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

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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 developments have provided direction and opportunity for current and future research trends. Computational techniques targeting these imaging technologies permit quantification of spatial ventilation with potential for increased reproducibility, resolution, and robustness over traditional spirometry and radiological readings [1, 2].

One of the most frequently used image-based biomarkers for the study of pulmonary development and disease is based on the quantification of regions of limited ventilation, also known as *ventilation defects*. These features have been shown to be particularly salient, for example ventilation defect volume to total lung volume ratio has been shown to outperform other image-based features in discriminating asthmatics vs. non-asthmatics [3]. This has motivated the development of multiple automated (and semi-automated) segmentation algorithms which have been proposed in the literature [4–8] and are currently used in a variety of clinical research investigations (e.g., [9]).

Despite the enormous methodological progress, recent developments in maching learning (specifically "deep learning" [10]) have generated new possibilities for quantification with improved capabilities in terms of accuracy, robustness, and computational efficiency. Deep learning, a term connoting neural network architectures with multiple hidden layers, has gained prominence in recent years due, in large part, to the annual ImageNet Large Scale Visual Recognition Challenge [11]. Specifically, one of the participants of the 2012 ImageNet challenge, a convolutional neural network colloquially known as "AlexNet" [12], significantly surpassed anything that had been proposed previously. The subsequent outgrowth of research has resulted in significant developments in various image research areas including classification, segmentation, and object localization and has led to co-optation by the medical imaging analysis community [13].

In this work, we develop and evaluate a convolutional neural network segmentation framework, based on the U-net architecture [14], for functional lung imaging using hyperpolarized gas. One of the drawbacks to deep learning approaches are the large data requirements for the training process oftentimes necessitating ad hoc strategies for simulating additional data from available data—

typically termed *data augmentation*. While common approaches to data augmentation [15] might include the application of randomized simple geometric transformations (e.g., translation, rotation and shearing) and/or intensity adjustments (e.g., brightness and contrast), we propose a much more sophisticated approach tailored to medical imaging scenarios. In the proposed approach, an optimal shape-based template is constructed from a subset of the available data. Subsequent pairwise image registration between all training data and the resulting template permits a "pseudo-geodesic" propagation of each image to every other image converting a data set of size N to an augmented data set of size N^2.

To enhance relevance to the research community, we showcase this work in conjunction with the introduction of *ANTsRNet*—a growing open-source repository of well-known deep learning architectures which interfaces with the Advanced Normalization Tools (ANTs) package [16] and its interface with the R statistical project (i.e., ANTsR) [16]. ANTsRNet is developed using Keras—a high-level neural network API [17]. All code, data, and network models have been made publicly available.

2 Materials and Methods

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