Region-Based Growing Algorithm for 3D Reconstruction from MRI Images

Baijiang Fan, Yunbo Rao, Wei Liu
School of Information and Software Engineering
University of Electronic Science and Technology of China
Chengdu, Sichuan
e-mail: 489405435@qq.com, raoyb@uestc.edu.cn

Qifei Wang
EECS Department
University of California Berkeley
CA, USA
e-mail: qifei.wang@gmail.com

Huaiyu Wen
Chengdu Univeristy
Chengdu, China
e-mail: 235934112@qq.com

Abstract—**Accurate 3D reconstruction of human tissue is a challenge problem in medical imaging. In this paper, a novel 3D reconstruction method of human brain MRI images is proposed based on the segmentation of human tissue. First, we propose a novel region-based growing algorithm to get points of an MRI image. Then, the moving cubes algorithm is used to reconstruct the accurate 3D object model. Further, in order to display well, a multiple angle observation is provided in our experiment. Experimental results show that the proposed method is better than the traditional methods.**

Keywords-3D reconstruction; region-based growing; image segmentation; multiple angle observation

I. INTRODUCTION

In recent years, magnetic resonance imaging (MRI) has been widely used for various medical purposes [1]. However, the traditional MRI only provides two dimensional (2D) images, and cannot been used to create an explicit three dimensional (3D) model [2]. Therefore, reconstructing 3D model from 2D MRI images becomes an active research topic. The key challenge is how to obtain 3D data with high accuracy from original MRI images. The traditional methods of improving the 3D point accuracy are by improving the accuracy of region-based growing. Lavoue et al. [3] improved the traditional seed selection scheme by dividing the pixels of the image into 9 types according to plus-minus of mean curvature and the Gaussian curvature. However, there are three main limitations of this algorithm: (1) the proposed method ignores the vertex points on the sharp edge, (2) the edge that dihedral angle is greater than the given threshold, (3) using the sharp edge information to improve the growing conditions doesn't work well on all cases. Zhang et al. [4]. used Gauss curvature to assign all vertex, and set the vertex which has the larger minus Gauss curvature as the board by the threshold and minimum criteria. Their approach chooses work on MRI images since MRI images always lack of feature points and are gray scale images without much color changes.

In this paper, we propose a novel 2D region-based growing algorithm aimed at dealing with complex MRI images. The seed element randomly from non-board vertex, and extends until meeting board vertex or cannot find new point. This method is easy to implement, but the results heavily depend on the threshold which is empirically set by user.

Some recent approaches segment image into small facets and separately dealing with these facets [5]. However, these methods only demonstrate good performance on general images, but not on the MRI images. Some other researches [6] proposed to automate the seed selection. However, this method selects seed elements based on features similarity or thresholding techniques which makes these methods do not segmentation results are further used to reconstruct the 3D model. Fig. 1 demonstrates the framework of the proposed 3D reconstruction approach. In the first step, we use a novel region-based growing approach to get 3D points from a set of MRI images. In the second step, we use these 3D points to reconstruct the 3D model, and then display the result in different view angle.

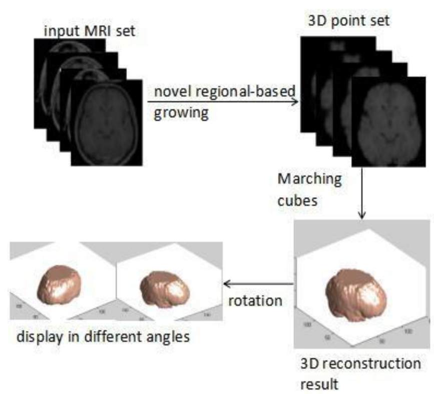

Figure 1. Framework of our method.

This paper is organized as following: The region-based growing and the 3D reconstruction algorithms are introduced

978-1-5090-6238-6/17/$31.00

in Section II and III, respectively. The experimental results and analysis are presented in Section IV. The conclusions are summarized in Section V.

II. REGION-BASED GROWING ALGORITHM

Generally, region-based growing includes three steps: (1) set a point on the image as a seed element. The seed element is the initial state of the segmentation; (2) start the growing process from the seed element, and absorb the points that connect to the seed and satisfy the growing requirements, but have not been signed; (3) use the points which satisfy the growing requirements as seed element, and continue to grow. When there is no new point can be added, or all points have been signed, the growing process is ended.

In this paper, we propose a novel region-based growing algorithm. The detailed procedure of the proposed method is described in Fig. 2. Our approach uses one seed element and three special growing requirements in the growing process. After each grows, we change the pixel value of seed element to keep the growing result precise.

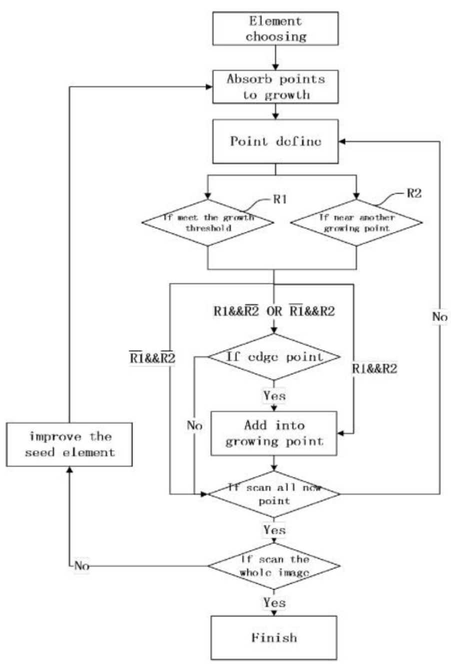

Figure 2. The flowchart of our proposed region-based growing algorithm.

A. Improved Element Absorbing Method

The traditional region-based growing algorithm use recursive search to scan the images [7]. In this kind of algorithms, the eight pixels connected to the seed element are added into a candidate list. In the first grow, points in list meet the growing requirement are marked as connected region and used as new seed elements for the next grow. The added pixels are removed from the candidate point list. The pixels connected to the new seed elements are added into the candidate list thereafter. However, since the pixels in the MRI images of human body tissue are highly dispersed, the traditional growing approaches are difficult to perform a complete scan of all pixels.

We improved the traditional growing algorithm by defining a growing region. As shown in Fig. 3, we use parameter W_k to control the width of the growth area. W_k is the width of each growing region. If W_k is small, the region-based growing method will be slow but precise. In the first grow, pixels in the growing region that most next to seed element will be added into the candidate list. After the first growing, pixels in the second growing area will add into list.

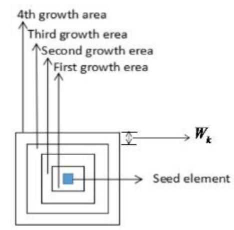

Figure 3. The diagram for improved element absorbing method.

B. Growing Requirements

Traditional region-based growing method grows from the seed element and chooses growing pixels connected to the seed element. However, it is easy to encounter the situation that the same organization part in an image scattered in different places on a MRI image so that these parts can not be found. In our work, each pixel is classified into candidate pixel or not by the following three Boolean criteria. Table I shows the classification criteria and the classification output Z denotes the Boolean output of the three input Boolean criteria for each pixel. If Z is 1, the pixel is treated as a candidate pixel for the current growing. The detailed descriptions are as following:

[*IF _ GROW*]: if the pixel meets the growth threshold;

[*IF _ NEXT*]: if the point is next to the current seed point;

[*IF _ EDGE*]: if the point is an edge point;

TABLE I. PIXEL CLASSIFICATION CRITERION (1 REPRESENT YES,0 REPRESENT NO)

IF _ GROW	*IF _ NEXT*	*IF _ EDGE*	*Z*
1	1	1/0	1
0	0	1/0	0
1	0	1	1
1	0	0	0
0	1	1	1
0	1	0	0

Here we denote IF _ GROW, IF _ NEXT, and IF _ EDGE by R1, as R2, and as R3. By using these three parameters above, each pixel of an image can be classified into one of the four types below:

TYPE A $$\overline{R1} \,\&\, R2 \,\&\, R3 => Z = 1 \tag{1}$$

TYPE B $$R1 \,\&\, \overline{R2} => Z = R3 \tag{2}$$

TYPE C $$\overline{R1} \,\&\, R2 \,\&\, \overline{R3} => Z = 0 \tag{3}$$

TYPE D $$R1 = R2 => Z = R1 \tag{4}$$

Fig. 4 demonstrates the cases of type A and type B. We can notice that the new pixels in Fig. 4(a) and Fig. 4(b) are all growing points. The new pixel in Fig. 4(c) is not a growing point.

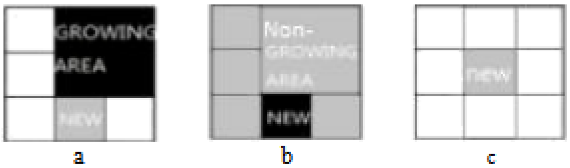

Figure 4. Pixel growing cases, (a) denotes type A, (b) and (c) denote type B.

Fig. 5 demonstrates the cases of type C and type D. Fig. 5(a) shows the case of type C where new pixel is not a growing pixel. Figs. 5(b) and 5(c) show the case of type D. If a new pixel meets the growing threshold in these cases, it is treated as a growing point.

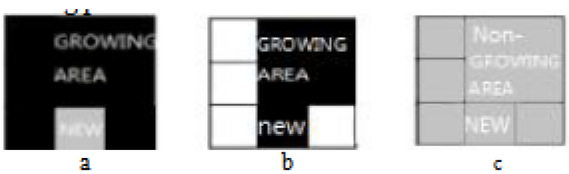

Figure 5. Pixel growing cases, (a) denotes type C, (b) and (c) denote type D.

The parameter IF_GROW is determined by the following equation:

$$\begin{cases} A(x,y) - A(x_i,y_i) < D => IF\_GROW = 1 \\ A(x,y) - A(x_i,y_i) \geq D => IF\_GROW = 0 \end{cases} \quad (5)$$

where $A(x,y)$ is the gray value of standard element, $A(x_i,y_i)$ is the gray value of the element which we need to handle, D is the predefined threshold which is empirically set to 10.

The parameter, IF_EDGE, is determined by Sobel edge detector.

According to the Table I above, the type of an element can be indicated as following:

$$Z = (IF\_GROW \,\&\, IF\_EDGE) \,||\, (IF\_NEXT \,\&\, IF\_EDGE) \quad (6)$$

C. Seed Element Improve Method

As equation (5) shows, the value of IF_GROW is decided by gray value of seed element and the threshold D. We set the gray value of seed element as *ParamJ*. *ParamJ* has remarkable influence on growing results. In order to get an accurate result, *ParamJ* needs to be updated after each growing process. The proposed method uses the following two steps to update *ParamJ*:

Step 1: get the average gray value of new growing pixels $ParamN$.

$$ParamN = \frac{\sum_{i=1}^{n} A(x_i,y_i)}{n} \quad (7)$$

Step 2: update $ParamJ$ by the following equation,

$$ParamJ = \sqrt{|ParamJ - ParamN|} * \sqrt{ParamJ * ParamN} \quad (8)$$

III. 3D Reconstruction

In this paper, we combine marching cube algorithm with our region-based growing method to reconstruct the 3D model. Marching cube algorithm can obtain a desirable 3D reconstruction result since each MRI slice has the same resolution [8]. The process of marching cube algorithm can be summarized as the following three steps:

1) Read two adjacent images from a data-set and build a cube. Compare the vertex data of the cube to the threshold, and decide the inside and outside condition of these vertex.

2) Decide the pattern of isosurface by the inside and outside condition.

3) To produce a smooth 3D reconstruction surface. In our work, we propose a novel method, which the data-set can be smoothed by Gauss filtering before extraction [9].

3D rotation can display result clearly by transform the 3D model into different visual angle. The 3D transform of the object is achieved tomography equations.

$$\begin{aligned} &[x\_1, y\_1, z\_1, 1]\text{\^{}}T = H * p \\ &= [R, T; 0, 1] * [x\_0, y\_0, z\_0, 1]\text{\^{}}T \end{aligned} \quad (9)$$

H denotes the tomography matrix, which is composed by the 3x3 rotation matrix T, 1x3 translation vector T. The vectors [x_0, y_0, z_0, 1] and [x_1, y_1, z_1, 1] denote the original and the transformed coordinates of the 3D point in global coordinate frame.

IV. Experimental Results

In this section, all experiments are performed on a workstation with Pentium (R) Dual-Core 3.06 GHz CPU and 4GB memory. All the algorithms are implemented by MATLAB.

We use marching cube algorithms on original brain MRI data to test the marching cube algorithms, the results are as the following in Fig. 6. The 3D result is clear and smoothly.

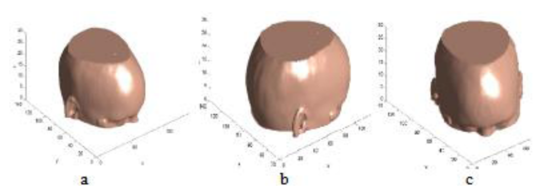

Figure 6. MC reconstruction results of human head. (a) the head model without rotation, (b) and (c) are the rotation result of 75° and 300° facing negative direction of y-axis.

Fig. 7 shows the proposed algorithm results, which use region-based growing method on a single MRI image.

We can find that our approach gets complete and accurate growing result. To compare with traditional region growing methods, we choose a traditional region-based growing method, FCM cluster and seeded region-based growing method [7], to handle the same image. From the results in Fig. 8, it is clear that our approach can get more accurate brain segmentation than the approach proposed in [7].

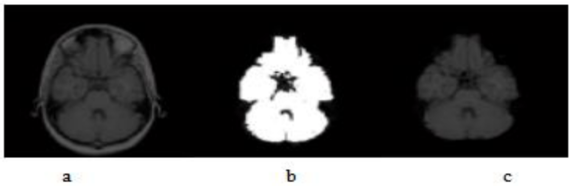

Figure 7. The result of single MRI.(a) the original MRI image, (b) the dichotomy binarized results, (c) our results.

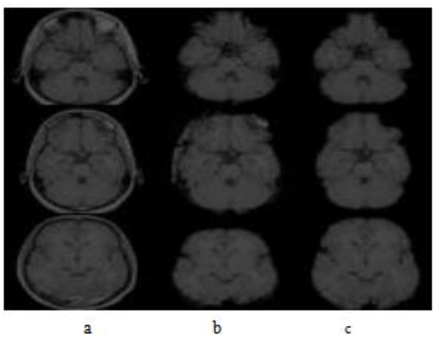

Figure 8. Region growing results, (a) input image, (b) the growing result by traditional region-based growing method [7], (c) our method.

Using the results of region-based growing algorithm, we build the 3D model of human brain as Fig. 9. We rotate the model to observe it in different angles.

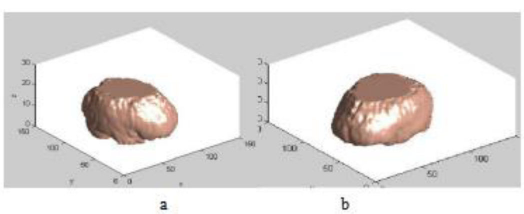

Figure 9. 3D brain model by improved region-based growing method (a) the front view of brain model, (b) side view of brain model.

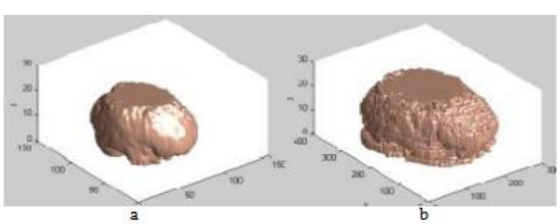

Figure 10. 3D model reconstruction result comparison, (a) reconstruction result using result of proposed method, (b) reconstruction result using traditional region-based growing method.

Fig. 10 shows the 3D reconstruction result obtained with our proposed algorithm and the reference region-based growing approach [7]. It is easy to find that our approach significantly outperforms the reference approach in both the shape and the surface accuracy of the model.

Table II shows some quantitative results of 3D object reconstruction between our approach and the reference approach.

According to Table II, our method is more accurate than the traditional approach as the number of fault pixel is reduced by 87.9%. Moreover, our method has less hollows and higher accurate rate than the traditional approach with slightly increasing execution time.

TABLE II. COMPARE OF AVERAGE GROWING RESULT

	Our method	Traditional method [7]
Number of faults(pixel)	135	787
Number of hollows(pixel)	72	349
Execute time(secs)	12.51	7.12
Accurate rate	90.52%	62.84%

V. CONCLUSION

We present a novel region-based growing algorithm for 3D object reconstruction from MRI images. We combine the method with marching cubes algorithm to get accurate 3D reconstruction model of human brain. Experiment results show that our proposed algorithm can get accurate growing result, and the result can be used to build 3D model without further processing. The proposed approach can be widely applied for various medical purposes.

ACKNOWLEDGMENT

This work was supported by the Sichuan Natural Science Foundation (No. 2017JY0229), the Industrialization Development Foundation of Chengdu Research Institute of UESTC (No. RWS-CYHKF-02-20150003). Fundamental Research Funds for the Central Universities of China (No. A030-13023001050). Department of education program of Sichuan Provincial (CR1627, JGYQ2016034, PD TR2016-003, SLQ2016B-01, MSSB-2016-01).

REFERENCES

[1] W.D Chen, Y.L Li, P Xu. "Three-dimensional digital model of the anterior cruciate ligament based on magnetic resonance imaging." Journal of Clinical Rehabilitative Tissue Engineering Research, 2011, 15(52):9725-9728

[2] AD Scott, M Wylezinska, MJ Birch, ME Miquel, Speech "MRI: morphology and function. Physica Medica," 2014, 30(6):604-618

[3] G. Lavoue, F. Dupont, A. Baskurt. "Curvature tensor based triangle mesh segmentation with boundary rectification." IEEE Computer Graphics International. Crete, Greece, 2004:10-17.

[4] Y. Zhang, J. Paik, A. Koschan, M. A. Abidi. "A simple and efficient algorithm for part decomposition of 3D triangulated models based on curvature analysis." International Conference on Image Processing. 22-25 Sept. 2002:273-276.

[5] D Holz, S Behnke. "Approximate triangulation and region growing for efficient segmentation and smoothing of range images." Robotics & Autonomous Systems, 2014, 62(9):1282-1293.

[6] A Melouah. “Comparison of automatic seed generation methods for breast tumor detection using region growing technique,” Computer Science and Its Applications.2015:119-128.

[7] K Thiruvenkadam,P Nagaraja. “Brain tumor segmentation of MRI brain images through FCM clustering and seeded region growing technique.” International Journal of Applied Engineering Research, 2015, 10(76):427-43

[8] H Singer. “Conditional Gauss–hermite filtering with application to volatility estimation.” IEEE Transactions on Automatic Control, 2015, 60(9):2476-2481.

[9] N P. Patel, “3D volumentric visualization of MRI images with improved marching cube.” Lambert Academic Publishing, SBN: 978-3 -659- 9433 1-7.October 2016.