ABSTRACT

This paper deals with segmentation of the lung tissues from low dose CT (LDCT) scans of the chest. Goal is correct segmentation as well as maintaining the details of the lung region in the chest cavity. In particular, it is essential that the lung nodules inside the lungs as well as on the boundary regions be maintained for subsequent steps that aim at automatic detection and classification of nodules from LDCT scanning; a step for early diagnosis of lung cancer. An approach for segmentation based on combination of EM algorithm and morphological operations is presented. This algorithm is compared with respect two other approaches that are based on level sets and energy optimization by the Graph Cuts technique. Performance evaluation is conducted on a labeled data set from the Early Lung Cancer Action Program (ELCAP) database. The new segmentation approach provides comparable results to Level sets and Graph-Cuts, with the advantage of faster execution time, and minimal user interception.

Index Terms— Segmentation, Lung Nodules, Statistical Models

1. INTRODUCTION

Image segmentation is a fundamental step in image analysis. The image formation process can be exploited in separating the classes represented in an image or volume. Intensity-based representations, as the output of all biomedical imaging modalities, leave the gray scale or pixel/voxel values as the main source of information. Image formation may also provide an indirect information about an image or a priori information. This a priori information may take the form of shape and texture. The image segmentation process takes advantage of all pieces of information in order to provide connected separable regions. One can expect that various segmentation approaches exist as the imaging modalities vary and the inherent characteristics of objects vary a great deal as well. These issues and other factors related to the accuracy of the imaging process and the intended application made image segmentation an important area of research since the dawn of digital picture processing in the late 1960s.

When performing segmentation to lung tissue, specifically, there is one crucial concern that must be taken into account when extracting the lung tissue from its surroundings; how well does the approach segment the lung tissue without losing nodules connected to the pleural wall?

It would be a futile effort to survey the approaches developed in the past 40 years, which runs into tens of thousands of papers in the technical literature. In the way of a short and concise reference to some of the work in the literature that dealt specifically with lung segmentation from chest CT scans we refer to the following studies. Hu et al. [1], used a thresholding technique based on the characteristics of the CT data. Brown et al. [2] integrated region growing and morphological operations with anatomical knowledge to segment lung volume. Although shape-based, or Atlas-based (e.g.,[3]), segmentation overcomes the problem of gray level inhomogeneities, the creation of a general 3D shape model of the lung is not an easy task. Conventional methods that perform lung segmentation in CT depend on a large contrast in Hounsfield units between the lung and surrounding tissues. Although these methods accurately segment normal lung tissues from LDCT, they tend to fail in case of gray level inhomogeneity, which results from the abnormal lung tissues.

Boykov and Jolly (e.g., [4]) introduced an interactive segmentation framework for segmenting the lung tissue. In that work, the user must identify some voxels as object and others as background seeds. Then graph cut approach is used to find the optimal cut that completely separates the object seeds from the background seeds. Lombaert et al. [5] performed graph cuts on a low-resolution image/volume and propagated the solution to the next higher resolution level by only computing the graph cuts at that level in a narrow band surrounding the projected foreground/background interface. Although the results of these approaches looked promising, manual interaction was still required. Interactive segmentation imposes some topological constraints reflecting certain high-level contextual information about the object. Chen et al. [6] used morphological operations and graph cuts to segment the lung from radiographic images automatically. In that work, an outer boundary is initialized for each lung region by shrinking 10 pixels from the boundaries of both vertical halves of an image. This
method does not work in axial CT slices, where there is a lung part in the middle of the image. Inner boundaries were obtained by dilating the “regional minimum”. However, due to the inhomogeneity in the given image, there were many “regional minimums” so they selected a “regional minimum” based on a threshold; thus the algorithm involves various manual adjustments, which are difficult to perform in axial CT lung slices due to gray level inhomogeneities.

The above studies are just a sample of a very vast literature on the subject of image segmentation; see Sluimer et al. [7] for more exhaustive survey. An evaluation of nodule detection approaches was conducted in [8][12].

This paper introduces a statistical region growing approach that exploits the major characteristics of the lung CT, and then a smoothing filter in the form of morphological dilation is applied on the contours to avoid loss of nodules attached on the lung wall. The algorithm is compared to two in house algorithms based on Graph Cuts [9] and Level sets [10]. The three approaches are evaluated on a labeled sample of LDCT scans from the ELCAP program using to quantitative segmentation metrics.

This paper is organized as follows: section 2 describes each of the three segmentation approaches; section 3 presents experimental results and validation; section 4 concludes the paper.

2. LUNG SEGMENTATION

Fig. 1 shows the gray level histogram of a typical slice from a LDCT scan of the chest.

An obvious characteristic is the bimodality nature of the histogram and the clear distinction between the modes. A statistical approach that models the density function by a linear combination of Gaussian (LCG) may be deployed. The model has the following form (e.g., [11]):

\[
\hat{f}(x) = \sum_{j=1}^{C} w_j \theta(x|\theta_j),
\]

where \(\theta(x|\theta_j)\) is the \(j^{th}\) kernel function, \(w_j\) is the corresponding weight and \(C\) is the number of kernels. The Gaussian function is amongst the most used kernels in the above model. The LCG possesses various computational and mathematical characteristics that make it attractive, in particular its integrability, continuity, and the fact that a well-established approach for estimation of the parameters \(\theta_j, j \in [1, C]\) exists via the Expectation-Maximization (EM) algorithm [11].

As the modes in the LDCT chest scans are clearly distinct hence, the EM algorithm will have an easier job and will be even faster when it is fed with an accurate estimate of \(C\) a priori. Therefore, the parametric density \(f(x)\) in Eq. 1 is completely identifiable for LDCT scans of the chest. The first step would be to select a segmentation threshold to separate the lungs from the rest of the chest cavity. Algorithmically, this threshold is obtained by multiple iterations to maximize the separability between the lung and the rest of the chest cavity. A threshold is selected to isolate the thoracic region from the CT slice background; the lung parenchyma is then extracted from the segmented thoracic region.

As always, with histogram-based approaches, some region interferences is deemed to happen, especially as the boundaries are usually ragged and contains various areas of similar gray scale distributions. Morphological dilation using a circular structuring element is then applied as a smoothing filter on the contour of the segmented lung region in order to avoid losing nodules which are attached to the lung walls. To decrease the sensitivity of the segmentation result to the structuring element diameter, we apply it to the inner and outer lung region contour. Fig. 2 summarizes the approach.

![Fig. 1: The gray level histogram of a typical LDCT slice.](image)

![Fig. 2: A block diagram of the statistical segmentation method.](image)
does not offer major advantage when the scan resolution and nodule sizes are close. The overall algorithm may be summarized as:

**Algorithm 1:**
- **Step 1:** Load the slices serially and obtain the gray level histograms.
- **Step 2:** Apply the EM algorithm to obtain a fitting for the PDF function representing the histogram, and obtain an optimum segmentation threshold for the lung and the rest of the chest regions.
- **Step 3:** Enhance the boundary region (interface of the lung and the chest cavity) by successive morphological operators. We note that these steps are not time demanding and an entire scan may be segmented in minutes on a powerful PC.
- **Step 4:** Use the intensity model and GMRF model to assign a random field (GMRF) with nearest 6-neighborhood was used to model the spatial interaction. The overall algorithm may be summarized as follows:

**Algorithm 2:**
- **Step 1:** Estimate the marginal densities of the lung and its background using model.
- **Step 2:** Produce an initial labeled volume $\hat{f}$ using the intensity model's threshold. Estimate an initial value of the interaction parameter $\gamma$ from $\hat{f}$.
- **Step 3:** Integrate the intensity model and GMRF model to obtain MAP estimate of the region boundaries using Graph Cuts approach.
- **Step 4:** Update the estimation of the interaction parameter $\gamma$ and repeat until the desired labeling is obtained.

**Level Set Approach [10]**

Farag and Abdelmunim introduced a new level function defined as a vector distance rather than a scalar method (e.g., [10]). The level set function $\phi$ is used to represent the evolving region and shapes which are invariant to translation and rotation. Given a curve/surface $V$ that represents boundaries of a certain shape, the following level set function can be defined as, $\Phi : \mathbb{R}^4 \rightarrow \mathbb{R}^3$ where $\Phi(x,t) = [\Phi_1(x,t), \Phi_2(x,t), \Phi_3(x,t)]$ is defined as the minimum Euclidean distance between the point $X = [x,y,z]^T$ and a curve/surface $V$. The evolving region is a propagating front embedded as the zero level or a higher dimensional function $\Phi$.

The intensity segmentation is described by the function $\Phi_i$ which changes based on a certain energy description. If the point belongs to the associated object, the front region expands, otherwise it contracts. The point classification is based on the Bayesian decision at point $X$. Each region is defined by a Gaussian distribution. The overall algorithm may be summarized as follows:

**Algorithm 3:**
- **Step 1:** Manually select the initial seeds inside the region of interest.
- **Step 2:** For the bi-model in this work, assume object and background classes have Gaussian distribution.
- **Step 3:** Obtaining edges and iteratively estimate the mean and standard deviation of the object and background
- **Step 4:** Perform pixel labeling by Bayesian decision
- **Step 5:** Repeat steps 3 and 4 until convergence.

The intensity model (Eq. 1) is used in all methods. Hence, a parallel implementation of the three approaches is possible for hybrid (decision fusion) of segmentation approaches.

**4. PERFORMANCE EVALUATION**

**Dataset:** In this paper we use the ELCAP public database, which contains 50 sets of low-dose CT lung scans taken at a single breath-hold with slice thickness 1.25 mm. The locations of the 397 nodules are provided by the radiologists, where 39.12% are juxta-pleural nodules, 13.95% are vascularized nodules, 31.29% are well-circumscribed nodules and 15.65% are pleural-tail nodules. The official reports indicate the mean nodule diameter to be 8.5 mm with standard deviation 3.6. The ELCAP database is of resolution 0.5x0.5mm.

**Quality measure:** The quality of segmentation, with respect to the ground truth (labeled by the radiologists), is measured using three measures: 1) The sum square difference (SSD), 2) Co-registration by mutual information (MI), and 3) Number of visible nodules in the segmentation output. We also applied the MI measure of the ground truth vs. the ground truth in order to calibrate that scale. Figure 3 shows sample results of the segmentation algorithms.

As expected, segmentation resulted in removal of very small nodules (1 to 2 pixels) attached to the pleural
surface. The three algorithms maintained the visible nodules. The overall accuracy for Algorithm 1 was 93.5% but it proved to be the fastest among the three algorithms.

Table below shows the accuracy measures for the sample in Fig. 3. Obviously the three algorithms are robust for segmentation of the lung tissues; Algorithm 1 is simplest, fastest and requires the least human intervention.

<table>
<thead>
<tr>
<th>Groundtruth vs. Algorithm 1</th>
<th>Groundtruth vs. Algorithm 2</th>
<th>Groundtruth vs. Algorithm 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSD</td>
<td>MI</td>
<td>SSD</td>
</tr>
<tr>
<td>0.0152</td>
<td>99.4375 %</td>
<td>0.0042</td>
</tr>
<tr>
<td>0.0144</td>
<td>99.4519 %</td>
<td>0.0038</td>
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<td>0.0139</td>
<td>99.4653 %</td>
<td>0.0044</td>
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<tr>
<td>0.0114</td>
<td>99.6130 %</td>
<td>0.0124</td>
</tr>
<tr>
<td>0.0102</td>
<td>99.6019 %</td>
<td>0.0094</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS AND EXTENSIONS

In this paper we examined the segmentation process which isolates the lung tissue from the rest of the chest and thoracic regions in the CT scans. We studied three algorithms developed in the CVIP Lab and evaluated their performance on well-described data set that is manually segmented. Accuracy of the algorithms, with respect to the ground truth, is measured in terms of square error distance (SED) and the mutual information (MI), in addition to maintaining the nodules, and the overall execution time. This comparison provided confidence in the three approaches; Algorithm 1 is faster and more flexible, and requires no human intervention. Algorithm 1 has also been shown to be robust for subsequent analysis of lung nodule detection. Various algorithmic details are shown in [12].

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6. REFERENCES