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3D DIGITAL RECONSTRUCTION OF BRAIN TUMOR FROM MRI SCANS USING DELAUNAY TRIANGULATION AND PATCHES

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ABSTRACT

In this paper we present two approaches to reconstruct 3D shapes of brain tumours from MRI images. The first approach is reconstruction of 3D images from set of 2D segmented slices of MRI brain by using thresholding and morphological operations; contour plot and patches. The second approach is a better one where in we reconstruct a tumour by using same segmentation process and altering the 3D reconstruction algorithm that uses sobel operator, boundary extraction, Delaunay triangulation and alpha shapes. The volume to area ratio of the tumour and the distance between points on head and the points on tumour is estimated. Delaunay Triangulation affords distinct advantages, such as: its ability to describe the surface at different levels of resolution, efficiency in storing data, ease of storage and manipulation, easy integration with raster databases, smoother, more natural appearance of derived terrain features. However, we also encounter a few disadvantages such as: in many cases it requires visual inspection and manual control of the network, various grid sizes cannot be used to reflect areas of different complexity of relief.

Keywords: brain tumour, magnetic resonance (MR) image segmentation, 3D reconstruction, contours based Delaunay triangulatio**n.**

1. INTRODUCTION

The 3D reconstruction of the tumour from medical images is an important operation in the medical field as it helps the radiologist in the diagnosis, surgical planning and biological research. To properly diagnose and treat cancer, an oncologist needs to know the following tumour characteristics: specific type, dimensions, location, internal organs affected, cancer stage, appearance, growth rate, etc. Accurate estimation of these parameters allows an oncologist to estimate the operability of the tumour and the prognosis of the patient [5].

A primary brain tumour originates in the brain; it may either be cancerous or benign. Benign tumours are not aggressive and generally they don't spread to the surrounding tissues, but they can be life threatening. Children who receive radiation to the head have a higher risk of developing a brain tumour as compared to adults. People who have certain rare genetic conditions such as neurofibromatosis or Li-Fraumeni syndrome also carry a higher risk of developing a brain tumour when their head is irradiated. Genetic factors account for a fraction of the approximately 35,000 new primary brain tumours diagnosed each year. Age is also a risk factor: people over the age of 65 are diagnosed with brain cancer at a rate four times higher than young people [5].

Recent Developments in MRI include 2D Fast Spin-Echo Imaging, Driven Equilibrium Fourier Transform Imaging, Balanced SSFP Imaging, Vastly Interpolated Projection Reconstruction Imaging, 3D FSE Imaging, High-Field MRI, Cartilage Thickness and Volume Mapping. Brain tumour image processing, segmentation, feature extraction, classification, 3D modelling, and Volumetric analysis have been reviewed by A.Sakthi Bharati*et al*. [13].

2. PROPOSED METHODOLOGY

The objective of this work is to implement an algorithm which gives better 3D reconstruction of brain tumours of MRI images. The main task of 3D reconstruction of the tumour from a set of 2D parallel cross sectional images is divided into several subtasks as shown in Figure-1. The main techniques followed in this work are:

- Segmentation of the desired object from MRI scans with Sobel Operator and morphological operations.
- Reconstruction of the 3-D model with Delaunay's triangulation
- Visualizing the resulting model using triangular surface

VOL. 10, NO 20, NOVEMBER, 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

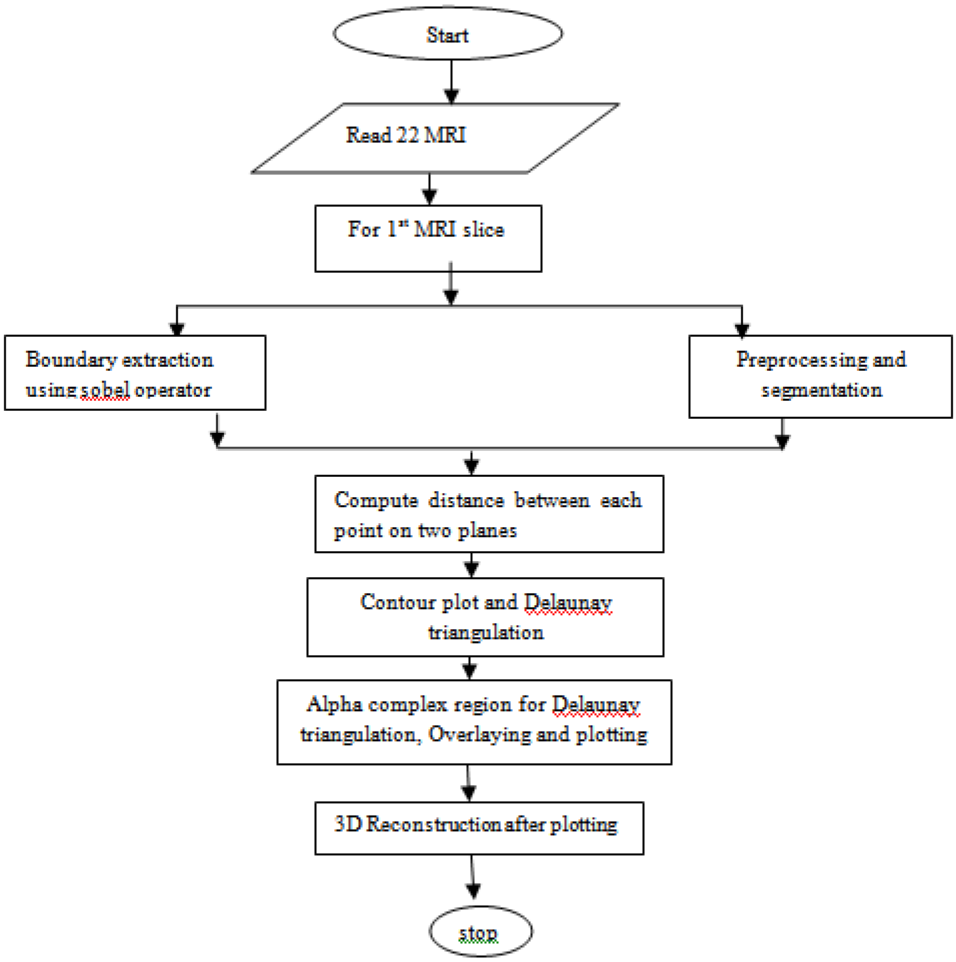

Figure-1. Flowchart of the proposed 3D tumour reconstruction approach.

2.1 Reconstruction of Head Model

The reconstruction of head is identification of the head's edges in the sample images. 18 images have been considered in this work. Edges are places in the image with strong intensity contrast. Since edges often occur at image locations representing object boundaries, edge detection is extensively used in image segmentation when the intent is to divide the image into areas corresponding to different objects. Representing an image by its edges has the further advantage that the amount of data is reduced significantly while retaining most of the image information. Detect edges by convolving the image with an appropriate kernel in the spatial domain. This involves boundary tracing and sobel edge detection as shown in Figure-2.

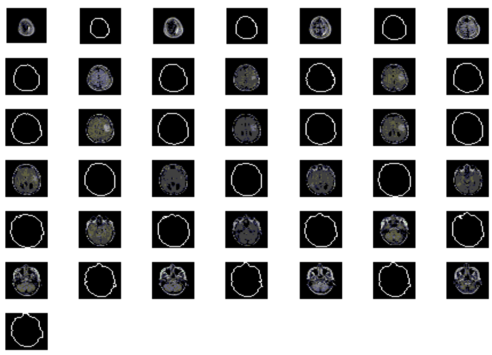

Figure-2. Boundary extraction of sample images.

2.2 Pre-processing and Segmentation

Noise can mask and blur the important features in an MR image and thus make the subsequent steps in image analysis difficult. In this work, noise has been eliminated from the MR images by applying 3×3 median filter resulting in the smoothening of edges in the image. To improve the perceptibility of the tumour and other

VOL. 10, NO 20, NOVEMBER, 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

structures in the brain, blunt masking was used after median filtering. A 3×3 blunt filter was constructed using the negative of the 2D Laplacian filter. The sizes of filters were chosen empirically. Image contrast was enhanced by applying histogram equalization. As the analysis has to be performed on brain region, the skull region was eliminated from each MR image of the brain by converting original MR image to a binary image and retaining only the pixels in the largest connected component which corresponds to the brain region.

2.3 Mathematical Morphology

Mathematical morphology offers a wide range of operators which may be used in image processing. These operators, which have their basis in set theory, are particularly useful for the analysis of binary images. They are generally used in edge detection, noise removal, image enhancement and image segmentation. The two most basic operations in mathematical morphology are erosion and dilation. Both of these operators take two pieces of data as input: an image to be eroded or dilated, and a structuring element (also known as a kernel).

Erosion and dilation are essentials in the morphological process; in fact most morphological operations are based on these operations. Erosion with A and B assets in Z2, where every element of Z2 is a set of ordered pairs (2D vector) with coordinates (x, y), the erosion of A by B, denoted AΘB, is defined as:

$$A\Theta B = \{z \mid (B)z \subseteq A\}$$

That is, the erosion of A by B. This is the set of all points z such that B translated by z is contained in A. It is assumed that B is the structural element.

Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbours in the input image. The rule used to process the pixels defines the operation as to be either dilation or erosion. Figures 3 and 4 shows the result of segmentation.

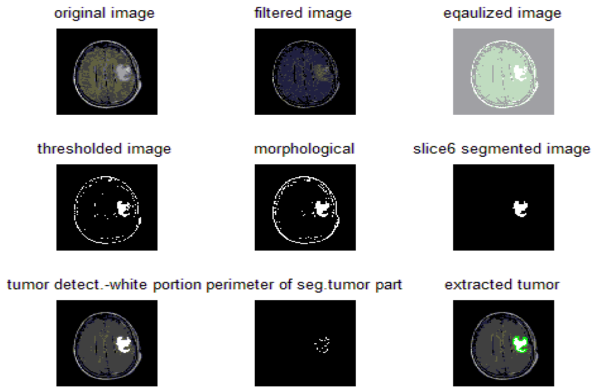

Figure-3. Segmentation of sample image.

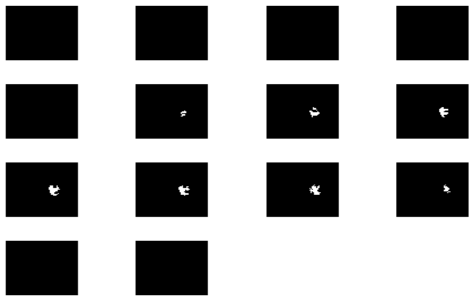

Figure-4. Tumor extraction by segmentation process.

2.31. Superimposition

The process of 3Dreconstruction for the description of the tumour-occupied region and boundaries of human head is taken under consideration. Calculate the contour plot of the matrix Z using vectors x and y to control the scaling on the x and axes. Contours are the outline of the object; a function *f* considered in terms of relation$\triangleright$, reference to the contour sets of the function is implicitly to the contour sets of the implied relation, $(a \succcurlyeq b) \Leftarrow [f(a) \triangleright f(b)]$Once the series of images have been segmented, the contours are superimposed in 3*D*; these contours are shown in Figures 5 and 6.

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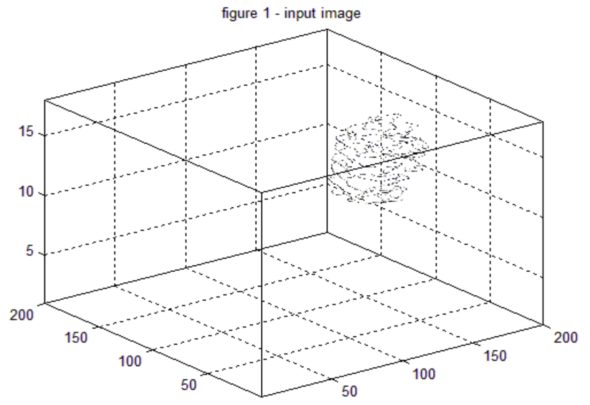

Figure-5. Superimposition of 3D contours of segmented slices.

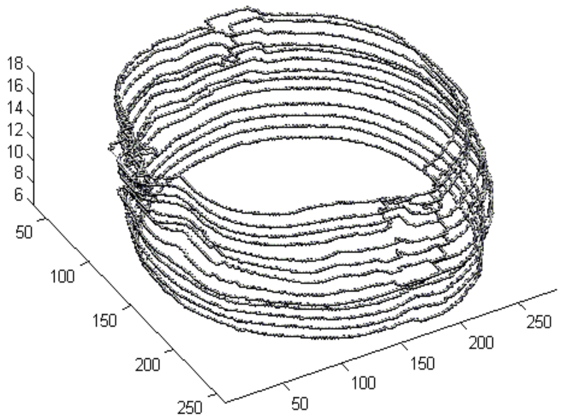

Figure-6. Superimposition of 3D contours of boundaries of sample slices.

3. 3D RECONSTRUCTION ALGORITHM-METHODOLOGY

We include herewith a comparison between two 3D reconstruction algorithms namely stacking algorithm of 2D segmented slices and reconstruction using Delaunay triangulation and patches.

3.1 Stacking algorithm

Stacking algorithm is overlaying the individual segmented 2D slices one on top of the other. A patch graphics object is composed of one or more polygons that may or may not be connected. This can be defined by specifying the coordinates of its vertices and some form of colour data. Patches support a variety of colouring options that are useful for visualizing the data superimposed on geometric shapes [7]. There are two ways to specify a patch:

- By specifying the coordinates of the vertices of each polygon, which will be connected to form the patch.
- By specifying the coordinates of each unique vertex and matrix that specifies how to connect these vertices.

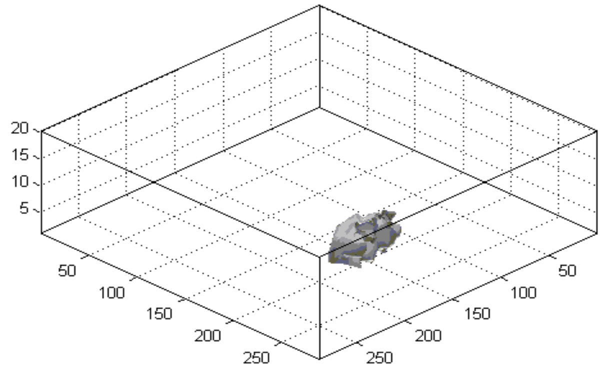

Figure-7. 3D Visualizing using stacking.

3.2 Delaunay triangulation and alpha shapes

The points on the boundary are used to build up a 3D set of points ("point cloud"), which allows generating a tetrahedral mesh as shown in Figure 9 & 10 using Delaunay Triangulation result shown in fig.7 & 8. Delaunay triangulation for a set P of points in a plane is a triangulationDT (P) such that no point in P is inside the circumcircle of any triangle in DT (P). Delaunay triangulations maximize the minimum angle of all the angles of the triangles in the triangulation; they tend to avoid skinny triangles. Properties of DT in region are as follows [8].

Let *n* be the number of points and *d* the number of dimensions.

- The union of all simplices in the triangulation is the convex hull of the points. The Delaunay triangulation contains O (n⌈d / 2⌉) simplices.
- In the plane (d = 2), if there are b vertices on the convex hull, then any triangulation of the points has at most 2n − 2 − b triangles, plus one exterior face (see Euler characteristic). In the plane, each vertex has on an average, six surrounding triangles.
- In the plane, the Delaunay triangulation maximizes the minimum angle. Compared to any other triangulation of the points, the smallest angle in the Delaunay triangulation is at least as large as the smallest angle in any other.
- A circle circumscribing any Delaunay triangle does not contain any other input points in its interior. If a circle passing through two of the input points doesn't contain any other of them in its interior, then the segment connecting the two points is an edge of a Delaunay triangulation of the given points.
- Each triangle of the Delaunay triangulation of a set of points in d-dimensional spaces corresponds to a facet

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ARPN Journal of Engineering and Applied Sciences

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of convex hull of the projection of the points onto a (d + 1)-dimensional paraboloid, and vice versa.

- The closest neighbour b to any point p is on an edge bp in the Delaunay triangulation since the nearest neighbour graph is a sub graph of the Delaunay triangulation.
- The Delaunay triangulation is geometric spanner: the shortest path between two vertices, along Delaunay edges, is known to be no longer than $\frac{4\pi}{3\sqrt{3}} = 2.418$ times the Euclidean distance between them.

4. RESULTS

The following diagrams show the head, tumour when together and when separated.

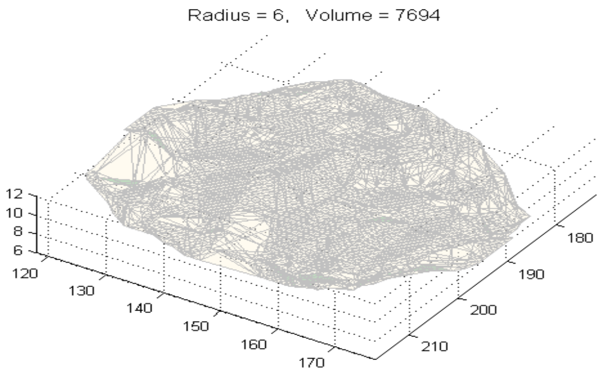

Figure-8. 3D Reconstruction of tumour using Delaunay triangulation.

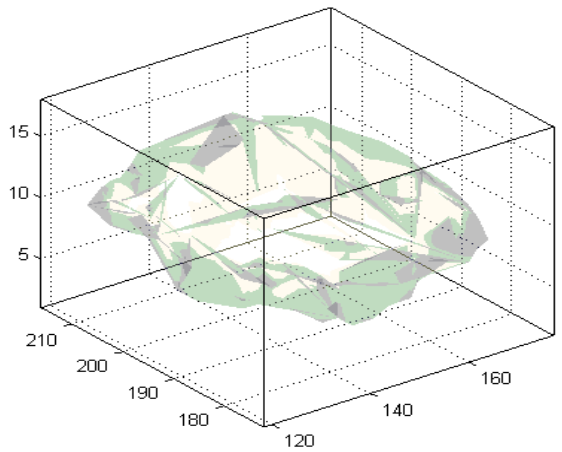

Figure-9. 3D Representation of tumor.

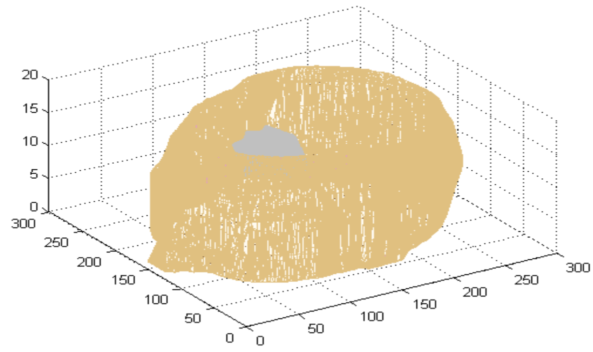

Figure-10. 3D Reconstruction of tumour with human head using Delaunay Triangulation.

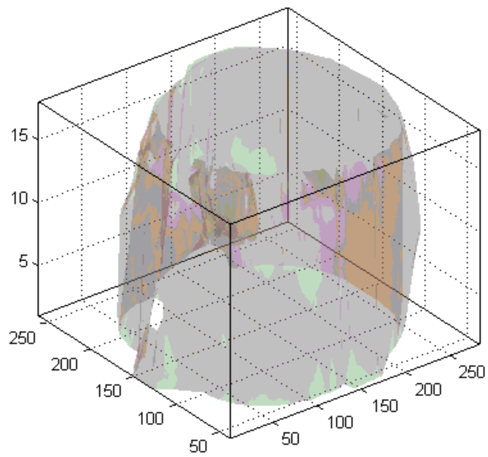

Figure-11. 3D Representation of tumour with head.

5. CONCLUSIONS

In this paper we have proposed a novel method for 3D reconstruction. The method mainly includes Delaunay triangulation alpha shapes and patches; the first approach used is the 3d reconstruction from its 2d contours using a sequence of 2d contours, detected by Segmentation process. The second approach improves the segmentation quality and the 3D reconstruction of the tumor by determining the volume area ratio and distance between points on head and the points on tumour.

This method will help to find the exact location of the tumour and the size of the tumour which will be of help to the oncologist to make objective decisions about diagnostics and treatment of the condition [6].

Future work

Future work on the lines of the present work may include finding the characterization of brain tumour growth, i.e. growth rate of the tumour and tumour characterization. This work can be extended to various parts of the body like throat, pelvis and lungs for identifying cancer [1].

ARPN Journal of Engineering and Applied Sciences

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