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Comparison of 3D Segmentation Algorithms for Medical Imaging

Hakan BULU and Adil ALPKOÇAK

Dokuz Eylul University, Dept. of Computer Engineering,
Buca 35160, Izmir, Turkey
{hakan.bulu, adil.alpkocak}@deu.edu.tr

Abstract

In this paper we present an evaluation of four different 3D segmentation algorithms with respect to their performance on three different CT Data Sets. The segmentation algorithms evaluated in this study are seeded region growing, volumetric segmentation using weibull E-SD fields, automatic multilevel thresholding by using OTSU method and unseeded region growing. The main results gained from our experimentation are given.

1. Introduction

Today, modern visualization techniques provide extremely accurate and high quality 3D images of anatomical structures. However, their usage for efficient analysis is still limited, because the complex structure of medical images with a large number of anatomical organs which are bunched together prevents the doctors to view in different ways. Some visualization tricks, such as making an object transparent, cannot solve this problem. To solve the problem, the anatomical structure or the region of interest needs to be separated or delineated, which allows to view it individually [1]. This technique is called image segmentation in medical imaging.

Image segmentation is generally considered as a very difficult problem due to very large size of datasets, complexity, and variation of the anatomic organs. Noise and low contrast may cause the boundaries of anatomical structures to be inaccurate and disconnected. Therefore the main challenge of the segmentation algorithms is to extract the boundaries of organs or region of interests and to separate it out from the remained datasets.

Many approaches for the segmentation proposed in literature vary widely depending on the specific application, imaging modality (CT, MRI, etc.), and other factors. For example, the segmentation of colons has more different issues than the segmentation of lungs. The algorithm, which gives perfect results for one application, might not even work for another. Besides these, the outcome of the segmentation algorithms can be affected by the general imaging artifacts such as noise, motion and partial volume effects. For instance, a segmentation algorithm could be robust to noise, but it might be failed in the presence of partial volume effects. This variety in requirements creates a challenging problem for the segmentation algorithms. Currently, we do not have a magic segmentation method providing satisfactory results for any type of medical dataset. Generally, a segmentation algorithm approach could be consisted many segmentation algorithms, which are applied one after another. Therefore the selection of an appropriate algorithm or approach for 3D segmentation of medical volumes for a particular domain is the main issues to be solved.

To date, many 3D segmentation techniques have been proposed for Medical volumes. Some researchers has suggested to use multilevel banded graph cuts for image segmentation [6]. T. Srinark and C. Kambhamettu developed an approach on multiresolution surfaces [7]. Y. Boykov and M.P. Jolly use graph cuts for interactive organ segmentation [10]. On the other hand, J. Rodrigues et.al. used well-known octree structures for fast segmentation of 3D data [8]. P.W. de Bruin et.al. proposed an approached based on connected orthogonal contours for interactive 3D segmentation [9] and Y. Fan use parallel genetic algorithms for

volumetric segmentation of brain images [11]. H. Tek and B.B. Kimia use three-dimensional bubbles [12]. M.M. Dickens and his friends use 3D active shape models for volumetric segmentation [13]. Sarang Lakare [1] reviewed various segmentation algorithms found in the literature and suggested a classification of algorithms into three categories: structural techniques, statistical techniques and hybrid techniques.

In this paper, we present a review and provide a comparison of four different 3D segmentation algorithms which may be applicable to medical volumes. We choose four different algorithms and tested them on three different CT datasets for comparing their results. The algorithms are Seeded Region Growing (SRG), Weibull E-SD Fields (WESDF), Automatic Multilevel Thresholding by Using OTSU Method (OTSU) and Unseeded Region Growing (USRG).

Rest of paper is organized as follows: The next section briefly reviews the four algorithms to be considered. Section 3 gives the details of application we have developed, experimentation that we have conducted and the major results we gained. The last Section concludes the paper and gives a look at the futures studies on this subject.

2. 3D Segmentation Algorithms

3D medical volumes can envision as consecutive 2D images or slices stacked together. Therefore many of the 2D segmentation techniques may be easily extended into 3D images by adding a depth dimension to an image. These slices are made up of pixels. So, for 3D images pixel (x, y) become a voxel (x, y, z) namely volume pixel. A voxel represents a quantity of 3D data just as a pixel represents a point or cluster of points in 2D data. It is used in scientific and medical applications that process 3D images.

In this subsection, the 3D segmentation algorithms considered in this study are explained briefly. The algorithms evaluated in this study are Seeded Region Growing (SRG), Weibull E-SD Fields (WESDF), automatic multilevel thresholding by using OTSU method (OTSU) and Unseeded Region Growing (USRG). Basically, these algorithms can be group into two, as automatic and as semi-automatic. SRG and WESDF can be grouped as semi automatic and OTSU and USRG algorithms can be grouped as full automatic segmentation algorithms. The algorithms are evaluated with respect to their implementation difficulty, common usage and some subjective results.

2.1. Seeded Region Growing (SRG)

SRG is a technique to extract a connected region from a 3D volume based on some pre-defined connecting criterion. This criterion can be as simple as the voxel intensity or could be the output of any other segmentation algorithm. In its simplest form, SRG requires a seed point to start with. From the seed point, the algorithm grows till the connecting criterion is satisfied. We can define the connection criteria $\delta(x)$ as follows;

$$\delta(x) = \left| v(x, y, z) - mean(\text{Region}) \right| \tag{1}$$

here $v(x, y, z)$ is the intensity value of the current voxel. If $\delta(x) \leq t$, we can add current voxel to the Region, where t is threshold value and set from user. ($0 < t < 255$) [2].

2.2. Weibull E-SD Fields (WESDF)

Originally, this algorithm is not suggested for medical volumes. However, it is attractive due to its automatic nature. This segmentation technique aims to perform segmentation by making the volume data coarser. Firstly, $K \times K \times K$ cubes are generated from the volume data. They are called K-Voxel consisting of voxels. Each K-voxel is assigned two values;

Expectancy and Standard Deviation (E-SD). Second, Weibull noise index is used to remove noise of image using. In this way, more precise E-SD values can be obtained. After calculating E-SD values, frequency of voxels having the same E-SD values is ploted. Segmentation is performed under the help of this plot. Algorithm assumes that the E-SD values of voxels in a region are relatively homogeneous and different from that in other regions.

A region R is called as a Spatially Distributed Object (SDO), if the expectancy and standard deviation for each K-voxel Δ in R are relatively constant, i.e.,

$$E[X_\Delta] \in (e_1, e_2) \text{ and } SD[X_\Delta] \in (d_1, d_2) \tag{2}$$

where e_1, e_2, d_1 and d_2 denote predefined constants with $e_1 \leq e_2$, $d_1 \leq d_2$, the random variable X_Δ is defined as X_R above.

Calculating Expectancy and Standard Deviation (E-SD) Value of K-Voxel are given as follows [4][5] :

$$E[X_\Delta] = \frac{1}{|\Delta|} \sum_{(x,y,z) \in \Delta} v(x,y,z) \tag{3}$$

and

$$SD[X_\Delta] = \sqrt{\frac{1}{|\Delta|} \sum_{(x,y,z) \in \Delta} v^2(x,y,z) - E^2[X_\Delta]} \tag{4}$$

where $|\Delta|$ denotes the number of voxels in K-Voxel and $v(x, y, z)$ is the intensity value of the 3D volume at (x,y,z) point [3].

2.3. Automatic Multilevel Thresholding by Using OTSU Method (OTSU)

Automatic thresholding is an important requirement in image segmentation. The basic idea of automatic thresholding is to automatically select an optimal gray-level threshold value separating objects of interest in an image from the background based on their gray-level distribution. The OTSU method was one of the most common threshold selection methods for general real world images. This method selects threshold values that maximize the inter-class variances of the histogram [4].

Automatic thresholding techniques can be roughly categorized as global thresholding and local thresholding. Global thresholding selects a single threshold value from the histogram of the entire image. Local thresholding uses localized gray-level information to choose multiple threshold values; each is optimized for a small region in the image. Global thresholding is simpler and easier to implement but its result relies on good (uniform) illumination. Local thresholding methods can deal with non-uniform illumination but they are slow. Simply, for every voxel;

$$v(x,y,z) = \{i, \text{if } t_i \leq v(x,y,z) \leq t_{i+1}\} \tag{5}$$

where $v(x,y,z)$ is intensity value of the 3D image at (x,y,z) point, $i = 0,1,2,...,m-1$ and m is threshold count which is defined by user. ($0 \leq t_i < t_{i+1} < ... < t_m \leq 255$)

2.4. Unseeded Region Growing (USRG)

USRG is a fully automatic segmentation technique suitable for 3D volumes. The base of the USRG algorithm resembles to SRG algorithm. The USRG segmentation procedure is

inherently iterative, and the following process is repeated until all voxels have been allocated to a region. For convenience, the user selects the initial starting point to be the first image voxel. Formally, the segmentation process initializes with region R_1 containing a single image pixel, and the running state of the segmentation process consist of a set of identified regions, $R_1, R_2, ..., R_n$. Let T be the set of all unallocated pixels which borders at least one of these regions;

$$T = \left\{ (x, y, z) \notin \bigcup_{i=1}^{n} R_i \wedge \exists k : N(x, y, z) \cap R_k \neq \phi \right\} \quad (6)$$

where $N(x, y, z)$ are immediate neighboring voxels of point (x, y, z). Further we define a difference measure;

$$\delta(x, R_i) = \left| v(x, y, z) - mean(R_i) \right| \quad (7)$$

where $v(x, y, z)$ denotes the image value at point (x, y, z), and i is an index of the region such that $N(x, y, z)$ intersect R_i. The growing process involves selecting a point $z \in T$ and region R_j where $j \in [1, n]$ such that

$$\delta(z, R_j) = \min_{x \in T, k \in [1,n]} \left\{ \delta(x, R_k) \right\} \quad (8)$$

If $\delta(z, R_j)$ is less than the predefined threshold t, then the voxel is added to R_j. Otherwise, the most substantially similar region R is selected satisfying following condition.

$$R = \arg\min_{R_k} \left[\delta(z, R_k) \right] \quad (9)$$

If $\delta(z, R) < t$, we assign the voxel to R. If neither of these two conditions applies then it is apparent that the voxel is significantly different from all the regions found. Hence, a new region, R_{n+1} would be identified and initialized with point z. In all three cases, the statistic of the assigned region must be updated once the pixel has been added to the region [5].

3. Experimentation and Evaluation

To perform the evaluations, we have developed an application on Microsoft .Net Platform by using C# programming language, and Visualization Tool Kit (VTK) is used for 3D visualization. Figure 1 shows the main window of our application. Here, all slices are displayed in Part 1. Part 2 contains selected slice from user and Part 3 shows DICOM Header information in XML Format. Part 4 shows us all regions produced by selected segmentation algorithm with their Region ID which is a unique number for separating one region from the others. Part 5 contains quick information of selected region such as Region ID, Voxel Count, Voxel Edge Count, Region Mean Value of selected region. And lastly, 3D image and algorithms result are displayed in Part 6 namely in the modal form.

We tested our algorithm on four different datasets. One of them is used for testing purposes only and the others are real Computed Tomography datasets, meanly medical datasets. Table-1 depicts some property of our datasets.

Table 1. Some property of our datasets

|	DS1	DS2	DS3
Modality	CT	CT	CT
Manufacturer	Siemens	Philips	N/A
Number of Slice	288	460	96
Format of Slice	DICOM	DICOM	PGM
Bits Allocated	16	16	8
Part of Body	ABDOMEN	NECK & HEAD	ABDOMEN
Row	512	512	512
Column	512	512	512
Noise	No	No	Yes
Regions	Kidneys, Urinary Bladder and Bone Tissue (Basin Bone & Backbone).	Brain & Spinal Cord and Skull	Kidneys , Liver and Bone Tissue (Backbone & Ribes)
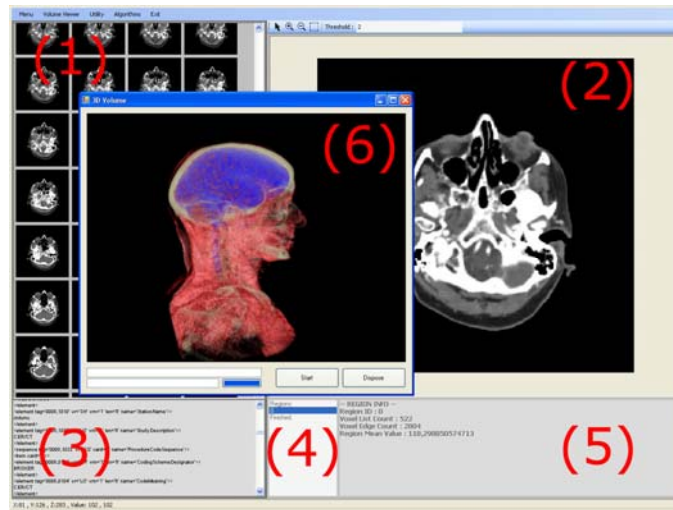
Figure 1. Main form of our application.

We use some scales for expressing algorithm's differences. Implementation values are changing between 1 and 5, here 1 is very hard and 5 is very simple. Noise Sensitivity denotes durability of the algorithm to the noise. Values are changing between 1 to 4, here 1 is algorithm is affected from noise too much and 4 is algorithm is not affected from noise. Time performance denotes algorithms running time and changing between 1 and 5. Where 1 is very fast and 5 is very slow. Result performance denotes algorithms success, meanly relation between desired region and produced region. Values changes 1 to 10. Where 10 is perfect and 1 is very bad. And finally, General Result denotes all opinion of us about related algorithm. Here 4 and 1 denote the worst and the best, respectively. All these scores are judged empirically based on our observations.

The experimentation results showed that SRG Algorithm, although it was not produced clear results on noisy images, it produced the right segmentation on the unnoisy images with the suitable threshold values. In addition to this, another advantage of this algorithm is simplicity of implementation. For our datesets, except DS3 it was produced satisfactory results.

The second algorithm WESDF did not produced satisfactory results on dataset, which does not have too much conrast differences between the segments. The main reasons of this unexpected result is that, E-SD Fields Algorithm consider that, if there is two K-Voxels and they have nearly same E and SD values, they should be in the same segment. But while doing that, the algorithm do not consider the location information of K-Voxels's voxels on the 3D volume.

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Table 2. Briefly Reviewing Of Comparison Of Algorithms

Algorithm	Implementation	Noise Sensitivity	User Interaction	Time Performance	Result Performance	General Result
SRG	4	1	Yes	2	8	1
OTSU	3	2	No	5 (for T = 4)	6	3
E-SD	2	3	Yes	4	3	4
USRG	4	1	Yes	2	7	2

We had the proper threshold values on the histogram of 3D images by using the OTSU Method. Originally, OTSU Method was successfully used for 2D images segmentation, but in this study we adapted it to 3D Volume and, it produced successful results.

Finally, USRG Algorithm, which is the prolongation of SRG, is failed on noisy images too, therefore we have used the same threshold values from SRG Algorithms in our tests. The region count was much more than expected, main reason of that, even seed points are changeable, threshold value is same for all seed points. In our opinion, threshold value should be updated for every new seed point. For our datasets, however the region count was more than we had expected, results were successful.

4. Conclusion

As a conclusion, we reviewed and provide a comparison of four different 3D segmentation algorithm on Medical Volume. All algorithms are tested on three different CT Data Sets and provide a comparison among them. We showed all segmentation results by using sample screen shots and segmentation parameters.

In future work, we plan to increase the number of segmentation algorithms to test on more medical datasets. While doing that, we will try to make our application more user-friendly.

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