Convolutional Neural Nets with Template-Based Data Augmentation for Functional Lung Imaging Segmentation

Nicholas J. Tustison[1], Zixuan Lin[1], Talissa A. Altes[2], Jaime F. Mata[1], John P. Mugler III[1], and Kun Qing[1]

[1]Department of Radiology and Medical Imaging, University of Virginia, Charlottesville, VA

[2]Department of Radiology, University of Missouri, Columbia, MO

Corresponding author:

Nicholas J. Tustison

ntustison@virginia.edu

Rationale and Objectives: We propose an automated segmentation pipeline based on deep learning for ventilation-based quantification which improves on previous methods in terms of robustness and computational efficiency. The large data requirements for the proposed framework is made possible by a novel template-based data augmentation strategy.

Materials and Methods: Convolutional neural net (i.e., U-net) models were generated using a custom multilabel Dice metric loss function and a novel template-based data augmentation strategy. Development occurred within *ANTsRNet*—a growing open-source repository of well-known deep learning architectures first introduced here which interfaces with the Advanced Normalization Tools package and the R statistical project. Training (including template generation and data augmentation) employed 500 images. Evaluation was performed on the remaining 1?? images through comparison with a previously reported automated segmentation algorithm based on Gaussian mixture modelling with Markov Random field (MRF) spatial priors.

Results:

Conclusions: The proposed deep learning framework yielded comparable results as the MRF-based algorithm. Such an approach reduces computational time without sacrificing accuracy.

Key Words: Advanced Normalization Tools, ANTsRNet, hyperpolarized gas imaging, neural networks, U-net

1 Introduction

Probing lung function under a variety of conditions and/or pathologies has been significantly facilitated by the use of hyperpolarized gas imaging and corresponding quantitative image analysis methodologies. Such computational techniques permit automated (or semi-automated) quantification of spatial ventilation with increased reproducibility, resolution, and robustness over traditional spirometry or radiological readings. Although multiple well-performing algorithms have been proposed in the literature and are currently used in clinical research, recent developments in maching learning (specifically deep learning) has generated new possibilities for quantification with improved capabilities in terms of robustness and computational efficiency. However, the benefits of these approaches are realized at a cost of large data requirements. In this work, we develop and evaluate a ventilation-based segmentation framework for hyperpolarized gas magnetic resonance imaging. To satisfy the large data requirements of such a framework, we propose a novel template-based data augmentation strategy for generating simulated data consistent with the population cohort. To enhance relevance to the research community, we showcase this work in conjunction with the introduction of *ANTsRNet*—a growing repository of well-known deep learning architectures which interfaces with the Advanced Normalization Tools package and the R statistical project.