Semi-Automated Lung Segmentation: 3D Volume Reconstruction from CT Scans

Micol Malosso (10617863)
Politecnico di Milano
Micol.Malosso@mail.polimi.it

Nastaran Ghaffari Elkhechi (10900702)
Politecnico di Milano
Nastaran.Ghaffari@mail.polimi.it

Abstract- A protocol based on Matlab has been employed to execute a series of pre-processing steps, facilitating semi-automated segmentation and subsequent volume extraction of the lungs. An evaluation of three distinct methods was conducted to determine the most effective technique for lung segmentation and to acquire a refined volumetric representation of the pulmonary structure, thereby enabling 3D visualizations derived from CT image reconstructions. The ultimate aim was to achieve accurate lung segmentation within images characterized by noise.
Keywords- **CT, Lung, Segmentation, Contrast.**

I. Introduction

Early detection of cardiothoracic and pulmonary disorders is critical for effective prevention. While Computed Tomogrophy (CT) serves as a key clinical tool, challenges arise due to diverse abdominal structures in its output, necessitating careful Region of Interest (ROI) selection. Our study proposes a protocol for CT lung image pre-processing, emphasizing enhanced lung contrast and thresholding-based segmentation. It also extends to 3D volume creation and evaluation of the workflow on noisy images. The protocol is tested on CT images acquired in different time frames, from the same subject, in order to test the applicability to provide a time evolution description of lungs volume [1].

II. Materials and Methods

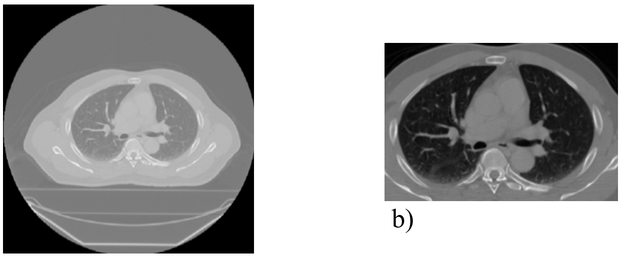
A. Data Collection

The CT image dataset for this study comes from Kitware, an open-source platform known for data management and visualization. We focused on the "Patient 0," examining a variety of images acquired at different time frames (T0 to T90). Each dataset includes slices covering the area from the lungs to the pelvis, allowing us to explore changes over time and study the anatomy in detail.

B. Pre-processing

The first crucial step involved the precise selection of the Region of Interest (ROI) using MATLAB's *imshow* and *imcrop* functions. This ensured accurate segmentation with minimized noise. The manually chosen ROI in the initial image was automatically applied to subsequent images for consistency and reduced workload [3].

Prior to initiating the segmentation phase, an exploration of some pixel intensity adjustment methods was conducted to assess their impact on enhancing contrast between the anatomical structures. The considered operators included histogram equalization, binarization, complementing, grey stretching, and power transformation. Through our evaluation, histogram equalization emerged as the preferred method for achieving optimal segmentation results. The decision to prioritize histogram equalization was based on its effectiveness in redistributing pixel intensities, resulting in a more balanced histogram and ultimately contributing to heightened contrast between different organs and structures [1,2].



a) b)

Figure1. a) The original image b) The cropped image (=ROI selection) c)

C. Segmentation

The first segmentation method tested was *Manual Thresholding*, which involves choosing a pixel intensity threshold to divide the image into regions, such as object and background. This method requires subjective judgment and can vary among operators. It required careful analysis of image histograms, later improved by histogram equalization to increase contrast. However, this approach presented challenges related to subjectivity in threshold selection. Therefore, after a careful study of methods found in the literature, it was then decided to use of *Otsu's Method* (Figure 2.a), making an improvement, is an automatic thresholding method based on maximizing the variance between pixel classes. To extend the analysis and provide an additional perspective, as the last segmentation technique, the *Gradient Method* was implemented, which exploits the Sobel kernel and aims to highlight image edges by identifying differences in pixel intensities.

Each segmentation technique was then supplemented with post-processing methods, using MATLAB functions such as *bwareaopen* and *imfill*, to refine the images by improving lung tissue continuity and removing artifacts at the edge [2,3].

D. Volume Creation

After performing the segmentation, a method was created for each of the three methods to create a 3D representation of the lung volume.

After identifying the most effective segmentation method, a graphical representation of the lung volume trend over time was created, revealing the natural rhythm of respiration. The graph begins with a high lung volume, indicative of full inspiration, followed by a gradual decrease, representing expiration. At the lowest point, corresponding to a complete exhalation, the volume increases again, marking the beginning of a new inhalation. This cyclic pattern, alternating inhalation and exhalation, is crucial for clinicians in analyzing respiratory function, effectively reflecting the vital dynamics of the respiratory system.

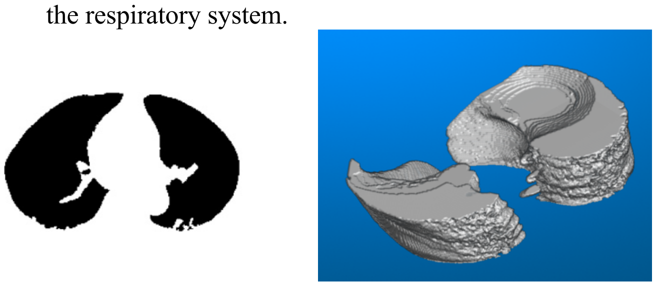


Figure 2. (a) Left: Segmented lung and (b) Right: 3D volume

E. Evaluation of the Workflow

Eventually, an experiment was conducted by adding Gaussian noise to the three segmentation methods. Using MATLAB's *imnoise* function, Gaussian noise was introduced into the DICOM images with specific parameters: 'gaussian'~ $(0, 10^{-4})$. This step was intended to test the robustness of each segmentation technique in the face of compromised image conditions, like those that may occur in real-world clinical situations.

Figure 3. Noisy segmented lung

III. Results

After implementing methods in Matlab, segmented lung images and 3D volumes were compared. *Manual thresholding*, despite histogram equalization improvements, initially produced noisy segmentations with unwanted artifacts. Refinements were applied to enhance image quality, but some small erroneous areas persisted, emphasizing the technique's subjective nature and limitations. In contrast, *Otsu's method* generated uniform, noise-free segmentations, ensuring accurate lung morphology delineation from the start. This automated approach eliminated interpersonal variability observed in manual thresholding. The *Gradient method* with the Sobel kernel effectively highlighted lung structure edges but occasionally led to over-segmentation. The method exhibited over-sensitivity to minor color or brightness variations in the image, misidentifying insignificant shades as significant edges.

The 3D volume analysis confirmed Otsu's method's excellent consistency in identifying lung tissue for detailed volumetric analysis. In contrast, Sobel's gradient technique, while effective in contour demarcation, produced more fragmented and inhomogeneous lung volumes. Manual thresholding, even with histogram equalization, showed limitations in accurately delineating lung boundaries, including surrounding tissues erroneously.

In the final analysis, the methods' response to added Gaussian noise revealed notable differences in distortion handling. The Sobel gradient method exhibited the least resistance, resulting in a rectangular block, indicative of significant loss of detail and inadequate segmentation. Surprisingly, manual thresholding with histogram equalization showed distinguished lungs even in noisy conditions, indicating that this method retains some reliability even under less-than-ideal conditions. Otsu's method displayed intermediate behavior, better than the Sobel method but not as effective as manual thresholding, indicating compromised performance in the presence of noise.

IV. Discussion

The study confirmed Otsu's method as the most effective approach for lung segmentation, demonstrating reliability in accurately identifying lungs and creating precise 3D volumes and overcoming the problems of subjectivity and inconsistency associated with other methods. It adapted optimally to variations in contrast and brightness, minimizing errors and ensuring reproducible results. While excelling in well-defined images and volumes, Otsu's method, compared to manual thresholding with histogram equalization, showed greater stability in the presence of Gaussian noise. These findings emphasize the need to consider image quality when choosing segmentation methods for clinical applications.

V. References

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