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A Survey on Image Segmentation for Using CT Images to Detect Lung Tumor

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***Abstract*— In this paper, an evaluation of a segmentation algorithm has been made considering four different segmentation approaches. Lung cancer is prominent cancer as it states large number of deaths of more than a million every year. It creates need of detecting the lung nodule at early stage in Computer Tomography medical images. X-ray computed tomography (CT) is widely recognized as one of the most sensitive diagnostic imaging modalities for lung analysis. A precursor to all of these quantitative analysis applications is lung segmentation. In each of the methods considered, the algorithm has been discussed, along with the advantages and disadvantages of each method. Finally, in the conclusion, a comparison has been made among all the discussed methods. The paper serves as a roadmap for those intending to get themselves familiarised with digital image segmentation.**

***Index Terms*— Computed Tomography, Gray-scaling, Segmenta- tion**

I. Introduction

X-ray computed tomography (CT) is one of the widely recognized imaging techniques for lung analysis such as lung nodule detection [1]- [3] and airway analysis [4]. With the advancement of modern CT imaging techniques, the thickness of a single image slice is reducing while the image resolution has been increasing which is resulting in a vast number of CT slices to be examined. A precursor to all of these quantitative analysis applications is lung segmentation [5].

Segmentation is partitioning or separating an image, based on several features into different segments. The aim of image segmentation is to group pixels into relevant image regions and it could be used to recognize the object, to estimate within mo- tion, image editing and compression. It is an essential method in analysis of a medical images. The segmentation method is used for grouping of different tissues, bones, cartilages etc., so that the area of our interest can be focused vividly.

In medical digital image processing, the common method of manually tracing the boundaries in image segments is laborious and subject to both interobserver and intraobserver variations [6]. Hence, a number of groups have developed techniques for computer-assisted segmentation of pulmonary CT images [7] [10]. In many such, some manual interac- tion is still required to select threshold values or edit the resulting segmentation. This kind of an approach is called semi-automatic approaches. More recently, Brown et al. [11] provided a knowledge-based, automatic method to segment chest CT im- ages. In their method, anatomic knowledge stored in a semantic network is used to guide low-level image processing routines. Rather than requiring manual intervention to define the anterior junction lines as in [8], Brown et al. used dynamic programming to search for the junction lines automatically.

Fig. 1. Comparison of different approaches

Quantitative evaluation of a segmentation algorithm is cru- cial because it can not only provide a reliable basis for its clinical applications but also indicate its relative performance compared to other existing algorithms [12]. In this paper we compare the results, accuracy and efficiency of such different approaches and present our conclusion.

II. SEGMENTATION METHODS AND ITS ANALYSIS

A handful of Segmentation methods is picked and are analysed in this section.

Jiantao Pu et. al. [6], has proposed an adaptive border marching (ABM) algorithm for automatic segmentation of chest CT images. Its uniqueness lies in the fact that it smoothes the lung border in a geometric way and can be used to reliably include juxtapleural nodules while minimizing oversegmentation of adjacent regions such as the abdomen and mediastinum.

The process contains two main parts. The first part is the preprocessing stage. It is further divided into three part: Gaussian smoothing, Gray-level Thresholding and Floodfill Non-lung Region. The second stage aims to correct the defects caused by the exclusion of juxtapleural nodules. This stage too is divided into three parts: Lung border tracking, Adaptive border marching (ABM), and Lung region computation. The ABM step is the main contribution of this paper, and its novelty lies in the fact that it smoothes the lung border in a geometric way and can be used to reliably include juxtapleural nodules while minimizing oversegmentation of adjacent regions such as the abdomen and mediastinum.

Advantages: ABM is robust, efficient and straightforward to implement, and once the chest CT images are input, there is no further interaction needed from users. The clinical impact of this method is in potentially avoiding false negative CAD findings due to juxtapleural nodules and improving volumetry and doubling time accuracy. This method also takes care of the oversegmentation issues. The computation time of our method is under 1 min per case on average using a typical PC computer (AMD AthlonTM 64 X2 Dual, 2.11 GHz, 2 GB RAM).

Disadvanatages: The marching step length has to be assigned an arbitrary value that is larger than the circumference of any juxtapleural nodule. Choosing this initial guess is not a trivial task. The scale factor used determines the rate of change of the marching step length during the adaptive process. A smaller scale factor will lead to a rapid change of marching step, while a larger one will lead to a slow change of the marching step. When the marching step is changed too quickly, the optimum marching step might be skipped, thus leading to an undesirable result.

Zhaoxue Chen et. al. [5], has discussed an efficient lung seg- mentation method based on special distributing characteristics of pixel intensity in lung CT images. This methods follows two main steps: (a) Image preprocessing, to remove noise in a lung CT image; (b) Lung region segmentation method associating image threshold approach and region flood filling.

In this approach, the lung regions is segmented from the whole CT image, but some artifacts are still left. These artifacts are classified into two classes: one that exists outside the lung part, and another sort is located at the pulmonary parenchyma part, which is always from the isolated bronchi or lung nodules. While the one outside the lung region is removed by flood filling, the one inside is removed by the application of morphology and area filter approach.

Advantages: The method introduced in this paper is simple and easy for implementation with no complex algorithm in the steps. Classification of the artifacts into two classes is an added advantage of this algorithm.

Disadvanatages: The paper only claims the algorithm to be efficient. However no analysis has been made on accuracy or performance. Hence with such in sufficient data, the use of such an algorithm has to be questioned.

Shiying Hu et. al., [14] in their paper presents a fully automatic method for identifying the lungs in three-dimensional (3-

D) pulmonary X-ray CT images. The method has three main steps. First, the lung region is extracted from the CT images by gray-level thresholding. Then, the left and right lungs are separated by identifying the anterior and posterior junctions by dynamic programming. Finally, a sequence of morphological operations is used to smooth the irregular boundary along the mediastinum in order to obtain results consistent with those obtained by manual analysis, in which only the most central pulmonary arteries are excluded from the lung region.

There are several distinctions between this method and previous work. First, instead of using a fixed threshold value, they use an optimal thresholding method [15] to automatically choose a threshold value that reflects the gray-scale characteristics of a specific dataset. Second, we use an efficient method to find the anterior and posterior junction lines between the right and left lungs. Finally, to obtain more consistent results across time and to leave lung structures with the lung, optional smoothing of the irregular boundary along the mediastinum is carried out.

This method was tested on a PC workstation with 300-MHz processor and 512-MB RAM. On average, 23 min are required to segment a 512×512 120 data set, plus an additional 12 min for the optional smoothing step.

Advantages: Describes a fully automatic method for identifying the lungs in CT images. The paper presents results by comparing the automatic method to manually traced borders from two image analysts. Averaged over all volumes, the root mean square difference between the computer and human analysis is 0.8 pixels (0.54 mm). The mean intrasubject change in tissue content over the three scans was 2.75% 2.29% (mean standard deviation).

Disadvanatages: The optimal thresholding is an iterative process. Hence it needs considerable amount of effort and computational resources. Furthermore, a comparison with optimal thresholding used in this paper, and a fixed thresholding is not made sufficiently. This study would have aided in justifying this new approach. The run time mentioned in the paper is significantly more than other approaches discussed above.

Otsu [16] has A non parametric and unsupervised method of automatic threshold selection for picture segmentation is presented. An optimal threshold is selected by the discriminant criterion, namely, so as to maximize the separability of the resultant classes in gray levels. The procedure is very simple, utilizing only the zeroth-and the first-order cumulative moments of the gray-level histogram. It is straight forward to extend the method to multi-threshold problems. Several experimental results are also presented to support the validity of the method.

The discussion in the paper is mainly on elementary case of threshold selection where only the gray-level histogram suffices without other a-priori knowledge. An optimal threshold is selected by the discriminant criterion; namely by maximizing the discriminant measure (or the measure of separability of the resultant classes in grey levels). The paper discusses in detail the mathematical formulation of thresholding and also possible extension of multi-threshold problems.

Advantages: The procedure is relatively simple. A straight forward extension to multi-thresholding problems is feasible by virtue of the criterion on which the method is based. An optimal threshold (or set of thresholds) is selected automatically and stably, not based on the differentiation(i.e. a local property such as valley), but on the integration(i.e.,a global property) of the histogram.

Disadvanatages: While, the method discussed in this paper is very general, the main focus of this paper is only on the thresholding parameter selection for gray-level histograms. Also, only zeroth and first order cumulative moments of the gray-level histogram has been used. Furthermore, being one of the earliest methods proposed, this methods lacks sufficient comparisons with other available approaches in this regard.

III. CONCLUSION

In this paper, different image segmentation methods are reviewed by carefully considering all the methods and parameters discussed in the above mentioned papers. While each proposed methods have its own advantages and disadvantages, it is necessary to review them individually before fixing upon a particular type of approach for our application.

Paper (Authors)	Parameters/Factors				
	Distinctive Features	Considering Over Segmentation	Considering Under Segmentation	Additional Smoothing Step	Runtime
Jiantao Pu et.al	Adaptive border marching	✓	✓	✓	About 1min.
Zhaoxue Chen Et. Al	Artifacts classification	✗	✗	✓	Takes a bit of time
Shiying Hu et. al	Optimal thresholding	✗	✗	✓	About 5 min.
Otsu	Threshold selection	✗	✗	✗	Takes a bit of time

Fig. 2. Comparison of different approaches

In the above figure-2, a comparison has been made on different methods discussed in this paper. This helps us in identifying the better approach which suffices our requirement. In [6], even though the algorithm is efficient and even the method considers over segmentation and under segmentation issues, but the main focus has been on juxtapleural nodules. In [5], the main focus is on removal of two kinds of artifacts. Although the procedure and algorithm looks simple, there has been no comparisons made with other methods, or even the performance analysis has not been made. Hence, with such insufficient data, it is difficult to make any comments on the approach. In [14], the main theme has been the usage of optimal thresholding. The optimal thresholding has been selected by an iterative process. But, no conclusive comparison has been made between varying threshold parameter and a fixed parameter. In [16] a general threshold selection method has been mentioned with detailed analysis and comparison with the experimental results even validates the approach.

IV. FUTURE WORK

Considering all the above mentioned approaches, it is evident that there is lots of scope for future work in this field. It is necessary to come up with a procedure which combines the advantages of each of the above mentioned methods, with very high efficiency and reliability.

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