Lung Tumor Segmentation and 3D Reconstruction Based on Region Growing and Correlation

Yiran Lei¹, Li Zheng and Ziang Lyu

Glasgow College, University of Electronic Science and Technology of China, UESTC, Chengdu, China

Yiran Lei: 2015200103024@std.uestc.edu.cn

Abstract. Accurate needle biopsy is indispensable for lung cancer diagnosis. The Computed Tomography (CT) scan is generally used to assist the biopsy to locate the tumor. In this paper, lung tumor segmentation and three-dimensional reconstruction methods are proposed and tested on CT images. For some common cases, we use region growing while for special cases, another algorithm testing the correlation between two images are presented. The experiments showed that the F-measure for region growing was 95.8% on average, and that of correlation was 86.4%.

1. Introduction

Lung cancer has been projected to be the first leading cause with estimated 154,050 death cases totally in the United States in 2018 [1]. One of the methods to diagnose lung cancer is sputum cytology screening, but the dividends are small yielding only one positive sampling of every 147 samples [2]. Compared with chest X-ray method, chest CT is more commonly used and can screen out more lung tumors. However, neither of them can identify the cancer and the stage.

CT-guided needle biopsy has become the dominant method to obtain tissue samples from lung tumors for lung cancer diagnosis. But the accuracy highly depends on the clinician’s skill and the patient’s compliance [3]. Complications like pneumothorax will deteriorate because of the inaccurate operations. Recognizing the above problems, we find it indispensable to use computer aided method to improve the accuracy for needle biopsy.

Many associated methods have been proposed. Image Overlay Guidance [4] directly overlays the shape of the needle held in clinician’s hand onto the real-time CT image and shows it on a screen. But the position of the needle still highly relies on the clinician’s judgement. Besides, many segmentation algorithms such as Iterated Graph Cut [5] and Random Walk [6] are applied to this field. To reconstruct the tumor well, as many as details from the original CT image should be retained, i.e., the boundary, the contrast and the threshold [7]. Region growing works well for searching the clear boundary even those close to the lung diaphragm or other organizations. However, an irregular tumor could greatly change the planar shape in the next image.

In this paper, we verify our methods with manual segmentation of 8 cases by the radiologist from Navy General Hospital. The rest of the paper is organized as follows: Section II introduces two methods; in Section III, we conduct a series of experiments and discussion on different kinds of samples; Finally, conclusions are drawn in Section IV.

2. Methods
We first use region growing algorithm, because region growing directly uses grey scale images transformed from original CT images, avoiding over-processing and the influence of colors. In some special occasions, the grey scales for pixels in a connected domain are too similar to determine the right pixel to be added. For instance, pixels for a transparent tumor have extremely low grey scales (Figure 1), which are easily mistaken for the invalid region. So, we use correlation algorithm to extract effective information. After finishing the reconstruction of the tumor, we finally draw the surface to help orientate the tumor.

![Figure 1. A semi-transparent tumor](image)

### 2.1 Region growing algorithm
Region growing method performs a contrast based on region growing [8] utilizing the HU. An initial seed point should be chosen as a reference for growing through human-computer interaction. Then according to the grey scale of the seed point, the pixel around it in the three dimensional, having the closest gray scale would be added to the region. In further growing steps, the judgement of the seed point depends on the mean value of the grey scales of all pixels in existed region. And the flowchart of this algorithm is shown in Figure 2.

| Step 1 Seed point location |
|----------------------------|
| Choose the image where the tumor has maximum cross section; Click the center of the tumor as the seed point. |

| Step 2 Region growing |
|-----------------------|
| Use ten connected domains for three dimensional growing; Set the growing threshold 0.02 after tests; Stop to draw lung surface after finishing growing. |
In Figure 3, we can see pixels in the tumor of each image have been marked as white points. And the 3D reconstructed tumor is drawn without the surface in this step.

**2.2 Correlation algorithm**

Closed domains in the Region of Interest (ROI) are labeled to be compared with the areas at the same position in adjacent images on both sides. And the correlation coefficient of the certain area in two images is limited to be larger than a threshold. Hence, it effectively remains the real part of the tumor, even if the grey scale is hard to be distinguished from the free space, and it simultaneously eliminates the invalid pixels.

| **Step 1 Pre-processing** |
|---------------------------|
| Choose the image in which the tumor has maximum cross section; Crop the image to get a tumor as ROI; Make the morphological processing to denoise; Label the closed domains in the ROI. |

| **Step 2 Correlation Computing** |
|----------------------------------|
| Compute the correlation coefficient of connected domains in two images; Store domains with correlation coefficient higher than the threshold to draw the whole tumor; Stop to draw lung surface after finishing growing. |
In order to get the similarity degree of two adjacent images, we compute the Pearson Correlation Coefficient \[9\] using

\[
r = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 (\sum_{i=1}^{n} (Y_i - \bar{Y})^2)}},
\]

where \(X\) and \(Y\) represent the two images.

In Figure 4, the same tumor in Figure 3 is signed and reconstructed by this algorithm.

Figure 4. Correlation result

2.3 3D reconstruction with lung surface

The lung surface is an indispensable information to orientate the position of the tumor. The surface is 3D reconstructed with the maximum cross section of tumor to the left and right sides within dozens of images to reduce the running time, rather than restore the whole surface.

Figure 5 shows the upper surface of lung reproduced according to the CT scale, and an eventual reconstruction combining the surface with the tumor.

Figure 5. Lung surface

| **Step 1** Edge extraction |
|---------------------------|
| Use Canny Edge Detect Operator to get the edge for one image; Row scan the image to remain the upper surface; Judge if the grey scale for the scanned pixel is one; Break to another column and then repeat the row scan |

| **Step 2** Coordinate registration |
|-----------------------------------|
| To recombine all slices into three dimensions, we first set the coordinate system. The column and row number of edge pixels map to X-axis and Z-axis, while the sequence of images maps to Y-axis; Make sure the size is matched with original CT images, so the scale for X and Z axes is 0.36cm and for Y-axis it is 0.63cm in our cases; Plot the upper surface by \textit{mesh}. |
3. Experiments and Results
We test some cases and collect 6 segmentation results (Figure 6) of them to show the accuracy of the 3D construction when using region growing. Since the second, third and fourth tumors are adjacent to other tissues, they will be segmented separately. And the third column shows the comparison between our results and the real tumors.

| Original | Tumor | Estimation |
|----------|-------|------------|
| ![Image](Original.png) | ![Image](Tumor.png) | ![Image](Estimation.png) |
| ![Image](Original.png) | ![Image](Tumor.png) | ![Image](Estimation.png) |
| ![Image](Original.png) | ![Image](Tumor.png) | ![Image](Estimation.png) |
| ![Image](Original.png) | ![Image](Tumor.png) | ![Image](Estimation.png) |
| ![Image](Original.png) | ![Image](Tumor.png) | ![Image](Estimation.png) |
| ![Image](Original.png) | ![Image](Tumor.png) | ![Image](Estimation.png) |

Figure 6. Segmentation results

For common tumors, the performance of two methods is similar with a high accuracy. Besides, for some tumors near other tissues, region growing method performs better. It can accurately separate tumor from interference with smoothy edge. The same tumor in the 3rd row of Figure 6 constructed by correlation is shown below (Figure 7). Though the tumor is also segmented by this method, it can not tell other tissues at a high accuracy if they adhere to the tumor.
In addition, the grey-scale values of a semi-transparent tumor are very low. Hence, some effective parts with extremely low grey scale values are signed as invalid areas using region growing. Yet, when we use correlation, these areas can be hold as they resemble the former or the latter piece. Figure 8 compares the performance of the two algorithms for a semi-transparent tumor.

After comparison, we find some differences of two methods. Because the region growing algorithm depends on the grey scale value to judge whether one pixel belongs to the tumor or not, it effectively use the feature that the HU values for different tissues, so this algorithm can reconstruct a tumor to a great extent. However, it is inaccurate if the seed point for a semi-transparent tumor has an extremely low grey scale value that is more close to the blank area rather than valid pixels. Yet, this problem does not exist in the correlation algorithm which uses binary images to do segmentation.

Table 1 reveals the estimations of the performance of region growing and correlation in 6 cases. To estimate our results, we calculate the Precision (P), Recall (R) and F-measure (F) [10] using

\[
P = \frac{TP}{TP + FP}
\]

...(2)
where TP means the relative pixels in retrieved area, FP means the non-relative pixels in retrieved area, FN means the relative pixels in not retrieved area, and the parameter ‘a’ is generally set as 1.

4. Conclusion
In this paper, we use region growing and correlation algorithms to do the segmentation and the 3D reconstruction for the lung tumor. From the results, we can see that region growing construct a tumor more accurately as the grey scale image has more details to shape the tumor better with F-measures 95.8% on average. The correlation method has an average F-measure of 86.4%.

In the cases that tumors are linked to blood vessels, inner wall of the lung and other tissues, the region growing algorithm can successfully detect tumors. While for semi-transparent tumors, the morphologic details are more reliable by comparing several small areas in two images. Therefore, the best way for tumor detection is to combine these two methods together to meet all situations.

To make the method more robust, first, the number of the seed point for region growing can be increased to 3 or 4 to get complete information for certain areas with different grey scale values. And we should use two algorithms together by judging the lower threshold of the grey scale values for the tumor at the beginning.

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