ground truth is the synthetic brain MRI database provided by the Montreal Neurological Institute that is currently considered to be the common standard for evaluating the segmentations of healthy brain MR images. For this purpose, we propose a method that generates realistic looking MR images with the associated ground truth by approximating the brain tumor generation process. Depending on the image acquisition model, images can be classified into various types; namely light intensity (visual) images, range or depth images, magnetic resonance images, thermal images and so on. Light intensity images represent the variation of light intensity on the scene and are the most common types of images we encounter in our daily experience [13]. A Range image is a map of depth information at different points on the scene. Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous.

II. MAGNETIC RESONANCE IMAGING

This technique of MRI has dependence over relaxation properties of magnetically-excited hydrogen nuclei of water molecules in the body. A brief exposure of radio-frequency energy burst is given to patient, which increase the energy and put nuclei in elevated state in the presence of a magnetic field. During the normal microscopic whirling of molecules the process of relaxation takes place which includes releasing of energy to surroundings [9]. Tissues are distinguished on the basis of relaxation rates and from this process, images are created. Initially this technique was known as nuclear magnetic resonance (NMR) but to avoid any association with nuclear radiation the term "nuclear" was removed [10]. MRI employs strong magnetic fields and non-ionizing radiation in the range of radio frequency, which is harmless to patients according to current medical knowledge. MRI is advantageous in creating better soft tissue contrast than X-rays which leads to production of high quality images, mainly in brain and spinal cord scans [4]. Improvements in the form of functional MRI (fMRI) and diffusion MRI have been developed that measures temporal variations (e.g., for detection of neural activity) and the diffusion of water molecules in anisotropic tissues such as white matter in the brain respectively [6]. Fast MRI techniques are proved to be great interest in a number of application areas including perfusion imaging based on Arterial Spin-Labeling (ASL) or Dynamic Susceptibility Contrast (DSC), functional neuroimaging (fMRI) and Diffusion Tensor imaging (DTI) [8].

III. VARIOUS SEGMENTATION TECHNIQUES

There are many segmentation techniques which are useful in finding segregated area in an image. Following are the techniques available for segmentation process.

A. Threshold Techniques

Make decisions based on local pixel information and are effective when the intensity levels of the objects fall squarely outside the range of levels in the background. Because spatial information is ignored, however, blurred region boundaries can create havoc [5].

B. Edge Based Method

The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world. It can be shown that under rather general assumptions for an image formation model, discontinuities in image brightness [5] are likely to correspond to:

- Discontinuities in depth,
- Discontinuities in surface orientation,
- Changes in material properties and
- Variations in scene illumination

C. Region Based Methods

The image is partitioned into connected regions by grouping neighboring pixels of similar intensity levels. Adjacent regions are then merged under some criterion involving perhaps homogeneity or sharpness of region boundaries. Over stringent criteria create fragmentation; lenient ones overlook blurred boundaries and over merge [14].

D. Clustering Method

Clustering groups data instances into subsets in such a manner that similar instances are grouped together, while different instances belong to different groups. Usually referred to as the active contour model, starts with some initial boundary shape represented in the form of spline curves, and iteratively modifies it by applying various shrink/expansion operations according to some energy function. Although the energy-minimizing model is not new, coupling it with the maintenance of an "elastic" contour model gives it an interesting new twist. As usual with such methods, getting trapped into a local minimum is a risk against which one must guard; this is no easy task.

IV. MERGING TECHNIQUES

There are many merging methods of segmentation process which are useful in finding segregated area in an image. Following are the techniques available for merging process of segmentation.

A. Region Growing

Many merging methods of segmentation use a method called region growing to merge adjacent single pixel segments into one segment. Region growing needs a set of starting pixels13 called seeds. The region growing process consists of picking a seed from the set, investigating all 4-connected neighbors of this seed, and merging suitable neighbors to the seed [15]. The seed is then removed from the seed set, and all merged neighbors are added to the seed set. The region growing process continues until the seed set is empty.

B. Region Merging

In this section, we will assume we have the 'larger size' segments as meant above available, but we still have an over segmentation of the image, so we still need to do region merging to obtain a proper segmentation. Such an over segmentation can, e.g., be obtained by:

- Watershed segmentation, or
- Multiple thresholding– followed by a labelling step,
- Using implicit snakes (with segments defined by the contours on the bottom right), or
- Series of region growing –with, say, using the grey value range criterion– with (0,0)as the first seed, and subsequent seeds picked from the unsegmented image parts until no pixels remain unsegmented, or
- Anything else you can think of.

The over segmentation can be reduced to a better segmentation by merging adjacent segments. A merging of two adjacent segments can be achieved by removing their common boundary.

C. Splitting and Split & Merge Methods

Where region merging is an agglomerative approach, region splitting is divise. We mentioned before that this difference makes that the two approaches are not opposites, but fundamentally different problems; the merging of two segments is straightforward, but the splitting of a segment requires that suitable sub-segments are established to split the original segment into. The problem of how to split a segment is of course itself a segmentation problem, and we can treat it as such: any segmentation method can be applied to the segment to establish sub-segments. Besides the hierarchical level, there is no intrinsic difference. The problem of how to decide if a segment need splitting can be solved using the same measures of region homogeneity mentioned in the section on region merging, e.g., a segment needs to be split if

- The grey value variance exceeds a threshold, or
- The variance of a texture measure exceeds a threshold, or
- The histogram entropy (or another histogram measure) exceeds a threshold, or
- High Edgeness pixels are present.

When a segment needs splitting, a faster approach than starting segmentation on the segment is to simply split it into four quadrants [16].

D. Binary Tree Quantization

Orchard and Bauman proposed in a divisive palette generation algorithm, which uses a local optimization strategy in selecting the splitting axis [14]. Previous splitting algorithms were limited to select splitting axis from one of the RGB coordinates [14]. Partition to be split is selected to be the one, which has largest distortion [14]. This can be approximated, by the largest eigenvalue of the covariance matrix of the vectors in that partition [14]. In Orchard's method, partition with the largest eigen value is chosen to be split. Idea in Orchards method is to find the splitting axis in such a way that minimizes the distortion. Intuitively such an axis is the direction or largest variance of that partition. This axis can be found with principal component analysis and it is called the principal axis or the eigenvector corresponding to the largest eigenvalue [14]. Cut-point is selected to be the projection of the centroid to the principal axis [14]. Problem with their method is that it assumes that best cut-point point is the projection of mean vector. The best case can happen, when two clusters are perfectly divided by that plane. It is easy to construct a counter example where that does not hold. For example, where splitting plane is orthogonal to principal axis and is going through the centroid. Centroid is taken as cut-point is clearly sub-optimal in this case.

V. PROBLEM DEFINITION

In base paper, authors proposed a clustering approach which is used for biomedical area. In particular, it is focused on MRI brain image segmentation process with modified fuzzy clustering. This work has not considered the noise removal and can be have better segmentation based on quantization. In our research we will focus on finding the brain tumor detection with help of binary tree quantization process with different clusters formation. Segmented image will detect the brain tumor.

VI. OBJECTIVES

To fulfill our require experimentation we will have following objectives

- To find the solution for detection of brain tumor.
- To provide optimized solution for highlighting the affected area of brain with segmentation in color images.

VII. METHODOLOGY

In our research, we will also focus on similar line of implementation by finding and segregating the area of images which have tumor in it. First of all, we will fetch database of color images which have brain tumor in it. These images are process for noise removal for more accuracy by median filters. Further these images will be process with binary tree based quantization clustering process. This process will provide us the clusters to work on. Normally it distributes three clusters into shape. These clusters are process with ROI (reason of interest) technique to find the exact area to highlight and in our research case, it is tumor in brain. Finally segmentation process will be used to make it distinguish from other parts of the brain. The process by which the clusters would be formed can be explained by

C ((x, - 4,)' el2 = e'R,,e

Since R is symmetric, the solution is the eigenvector e, corresponding to the largest or principal eigenvector X, of R. The total squared variation in the direction e, is therefore Once the principal eigenvector has been determined, points in C, can be sorted into two sets C2, and C2, + I in the following way:

C2, = {s E C,: eix, I eiq,}

C2n+l = {s E C,: etx, > eiq,}.

Finally, the new statistics for each node may be calculated by first calculating R2,, m2,, and N2, for node 2n, and then applying the relations .

For calculation of various parameters like PSNR value and MSE value the following equations would be used:

MSE=(double(input)-double(Compressed)) .^ 2
PSNR Value = 10 * log10(256^2 / MSE)

The flow diagram of the research is given below in figure below.

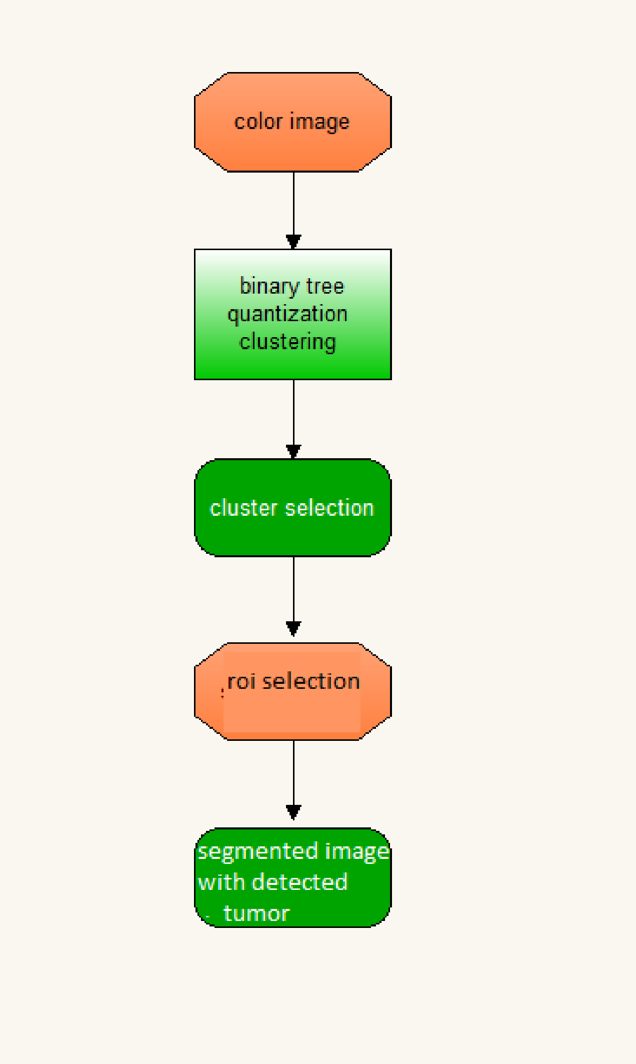

Figure 1: Flow for the Research

VIII. CONCLUSION

This Research is our continuous study and we will find the better results in highlighting the tumor in the segmented portion. In this paper we have studied various techniques for merging and segmentation process in the image processing for tumor detection. This Research is still in process and experimentation in running phase to test the proposed work.

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