Functional Lung Segmentation from CT-Images using Deep Learning

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Introduction

Computed Tomography (CT) is primarily used for radiotherapy planning while magnetic resonance imaging (MRI) is used as a secondary source given its ability to generate higher soft-tissue contrast[1]. Identifying organs at risk (OARs) such as the lungs, spinal cord and the heart is an essential step during radiotherapy planning to identify regions where minimizing radiotherapy dose will aid in avoiding radiation-induced injury to sensitive structures. For surrounding normal tissue that must receive radiation dose, understanding which portions perform worse allows for minimizing radiation-induced toxicity. This method of minimizing radiation dosage to higher-functioning lung regions while targeting radiation therapy towards lower-functioning lung regions is known as functional avoidance radiotherapy. One way to identify regions of lung with the highest function is to measure the pulmonary ventilation, which is the exchange of air between the lungs and the ambient environment, as well as perfusion, which is the flow of blood to alveolar capillaries[2]. This is typically accomplished by ventilation-perfusion scans. Preliminary research conducted through the Beaumont Health System demonstrated a method to create rapid pulmonary ventilation images from Four-dimensional Computed Tomography Ventilation Imaging (4DCT-VI) that avoids contrast, while maintaining robustness in the presence of noise[2,3,4]. 4DCT-VI generates ventilation images from the inhale and exhale 4DCT phases[5]. We proposed a deep learning technique for the generation of synthetic pulmonary perfusion images from 4DCT images alone with the potential to detect hyper- and hypoperfused regions of the lungs. The goal of this study is to derive functional avoidance contours from the synthetic 4DCT images that will be comparable to the functional avoidance contours generated from the ^{99m}Tc-MAA SPECT-CT perfusion images.

Aims and Objectives

Aim I: Identify, transfer and process 51 thoracic CT image cases with high resolution CT images of the entire lungs.

Aim II: Train a deep learning model to segment lungs on multiple CT image sequences from a single training set.

Aim III: Evaluate the model performance by a statistical comparison between results of automated vs. manual segmentation.

The long-term goal of this project is to develop a validated model to identify the lung borders on 4D-CT at Beaumont Heath System. If the proposed deep learning method is successful, it will aid in in the recognition and visualization of lung tissues via ventilation images, which would ultimately assist in the identification of areas of avoidance during radiation therapy planning.

Methods

A retrospective study identified 51 4DCT image studies of the lungs which included 24 pre- and 27 post-radiotherapy (RT) 4DCT images[10]. Large datasets, typically tens of thousands of elements, play a critical role in training accurate machine learning models[13]. Our dataset of 24 patient cases with 51 4DCT images of the lungs, which corresponds to approximately 200 axially reconstructed slices per image, was determined as a sufficient dataset size for training a model, and which can be acquired within a reasonable timeframe. Of 51 4DCT images, 41 images were used in the training set and 10 images were used in the testing set. Specifically, the training set was used to train the model and the testing set was used to evaluate the accuracy of the completely trained model. Using our proposed synthetic image generation technique, synthetic pulmonary perfusion images were created for all cases which had both pre- and post-RT 4DCT imaging (N=24). Then, for both the clinical and synthetic image pairs, perfusion functional avoidance contours were generated with the 50th percentile binary threshold (F50) technique[14]. The clinical and synthetic F50 segmentations were compared with Dice similarity coefficient, average surface distance (ASD), 95th Hausdorff distance (HD95), relative absolute volume difference (RAVD), precision and recall. Dice similarity coefficient is a spatially invariant metric which computes the proportion of similarity between the two contoured structures. Hausdorff distance is a metric which provides the maximum distance of the minimum mapping between the two contours, and 95% Hausdorff distance is the 95th percentile of the Hausdorff distances. The mathematical equations for calculating Hausdorff distance, Dice similarity coefficient, RAVD are provided below:

Hausdorff distance from X to Y:

$$d_{\mathrm{H}}(X,Y) = avg\left\{\sup_{x\in X}\inf_{y\in Y} d(x,y),\ \sup_{y\in Y}\inf_{x\in X} d(x,y)\right\}$$

, where sup is the supremum and inf is the infimum

Dice Similarity Coefficient (DSC) between X and Y:

$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$

RAVD = total volume of the segmentation/total volume of the reference

Results

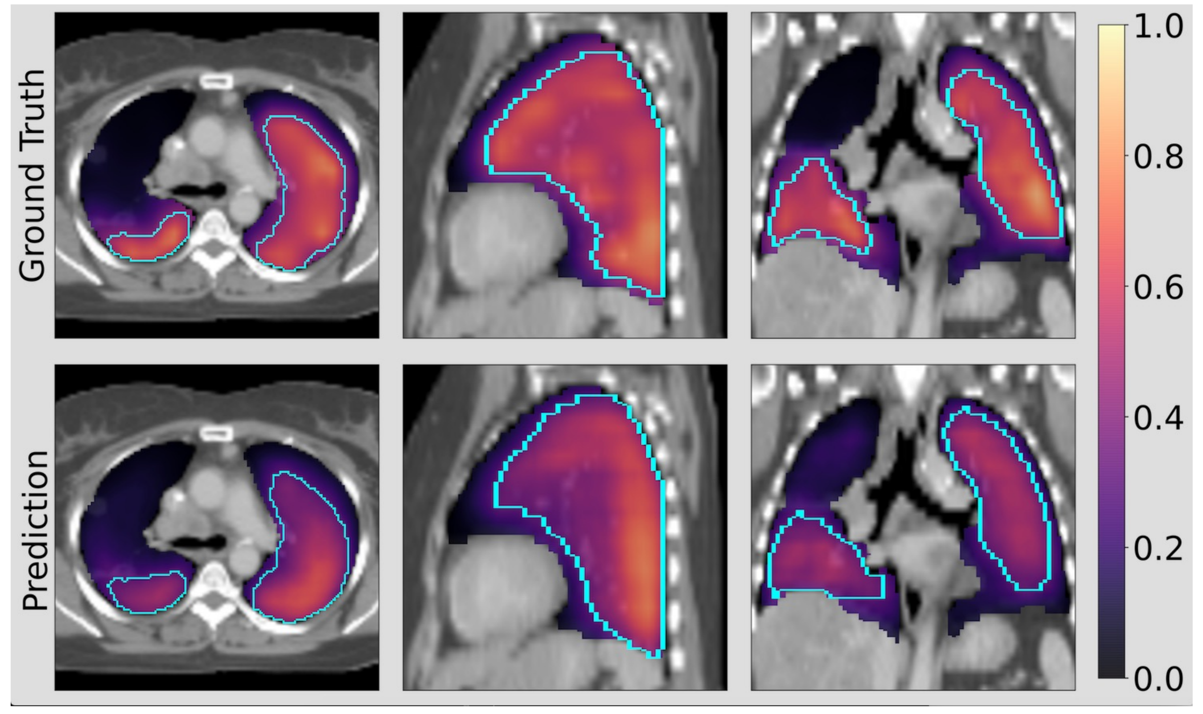

Figure 1: The ground truth (top) and predicted (bottom) SPECT volumes (study 3_1) with their corresponding F50 contours (cyan) superimposed (Dice: 87.0%; ASD: 2.9 mm)

Metric	F50 Contours
DICE (%)	78.0 (76.2-81.2)
ASD (MM)	6.23 (5.13-8.70)
HD95% (MM)	20.9 (15.8-26.4)
RAVD (%)	0.28 (-0.21-0.75)
PRECISION (%)	77.9 (76.0-81.1)
RECALL (%)	78.1 (76.7-81.3)

Table 1: Contour comparison metrics for each pre-RT (N=24) case, reported as median and IQR

The generated F50 contours of well-perfused lung were compared for the pre-RT cases (N=24) yielding Dice score of 78.0% (IQR: 76.2 – 81.2) and average surface distance of 6.23 mm (IQR: 5.13 – 8.70). Additional comparative statistics computed on the functional avoidance contours are given in Table 1. The synthetic F50 contour for this study was found to correlate well with the clinically derived contour (Dice: 87.0%; ASD: 2.9mm), as shown in Figure 1.

Conclusions

The results supported the hypothesis that a functional avoidance contour derived from 4DCT images of the lungs correlate well and warrant further investigations into the application in functional avoidance treatment planning.

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