International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 3, Issue 9, September 2014

3D Reconstruction of Brain Tumor from 2D MRI's using FCM and Marching cubes

Chethan kumar, Anitha kumari R D

Abstract— **Brain Tumor is an abnormal mass of tissue found in Brain. Some techniques like MRI and CT generate 2D images of internal parts of the body. As two dimensional images never give the actual feel of how a tumor exactly looks like, 3D reconstruction of the tumor is necessary for diagnosis, surgical planning and biological research. Diversity and complexity of the tumors makes it very challenging to visualize tumor in MRI. 3D image reconstruction is one of the most attractive avenues in digital signal processing especially due to its application in biomedical imaging. Work presents an efficient and effective approach to 3D reconstruction. It involves implementation of various steps like image pre-processing, image segmentation by FCM, Mesh generation by marching cubes algorithm and finally rendering to add realistic effects.**

Index Terms— **Brain tumor, Magnetic resonance imaging (MRI), 3D reconstruction.**

I. INTRODUCTION

Brain tumor is inherently serious and life-threatening because of its invasive and infiltrative character in the limited space of the intracranial cavity. Hence determining its pathology, volume and complexities is crucial for surgical planning and knowing the stage of cancer. Magnetic resonance imaging (MRI) is the commonly used imaging modality for non-invasive analysis of the brain tumor. MRI uses radio waves and magnetic fields to acquire a set of cross sectional images of the brain. That is anatomic details of the 3D tumor are presented as a set of 2D parallel cross sectional images. Representation of a 3D data in the form of 2D projected slices does result in loss of information and may lead to erroneous interpretation of results [1]. Also, 2D images cannot accurately convey the complexities of human anatomy and hence interpretation of complex anatomy in 2D images requires special training. Although radiologists are trained to interpret these images, they often find difficulty in communicating their interpretations to a physician, who may have difficulty in imagining the 3D anatomy. Hence, there is a need for 3D reconstruction of the tumor from a set of 2D parallel cross sectional images of the tumor. 3D visualization enables better understanding of the topology and shape of the tumor, and enables measurements of its geometrical characteristics. The extracted information is helpful in staging of tumor, surgical planning, and biological research [2]. Therefore, how to reconstruct a trustworthy surface from the sequential parallel 2D cross sections becomes a crucial issue in biomedical 3D visualization.

Manuscript received Aug, 2014.
Chethan Kumar, *ECE, Reva Institute of Technology and Management,. Bengaluru, India, +919035875242.*
Anitha Kumari R D, *ECE, Reva Institute of Technology and Management, Bengaluru, India.*

II. LITERATURE SURVEY

1. *Mathematical morphology for 3D modeling of brain tumor growth:*

This method is applied to medical images (MRI scan) of a brain affected by cancer. To do this, we use pre-processing to segment the tumor-occupied region while at the same time 3D reconstruction is done using Delaunay triangulation. The aim is to show how to characterize the growth of the tumor in 3D, through the application of dynamic structural elements, and at the same time to establish the tumors growth rate. The dilation process of morphology is used to characterize the tumors growth rate, because with this process the tumor occupied region can be enlarged depending on the structural element that has been assigned. This method is used to determine the change in the size of the tumor using samples taken at different intervals. The growth rate per iteration of the affected region depends directly on the structural element in the process.3D graphics give the specialist a better perspective on the size of the tumor under study, making a more efficient diagnosis possible.

2. *3D Reconstruction of tumors using OSTUs thresholding.*

This method for 3D image reconstruction is one of the most attractive avenues in digital image processing techniques, especially due to its application in biomedical imaging. It involves extraction of the tumor from the 2D slices of MRI brain images by OTSUs threshold technique and various morphological operations as well as Patch functions in MATLAB for reconstructing 3D image from a set of 2D tumor images. Extensive use of custom made user interface provides the user for ease interaction and visualization of reconstructed data. The volume of the tumor is also estimated based on the computation of these images. Doctors and Radiologists can now prepare and image thousands of samples and save on time per day using this automation. The main tasks used for reconstructing the 3D volume data from a series of slices are:

A. Enhancing the images and identifying the tumor.

B. Extracting the tumor from the source slices.

Two major strategies are considered to accomplish the needed segmentation process: boundary detection and homogeneous regions establishing. The boundary detection

ISSN: 2278 – 909X

means to find the regions with sudden variation of properties, delimiting the object boundary (bone tissue, for example). A homogeneous zone establishes means to select and to store different image pixels as function of their properties. The method shows the importance of acquiring the high quality MRI scans with sufficiently good resolution and contrast for automated volume measurement. It displays the tumor using the software. If the images are of good resolution and are of high quality then this method can produce attractive results which will be useful in in-depth investigation about tumor.

3. *Color based segmentation of tumor using FUZZY C-MEANS.*

A color based segmentation method uses the k-means clustering technique to track the tumor objects in the Magnetic Resonance (MR) brain images. The key concept in color-based segmentation algorithm with K-means is to convert a given gray-level MR image into a color space image and then separate the position of tumor objects from other items of an MR image by using K-means clustering and histogram-clustering. FCM algorithm is implemented using the data compression technique without including the weight factor in the cluster center updation criterion which further speeds up the process, yielding considerable segmentation efficiency. This modified FCM algorithm is used for clustering abnormal MR brain images. Average speed-ups of as much as 80 times a traditional implementation of FCM are obtained using the modified FCM algorithm, while yielding segmentation efficiency that are equivalent to those produced by the conventional technique. Thus, modified FCM algorithm is a fast alternative to the traditional FCM technique.

4. *Example Based 3D Reconstruction from Single 2D Images*

A novel solution to the problem of depth reconstruction from a single image is presented. In general, the problem of 3D reconstruction from a single 2D image is ill posed, since different shapes may give rise to the same intensity patterns. To solve this, additional constraints are required. Here, constrains of the reconstruction process by assuming that similarly looking objects from the same class (e.g., faces, fish), having similar shapes are obtained. Set of 3D objects are maintained in a database. The method uses a database of objects from a single class(e.g. hands, human figures) containing example patches of feasible mappings from the appearance to the depth of each object. Given an image of a novel object, we combine the known depths of patches from similar objects to produce a plausible depth estimate. This is achieved by optimizing a global target function representing the likelihood of the candidate depth. In addition, they have also shown how to employ method for the recovering an estimate for the occluded backside of the imaged objects.

5. *3D Reconstruction and Camera Calibration from 2D Images*

A 3D reconstruction technique from stereo images is presented that needs minimal intervention from the user. The reconstruction problem consists of three steps, each of which is equivalent to the estimation of a specific geometry group. The first step is the estimation of the epipolar geometry that exists between the stereo image pair, a process involving feature matching in both images. The second step estimates the affine geometry, a process of finding a special plane in projective space by means of vanishing points. Camera calibration forms part of the third step in obtaining the metric geometry, from which it is possible to obtain a 3D model of the scene. The advantage of this system is that the stereo images do not need to be calibrated in order to obtain a reconstruction. Results for both the camera calibration and reconstruction are presented to verify that it is possible to obtain a 3D model directly from features in the images. The problem is decomposed into a number of tasks, each task being associated with a specific geometric group. Existing techniques have been implemented and combined to form a relatively easy algorithm, which is straightforward to use. Minimal user intervention is achieved by automating most of the tasks.

6. *3D Reconstruction of Ultrasound Images*

The study investigates ultrasound imaging, speckle, 3Dultrasound imaging and 3D reconstruction without the need of position sensor, based on the theory of speckle decorrelation. It examines the limitations of conventional speckle decorrelation theory by employing a speckle detector based on an ellipsoid discriminant function. It evaluates a heuristic technique based on axial and lateral correlation functions to overcome a limitation due to coherent scattering as real tissues are dominated by coherent scattering while speckle decorrelation theory only holds for fully developed speckle. In addition to the heuristic technique, the use of a speckle detector to quantify the amount of coherent scattering for compensating the inaccuracies of elevational distances between US frames in real tissues is also investigated. Moreover, 3D reconstruction of ultrasound data is also obtained.

III. Design and Implementation

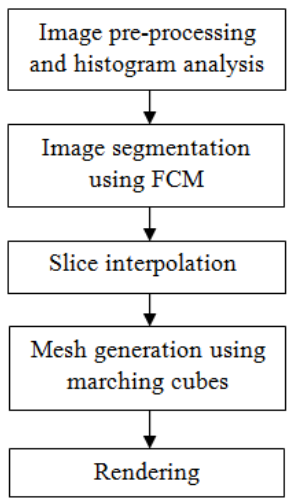

Fig 1: flowchart for 3D reconstruction.

1. *Image pre-processing and Histogram analysis*

Preprocessing is performed to improve the quality of the acquired images. The noise can mask and blur the important features in the MR image and thus make the further steps in medical image analysis difficult. Hence, to improve the perceptibility of the tumor and other structures in the brain, guassian filtering was used. Image

ISSN: 2278 – 909X

contrast was enhanced by applying histogram equalization. The normal slice consists of three regions white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). Where as a slice with tumor consists of four regions (WM, GM, CSF and tumor). Thus in order to determine whether the given MR image of the brain is normal or abnormal, the histogram of the brain region is computed. If the histogram consists of three peaks then the given MR image is considered as the normal slice and further processing of the MR image is not carried out. Otherwise, we consider that the slice contains the abnormal region and proceed to apply segmentation.

2. *Image segmentation using FCM*

Clustering is one of the widely used image segmentation techniques which classify patterns in such a way that samples of the same group are more similar to one another than samples belonging to different groups. The algorithm minimizes intra-cluster variance.

The algorithm is composed of the following steps:

- Choose a number of clusters.
- Initialize the fuzzy partition matrix U = [Uik].
- Set the loop counter b = 0
- Compute the centroid for each cluster, using the formula

$$v_i^{(b)} = \frac{\sum_{k=1}^{n} \left(u_{ik}^{(b)}\right)^q x_k}{\sum_{k=1}^{n} \left(u_{ik}^{(b)}\right)^q}$$

- Update membership function U^{b+1}

$$u_{ik}^{(b+1)} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{(q-1)}}}$$

- Repeat until the algorithm has converged (that is, the coefficients' change between two iterations is no more than, the given sensitivity threshold).

3. *Slice Interpolation*

After the segmentation, slices of the segmented tumor are stacked up to form the volume data in the 3D space. Generally, the set of slices acquired from the MRI device is such that the distance between the slices is larger than the distance between the pixels within the slice. The surface reconstructed with such a set of slices is inaccurate and not smooth. Thus in this work, the missing slices are estimated using interpolation technique.

4. *Mesh generation using Marching cubes*

Once we have the complete set of slices, we apply the MC algorithm proposed by Lorensen *et al.*, [4] to reconstruct 3D surface of the tumor from a set of 2D cross sectional images. The MC algorithm operates on a logical cube created from eight pixels; four each of two adjacent slices. It processes one cube at a time and determines how the surface intersects each cube using the isovalue of the surface and cube-isosurface intersection patterns shown in Figure 2.

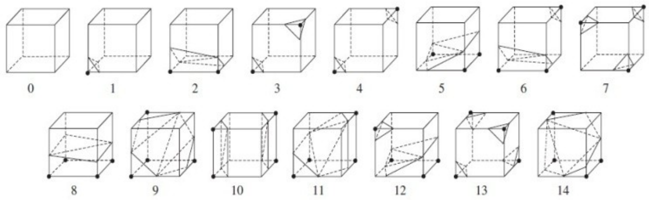

Figure 2: Cube-Isosurface Intersection Patterns

The algorithm for Mesh generation using Marching cubes is as follows:

- Read slices into memory
- Scan two slices and create a cube from four neighbors on one slice and four neighbors on the next slice.
- Calculate an index for the cube by comparing the eight density values at the cube vertices with the surface constant.
- Calculate an index for the cube by comparing the eight density values at the cube vertices with the surface constant.
- Using the densities at each edge vertex, find the surface edge intersection via linear interpolation.
- Calculate a unit normal at each cube vertex using central differences. Interpolate the normal to each triangle vertex.
- Output the triangle vertices and vertex normals.

5. *Rendering*

In the final step, realistic effects are added to the surface of the 3D model by applying Phong lighting model. First the normals of the triangle vertices in the mesh are computed by taking the average of the adjacent triangle normals. Then the shading model linearly interpolates the vertex normal and then applies the lighting model at each point on the surface to determine the intensity at that point and thus shades the entire surface.

IV. RESULTS

The proposed methods are implemented using MATLAB. All the experiments were performed on a personal computer with 2.40 GHz Intel i3-3110M processor and 4GB(3.85 GB usable) of RAM memory running under Windows 7 operating system. The input dataset consists of 22 cross-sectional MRI images of a patient having tumor.

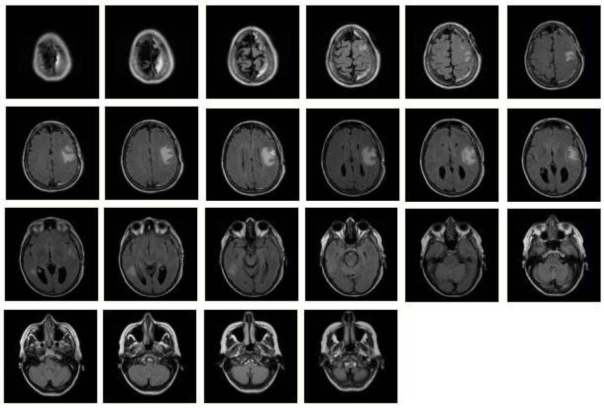

Fig 3: MRI data set of a patient.

ISSN: 2278 – 909X

The proposed 3D reconstruction approach involves automatic segmentation of the brain tumor. After identifying the abnormal slice, the tumor was segmented on that slice as shown in Figure 4.

Fig 4: slice having tumor after segmentation.

After the tumor segmentation, 2D tumor contours are arranged exactly in real spatial positions. This forms the volume data of the tumor. Figure 5 shows the meshing results after applying marching cubes algorithm.

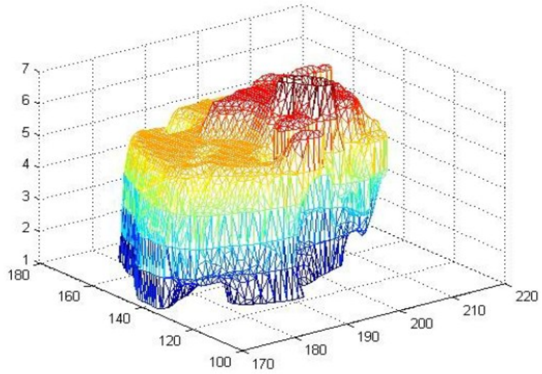

Fig 5: mesh generation.

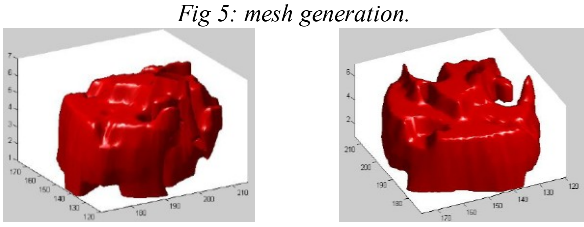

Fig 6: 2 views of the Tumor after rendering.

V. CONCLUSION AND FUTURE WORK

The 3D model of the brain tumor was reconstructed from 2D slices of brain by developing methods for segmentation, inter-slice interpolation and mesh generation. The tumor was segmented by using FCM technique. The skull part was removed by masking .The slices with tumors were stacked. By using Marching cubes Meshing algorithm the tumor was reconstructed. The experimental results show that our proposed 3D reconstruction approach can generate an accurate 3D model in less time. Thus it can assist the radiologist in diagnosis, identifying the tumor stage and treatment planning. 3D graphics gives a better perspective on shape and size, thus making more efficient diagnosis possible.

Since the FCM segmentation is non deterministic algorithm, an algorithm can be proposed to minimize the time for execution. Large numbers of triangles are generated by the marching cubes algorithm; hence an algorithm is to be designed to minimize the triangles so that the reconstruction time speeds up.

REFERENCES

[1] M. P. Arakeri and G. R. M. Reddy, *"Efficient fuzzy clustering based approach to brain tumor segmentation on MR images"*, Proceedings of CIIT 2011, CCIS. Springer, vol. vol. 250, (2011).

[2] N. Archip, R. Rohling, V. Dessenne, P. J. Erard and L. P. Nolte, *"Anatomical structure modeling from medical images"*, Computer Methods and Programs in Biomedicine, vol. 82, (2006).

[3] Megha P. Arakeri and G. Ram Mohana Reddy, *"An Effective and Efficient Approach to 3D Reconstruction and Quantification of Brain Tumor on Magnetic Resonance Images"*, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 6, No. 3, June, (2013).

[4] K Narayanan and Yogesh Karunakar, *"3-D Reconstruction of Tumors in MRI Images"*, International Journal of Research and Reviews in Signal Acquisition and Processing (IJRRWSAP),Vol. 1, No. 2, June (2011).

[5] Cort'es-P'erez, Castillo-Soria, and S. S'anchez-S'anchez, *"Mathematical morphology based on dynamic structural components for 3D modeling of brain tumor growth"*, International Journal of Computer and Information Engineering 3:4 (2009).

[6] S. Ananda Resmi and Tessamma Thomas, *"A semi-automatic method for segmentation and 3D modeling of glioma tumors from brain MRI"*,J. Biomedical Science and Engineering, 2012, 378-383.

[7] M. Rakesh and T. Ravi, *"Image Segmentation and Detection of Tumor Objects in MR Brain Images Using FUZZY C-MEANS (FCM) Algorithm"*, International Journal of Engineering Research and applications (IJERA), Vol. 2, Issue 3, May-Jun 2012, pp.2088-2094.

[8] Masroor A. and Dzulkii B.M, *"Segmentation of brain MR images for tumor extraction by combining K-means clustering and Anisotropic-Diffusion Model"*, International Journal of Image Processing, 2,(2008), 27-34.

[9] Muhammad Adil Hayat Khan, *"3D Reconstruction of Ultrasound Images"*, MSc Erasmus Mundus in Vision and Robotics (VIBOT) 13th,June008.

[10] Arpita Mittal, Sanjay Kumar Dubey, *"A Literature Review on Analysis of MRI Images of Rheumatoid Arthritis through Morphological Image Processing Techniques"*, International Journal of Computer Trends and Technology (IJCTT),volume4Issue4 April 2013.

[11] Arpita Mittal,Sanjay Kumar Dubey, *"A Literature Review on Analysis of MRI Images of Rheumatoid Arthritis through Morphological Image Processing Techniques"*, International Journal of Computer Trends and Technology (IJCTT),volume4Issue4 April 2013.

[12] Tal Hassner and Ronen Basri, "*Example Based 3D Reconstruction from Single 2D Images"*, Conference on Computer Vision and Pattern Recognition Workshop (CVPRW06), 2006.

[13] W. E. Lorensen and H. E. Cline, *"Marching cubes: a high resolution 3-D surface construction algorithm"*, Computer Graphics, vol. 4, no. 21, (1987).

[14] M. Garland and P. S. Heckbert, *"Surface simplification using quadric error metrics"*, SIGGRAPH '97 Proceedings of the 24th annual conference on Computer graphics and interactive techniques, **(1997)**.

[15] A. Castro, C. Bveda and B. Arcay, *"A new method for the initialization of clustering algorithms based on histogram*

ISSN: 2278 – 909X

analysis", IASTED International Conference on Visualization, Imaging and Image Processing, ACM, **(2007)**.

[16] Yong Yang, *"Image segmentation by fuzzy c-means clustering algorithm with a novel penalty term",* Computing and informatics, Vol. 26, 2007, 17–31.

ISSN: 2278 – 909X