Image Segmentation Guidance using Pet Information on CT Images in PET/CT Dual Modality

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Abstract. Medical image segmentation has always relied on evaluation and processing of the target image. In this paper we are using PET/CT dual imaging modality data to start and guide segmentation of regions of interest on CT image. The aim is to improved current semi-automatic techniques to become fully automatics. The images are acquired for extra pulmonary tuberculosis (EPTB) to indicate the area of infections. Two segmentation algorithms have been examined and tested; Seeded Region Growing (SRG) and Watershed using this technique and their results have been evaluated considering segmentation accuracy and time consumption. Overall, adopting the proposed approach for boundary maximum gray value in SRG yields the best results in terms of the accuracy, and acceptable time computation.

1 Introduction

Seeded Region Growing (SRG) algorithm is highly dependent on selection of initial seeds and pixel sorting orders [1-4]. Despite all the efforts to improve growing process and similarity measures, there are very few improvements on seed selection procedure. Many applications have considered seeds as separate inputs like the work by Mehnert and Jackway [3] or tried determining seeds based on previous knowledge on the nature of application as Gonzalez et al. proposed in an application of detecting defective welds in an X-Ray image [5]. Hojjatoleslami and Kittler [6], proposed an automatic seed selection based on a novel thresholding technique for detecting calcifications as possible initial seeds. Fan et al. [1, 2] proposed the use of color edge detection to obtain the simplified geometric structures of input image and appointed centroids of the neighboring labeled color edges as the initial seeds. All these algorithms and procedures process the target image only and do not consider the possibility of acquiring seeds from other related images.

This paper is an extension to the previously introduced method as guided SRG in our previous work [7]. In section two, four Growing Criteria (GC) for SRG algorithm have been tested along watershed transform to examine the usefulness of guided segmentation. The methods used have been described and their results and comparison

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have been depicted in section three. Finally, conclusion has been drawn in section four.

2 Methods

The idea of region based techniques is to segment an image by finding boundaries between regions based on discontinuities in gray levels [8]. Seeded Region Growing (SRG) algorithm starts with a set of seeds and from these seeds expands the region by checking neighboring pixels and regions [4]. Depending on what the nature of problem is, these seeds may vary in quantity and properties.

Here PET and CT pair images have been registered using cross correlation [8, 9] and by examining PET image, those pixels with maximum intensity value representing malignancies were selected as initial seeds. These seeds have been used as segmentation starting points in SRG and as references to select fractions in watershed as described in following sections.

2.1 Region Averaging

In region averaging at each step the average pixel value of the region grown so far is calculated and each neighboring pixel is compared with this average [4]. GC has been set to region average pixel value ± a threshold value *T* which is assigned by the user and controlled to achieve the closest result to desired segmentation.

2.2 Boundary Maximum Gray Value

This approach to defining GC has been introduced by Hojjatoleslami and Kittler [6]. The idea is to add a boundary pixel to the current region which has the highest gray value among the neighbors of the region. A threshold value *T* is set to avoid over growing into homogeneous areas and is controlled to satisfy the below formula:

$$\mathrm{Bmax} \leq \mathrm{Rmin} \tag{1}$$

$$\mathrm{Rmax} - \mathrm{Bmax} \leq \mathrm{T} \tag{2}$$

Where *Bmax* is the maximum gray level on the boundary, Rmax and Rmin are the maximum and minimum gray values of the region. Threshold value T is set to *30* in order to avoid over growing to homogeneous neighboring pixels.

2.3 Region Maximum Gray Value

Another aspect of GC is to compare candidate pixels with maximum gray value of the region grown so far [6]. Consider *Pmax* as the maximum gray value of the region, candidate pixel *P(x,y)* will be added to the region if it satisfies:

$$\mathrm{Pmax} - \mathrm{T} \leq \mathrm{P(x,y)} \leq \mathrm{Pmax} + \mathrm{T} \tag{3}$$

Where T is the preset threshold value used to control over segmentation.

2.4 Sliding Windows

In this method, two local mask Ms (16 by 16 pixels) and Ml (64 by 64 pixels) centered at the seed point coordinates will be defined as shown in figure 1 and based on the average pixel value of both masks, it will be decided whether the candidate pixel should be chosen from higher or lower valued neighboring pixels. The method is fully described in [7].

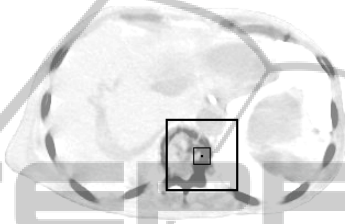


Fig. 1. Local mask *Ms* and *Ml* centered at the seed point coordinates on CT image.

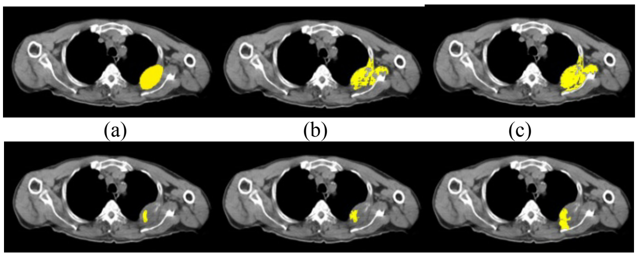
2.5 Watershed Segmentation

We have acquired watershed segmentation [10] to compare SRG segmentation results with a method other than region growing. Gradient magnitude of the image has been calculated using Sobel and linear filtering methods [11]. Since the gradient magnitude of an image has high pixel values along object edges and low pixel values everywhere else [5], and CT images usually have clear edges, it results watershed ridge lines to locate along object edges providing a suitable platform for segmentation.

Images have been completely segmented using watershed transform and those segmented fractions which contain seed points from PET image have been selected and merged to create the desired ROI.

3 Results

Fourteen images of patients having EPTB were used and the results of all segmentation algorithms on them were examined. Figure 2 shows sample results of applying segmentations algorithms on an image and the manually selected ROI for comparison. As can be seen, Figure 2(c) which is the segmentation result from SRG using sliding windows has the best accuracy in terms of covering the lesion. However, it deals with some over segmentation. Figure 2(e) which is the result of SRG using boundary maximum gray value, suffers from under segmentation. The region has not been grown enough to cover the lesion and only areas around seed points have been selected.



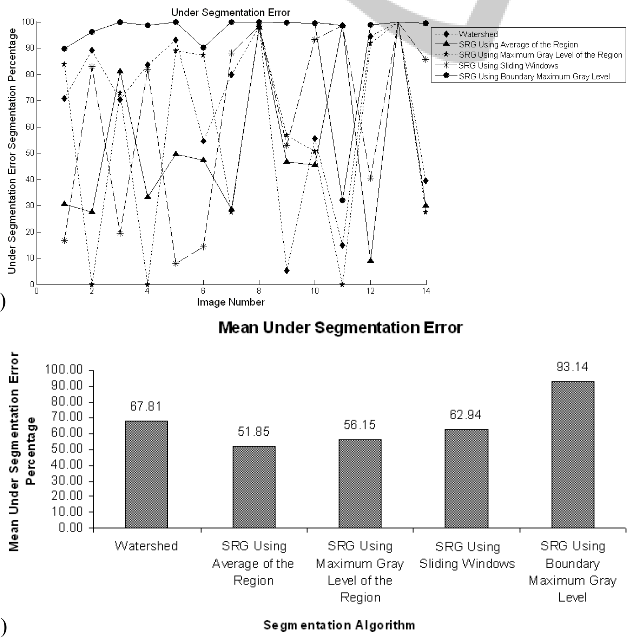
(a) (b) (c)

(d) (e) (f)

Fig. 2. Segmentation results, (a) desired manually selected ROI, (b) SRG using region averaging, (c) SRG using Sliding Windows, (d) SRG using boundary maximum gray value, (e) SRG using region maximum gray value, (f) Watershed segmentation.

Segmentation accuracy has been tested based on calculation of over and under segmentation factors. Time complexity of each method has also been taken into account. Figures 3 and 4 show the under segmentation and over segmentation results of the algorithms respectively.

As can be seen in Figure 3, among all segmentation methods, SRG using boundary maximum gray value suffers from under segmentation and SRG using region averaging has the least under segmentation error. This indicates that on the average, more areas of desired ROI will be covered using this algorithm. On the other hand, considering over segmentation errors in Figure 4, SRG with boundary maximum gray value presents the least over segmentation error and SRG using region maximum gray value suffers badly from over segmentation.



(a)

(b)

Fig. 3. (a) Under segmentation error percentage per image and (b) under segmentation mean error of all algorithms.

The time complexity of the procedure has been measured and is shown in Figure 5. Since at each step the average of the region grown so far needs to be calculated in SRG with region averaging, the time complexity of the whole process becomes too high when the region becomes relatively big. Other algorithms represent almost the same time complexities.

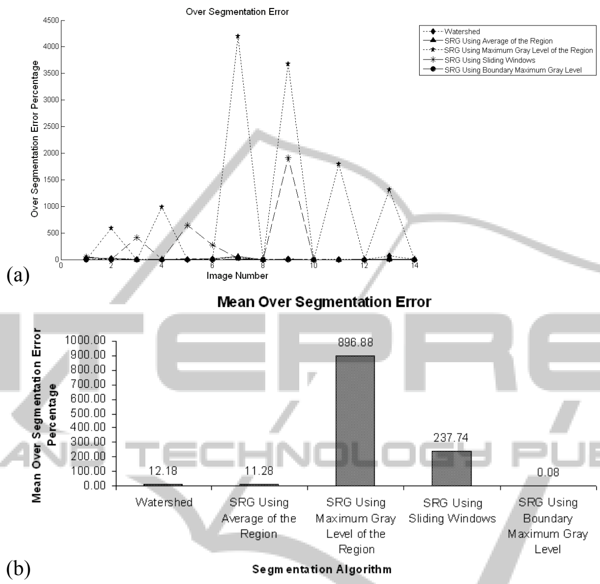


Fig. 4. (a) Over segmentation error percentage per image and (b) over segmentation mean error for all algorithms.

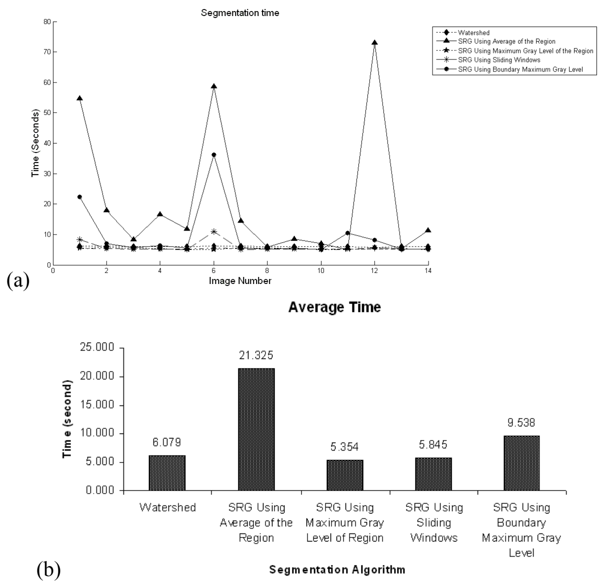


Fig. 5. (a) Time complexity of algorithms per image and (b) their average time.

4 Conclusions

Among segmentation algorithms, region growing highly depends on where the growing process starts and how to control it in order to avoid over growing to homogenous neighboring areas [12]. There for, we addressed the problem of blind segmentation and introduced an improved segmentation technique on images of Computed Tomography (CT) using images of Positron Emission Tomography (PET). We used the hotspot data provided by PET image as reference points to start the growing process in SRG and also as a measure to select segmentation fractions in watershed.

It was taken into consideration to introduce automated segmentation methods which result in less errors and best performance. The results were compared by defining three fidelity criteria from segmentation errors to time consumption.

Methods like using boundary maximum gray value and region maximum gray value had been introduced for certain application and not for segmenting CT images specifically. We tried to see whether with some modifications and applying data acquired from PET image they can be used for segmenting CT as well. The results support the fact that their accuracy is not acceptable in contrast with other segmentation techniques used throughout this paper.

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