3-D MEDICAL IMAGE REGION-GROWING BASED SEGMENTATION TECHNIQUES, CHALLENGES AND OPEN ISSUES

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ABSTRACT
Volumetric medical imaging acquisition technologies such as Computed Tomography (CT), Magnetic Resonance Tomography (MRT) and Positron Emission Tomography (PET) provide an effective means for non-invasive mapping of the anatomy of a subject. With these technologies being used every day there are enormous number of medical images, this has necessitated the use of computers in processing and analysis of these images. A significant task in medical image analysis is segmentation, whose goal is to partition a volumetric medical image into separate regions, usually anatomic structure (tissue type) that are meaningful for a specific task. In this paper region growing based segmentation techniques are discussed and the generic algorithms are given. The challenges and open issues in the medical field of this type of techniques are also highlighted. A recommendation of how the techniques can be used in the medical field is proposed.

KEY WORDS
Computed Tomography, Magnetic Resonance Tomography, Positron Emission Tomography, recommendation.

1. Introduction

Medical imaging acquisition technologies provide an effective means for non-invasive (without cutting or putting instruments inside body) mapping the anatomy of a subject. These technologies have enormously increased knowledge of normal and diseased anatomy for medical research. They are crucial components in patient diagnosis, prognosis, treatment planning, etc. With these technologies being used every day there are enormous number of medical images, this has necessitated the use of computers in processing and analysis of these images[1] .

The goals of using computers to support in patient diagnosis are to automate the process so that large number of cases can be handled with the same accuracy (fatigue, data overload and many other factors will not affect the results), achieve fast and accurate results, and to support fast communication.

A significant task in image analysis is segmentation, aiming to separate different regions of interest in a given image. Especially in medical imaging, segmenting and subsequent measuring of organs is a fundamental problem in diagnosis and treatment. The volumetric medical images that are obtained from medical imaging acquisition technology such as Computed Tomography (CT), Magnetic Resonance Tomography (MRT) and Positron Emission Tomography (PET) require the use of 3-dimensional segmentation techniques. In literature there are so many segmentation techniques that have been proposed but not all produce the required results [2-5].

Among these methods there are the generic ones that can be applied to a variety of images, the specialised that are used in specific area or for specific images from specific image acquisition technology and the ones that are used in succession[1]. Within these segmentation techniques some are automated or semi-automated [4]. The really dilemma is choosing the relevant segmentation technique to use at a given time or on the type of images[6].

A classical definition for segmentation is given as the partition of an image into non-overlapping, constituent regions that are homogeneous with respect to some characteristics such as colour, texture, motion or intensity. The union of the regions is the entire image and the regions are meaningful with respect to a particular application[7, 8]. The formal definition of this classical definition is expressed as follows:

If $P()$ is a homogeneity predicate defined on a group of connected pixels, then segmentation is a partition of the set I into connected subsets or regions $(R_1, R_2, R_3 ....\ \ .....,\ R_n)$ such that

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$$P(R_i) = True \;, if \; \exists a$$
$$\| P(R_i) - a \| < \varepsilon, \forall R_i \; (Uniform \;\; Region)$$

$$\bigcup_{i=1}^{n} R_i = I \; where \;\; i = 1, 2, \ldots\ldots n \;\; (complete)$$
$$R_i \bigcap R_j = \phi, \forall i \neq j \; (Disjoint)$$

$$P(R_i \cup R_j) = False \quad \forall i \neq j \; (Maximal \;\; Region)$$

The main problems in segmentation of medical images are due to noise, intensity non-uniformity and/or partial volume averaging [9, 10]. When images contain noise it means there is random (not present in the object imaged) variation of brightness or color information in images thus making the classification of voxels very uncertain. Images that exhibit intensity non-uniformity is where the intensity level of a single tissue class varies over the extent of the image. The partial volume averaging is where an individual voxel contain a mixture of tissue classes so that the intensity of a voxel in the image may not be consistent with any one class[3, 9].

In summary the real main problem is the selection of an appropriate algorithm or method (automated or not) for 3-D segmentation of medical volumes for particular domain. This has motivated us to do the survey for 3-D segmentation techniques so that we can recommend techniques suitable for an array of medical images. This paper will review the segmentation techniques classified as region growing based techniques, the challenges, open issues and then conclusion.

2. Region-Growing based Methods

Region-based algorithms require that neighbouring voxels within the same region are connected and similar according to some predicate [2, 11]. The region based methods are classified into two that is seeded and unseeded region growing methods. The notable difference is that in seeded region growing requires seed voxels which sometimes requires manual interaction while unseeded requires no explicit seed selection[5, 12].

The following section describes the algorithm of seeded region growing.

2.1 Seeded Region Growing

Seed choice is very critical in these algorithms in that there is need for a human interaction with the system in order to set the seed[13]. In medical circles medical personnel who has knowledge of the specialized area selects the seeds in the medical image.

The algorithm for the seeded region growing is as follows:

Step 1: Select a number of seed voxels and cluster them into n regions $(R_1, R_2, \ldots.. R_n)$, the positions of the initial seed voxels are set as $(v_1, v_2, \ldots. v_n)$

Step 2: Compute the difference of voxel value of the initial seed point (v_i) and its neighbouring voxels, if the difference is smaller than the threshold defined then the neighbouring voxel is classified into R_i, $where \;\; i = 1, 2, \ldots\ldots, \;\; n$.

$$P(R_i) = True \;, if \; \exists a$$
$$\| P(R_i) - a \| < \varepsilon, \forall R_i \; (Uniform \;\; Region)$$

Step 3: Recalculate the edge of R_i and set the edge voxels as new seed voxels, the mean voxel values of R_i have to be recalculated.

Step 4: Step 2 and 3 are repeated until all voxels in the volumetric image have been allocated to a suitable region.

Step 5: end

This method comes with so many variations depending on the decision to grow the region. The table 1 shows the criteria that can be used to grow the region.

Table 1: Criteria used to grow the region

Threshold set	Step 1 (Seed selection)	Step 2 (Growing Region)
Constant or Dynamic (Required)	One voxel $v_0 \in P$	• Compare the original voxel to any other voxel in the image $P(v_0, v_i)$ where $i = 1, \ldots, n$ • Compare voxel v_j to the neighbouring voxel v_i already in the region of original voxel v_0 • Compare voxel v_i to the entire region already collected (as the regrow the aggregate statistics are collected and then used)
Constant or Dynamic (Required)	Set of voxels $v_i \in P$ where $i = 1, \ldots, m < n$, n = total number of voxels in an image	• Compare voxel v_i to the statistics derived from the set of voxels
Not required	One voxel $v_{0_i} \in P$ and One voxel $v_{0_j} \notin P$ (Counterexample)	
Required	Every voxel in the image	• Compare voxels adjacent and merge when they fulfil the similarity criteria.

The threshold is set by human (medical specialist) and it is usually based on the intensity, gray scale or colour values. The selections of the regions ($R_1, R_2,\ldots\ R_n$) are chosen to be as uniform as possible. The real problem is that different specialists cannot choice the same seed and/or threshold but can select acceptable seed. In most cases the threshold is chosen from prior knowledge. The threshold can be global or local. This all require a specialist to determine the seed and threshold to be used in segmenting a particular set of images.

2.2 Unseeded Region Growing

In order to solve the subjectivity of image segmentation through the choice of the seed by the specialist then the unseeded algorithms were developed from the seed methods [5]. The main difference is that the seed is now embedded within the algorithm so the seed is chosen arbitrarily. This makes the method an automatic segmentation algorithm[14]. The following steps constitute the unseeded algorithm.

Step 1: Initialize with region R_1 containing a single image voxel v_0, and the running state of the segmentation process consist of a set of identified regions $R_1, R_2,\ldots,\ R_n$.

Step 2: A set of all unsigned voxels V that borders at least one of the regions is defined as[1]:

$$V = \left\{ v \notin \bigcup_{i=1}^{n} R_i \wedge \exists k : N(v) \bigcap R_k \neq \phi \right\}$$

Where $N(v)$ are neighbours of voxel v. A difference measure δ is calculated as:

$$\delta(v, R_1) = \left| f(v) - \mu_{R_i} \right|$$

Where $f(v)$ represent the image value at point v and i is index of the region such that

$$N(v) \bigcap R_i \neq \phi$$

Step 3: To grow the region, a point v_p that belong to V and a region R_j are selected where $j = 1,\ldots, n$ such that:

$$\delta(v_p, R_j) = \min \left\{ \delta(v, R_k) \right\}$$

Step 4: if $\delta(v_p, R_j) \leq T$ *then* $v_p \in R_j$ (the voxel belong to region)
else

Step 5: select R_c such that $R_c = \arg\ \min \left\{ \delta(v_p, R_k) \right\}$

Step 6: if $\delta(v_p, R_c) \leq T$ *then* $v_p \in R_c$
(the voxel is assigned to the region)
else

Step 7: Create a new region R_{n+1} and initialize the region with point v_p

Step 8: After the voxel has been assigned to a region, calculate the new mean value of the region.

Step 9: Repeat steps 2 to 4 until all the voxels have been assigned

Step 6: end

2.3 Threshold Selection

The fundamental factor in getting an acceptable image segmentation results in any field is the choice of the threshold. There are so many methods in literature used to obtain threshold values. In [15]the methods are categorized in six groups that is histogram shape-based, clustering-based, entropy-based, object attribute-based, spatial methods and local methods. These methods enable the automatic selection of threshold values. Choosing threshold using prior knowledge requires knowledge of the physical properties of an image object. The threshold may be defined as a value for which the segmented image reaches this a-priorily known value.

In medical field the threshold can be obtained through prior knowledge. Images obtained using Computed Tomography (CT) the voxel intensities are given in Hounsfield Units (HU) as given in table 2. The CT scanner uses a set of software algorithms to determine the amount of x-radiation absorbed by every element in a plane of tissue. Each of these elements is represented by a voxels on the video display, and the density (amount of x-radiation absorbed) is measured in Hounsfield units. This scale was developed by Sir Godfrey Hounsfield, who set the radio density of water at 0, and air at -1000.

This is advantageous for automatic organ/tissue segmentation, e.g. in connection with software applications for Computer-Aided Design/Computer-Assisted Manufacturing CAD/CAM surgical and implants planning [16].

Table 2: The voxel intensities of different tissues in Hounsfield Units (HU)

Hounsfield Units		
Tissue	Low	High
Air	-1000	-1000
Water	0	0
Fat	-150	-10
Muscle	10	50
Bone	250	1000
Lung	-100	1000
Liver	40	60
Kidney	30	50
Blood	40	40
Grey Mater	-45	-37
White Mater	-30	-20

2.4 Seed Determination

In determining the seed the following steps must be fulfilled:

Step 1: The seed voxel(s) candidates must not be on the boundary of two regions and/or not outlier.

Step 2: The candidate seed voxel(s) should have high similarity to its neighbours, which it should be inside the selected Region Of Interest (ROI) and has the highest similarity between its neighbours to accurately represent the region

Step 3: At least one seed voxel(s) must be generated for each extracted ROI.

Step 4: The distances measured from the seed voxel to its neighbours should be inside extracted region to allow continuous growing.

3. Challenges and Open Issues

The challenges encountered in segmenting medical images are that images contain noise, display intensity non-uniformity and are subject to partial volume average. So in developing the region growing based methods these challenges need to be addressed. Table 3 summarizes the challenges and open issues when developing these techniques.

Table 3: Summary of challenges and open issues in region growing based methods

	CHALLENGES	OPEN ISSUES
• noise	The reduction of noise	Finding existing or new algorithm to reduce noise of different medical images
• Seed	The selection of seed automatically or manually	To find an objective algorithms to help specialists to determine the voxels to be used as seed or select the seed autonomously
• Threshold	The selection of threshold	Finding an existing or new algorithm to determine the threshold to use in different regions.
• Seed positions	The selection of seed positions	Finding existing or new algorithm to determine the positions of the seeds that will allow the region to grow until all voxels that fulfil the a given criteria have been exhausted
• Automation	Automation of medical image segmentation	Finding algorithms for automating medical image segmentation that yield acceptable results in the medical field

4. Conclusion

Region growing techniques are rarely used alone in medical field. This is caused by the need to manually interact with the health specialist in order to specify the seed of the required regions. There are some region growing techniques that need no seed but all these techniques are sensitive to noise. This causes the segmented regions to have holes or to become disconnected.

The partial volume problem causes these techniques to connect different regions. Due to these problems encountered by employing these techniques, these techniques are usually used to delineate small and simple structures like tumours. We recommend that these techniques classified as region growing must not be used to segment medical images without a health specialist in attendance. In future we move to review other segmentation techniques in medical field.

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