A multi-channel deep learning approach for lung cavity estimation using hyperpolarized gas and proton MRI

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Abstract

Hyperpolarized (HP) gas MRI enables quantification of regional lung ventilation via clinical biomarkers such as the ventilation defect percentage (VDP). VDP is computed from segmentations derived from spatially co-registered functional HP gas MRI and structural proton (^{1}H)-MRI; although these scans are acquired at similar inflation levels, misalignments are frequent, requiring a lung cavity estimation (LCE). Here, we propose a multi-channel deep learning method for generating LCEs using HP gas and ^{1}H-MRI. We compare the performance of the proposed method to single-channel alternatives.

Keywords: Deep learning, segmentation, multi-channel, multi-modal.

1. Introduction

Hyperpolarized (HP) gas MRI enables quantification of regional lung ventilation via clinical biomarkers such as the ventilation defect percentage (VDP). VDP is computed from segmentations derived from spatially co-registered functional HP gas and structural proton (^{1}H)-MRI. To maximize spatial alignment, both modalities are acquired at a similar lung inflation; however, the scans are frequently misaligned. Image registration consistently underperforms in cases with large discrepancies in topology between functional and structural scans (Tahir et al., 2014). Therefore, a lung cavity estimation (LCE) that represents the lung cavity volume in the spatial domain of HP gas MRI is required; this volume poses significant segmentation challenges, resulting in considerable manual editing. Deep learning (DL) has shown promise for pulmonary image segmentation, and single-channel convolutional neural networks (CNNs) have been used for segmentation of HP gas MRI and ^{1}H-MRI scans separately (Tustison et al., 2021; Astley et al., 2020). We propose a multi-channel DL method for generating LCEs using HP gas and ^{1}H-MRI.

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2. Methods

The data set comprised 480 3D ^{1}H-MRI scans and HP xenon-129 (^{129}Xe)-MRI ventilation scans from 315 healthy participants and patients with numerous pulmonary pathologies. ^{1}H-MRI and ^{129}Xe-MRI scans were rigidly registered. A 3D nn-UNet (Isensee et al., 2018) CNN was trained with a PReLU activation function, ADAM optimization and cross-entropy loss function on patches of 96x96x96 voxels for 300 epochs. A learning rate of $1\text{x}10^{-5}$ and batch size of 2 were used. We assessed three DL methods by varying the input channels to the network as follows: 1) ventilation-only (^{129}Xe-MRI), 2) structural-only (^{1}H-MRI), and 3) multi-channel (^{129}Xe-MRI + ^{1}H-MRI). Training and testing sets of 422 and 58 scans, respectively, were used. Only one scan per participant was included in the testing set and thus no participant was included in both the training and testing sets. To evaluate manually-delineated expert LCEs, Dice similarity coefficient (DSC), average boundary Hausdorff distance (average HD), and relative error (XOR) metrics were computed. Friedman tests with Bonferroni correction were used to assess group differences between DL methods.

3. Results and Discussion

Figure 1 shows the qualitative performance of each DL method comparing the DL-generated LCEs to expert LCEs for three random cases. For all cases, the multi-channel method generated plausible LCEs and outperformed other methods.

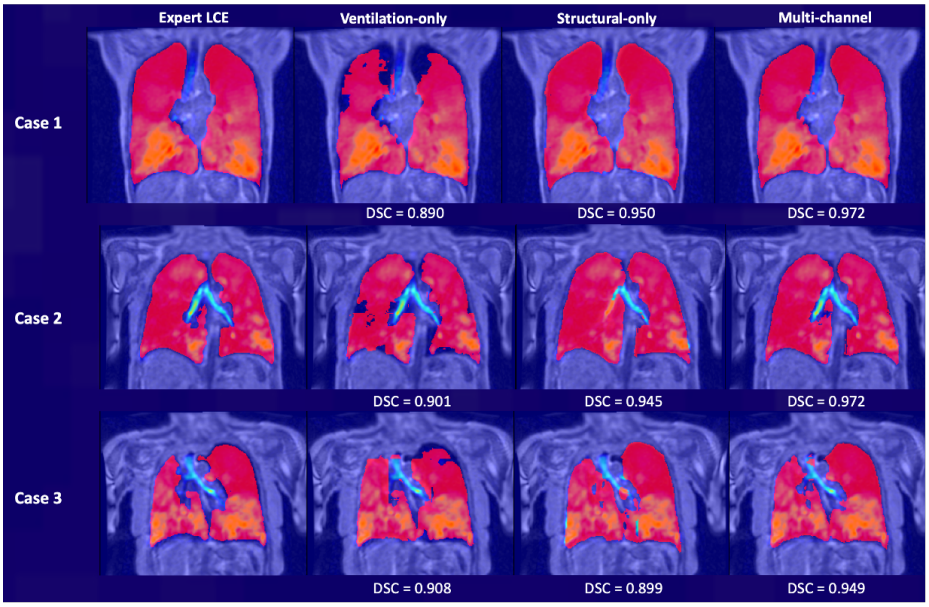

Figure 1: Example coronal slices showing ^{1}H-MRI fused with the corresponding ^{129}Xe-MRI overlaid with LCEs for three random cases. DSC values are provided.

Results for each DL method are provided in Table 1; the multi-channel method generated the most accurate segmentations across all metrics. For all three metrics, the multi-channel method significantly outperformed the single-channel methods ($p<0.001$).

Table 1: Quantitative results for the testing set (n=58) using DSC, average HD, and XOR metrics for the three DL methods. Median (range) values are provided.

LCE DL method	**DSC**	**Average HD (mm)**	**XOR**
Ventilation-only	0.952 (0.719, 0.979)	2.22 (0.762, 66.0)	0.095 (0.043, 0.749)
Structural-only	0.935 (0.797, 0.959)	4.19 (2.13, 11.5)	0.132 (0.082, 0.355)
Multi-channel	0.967 (0.867, 0.978)	1.68 (0.778, 37.0)	0.066 (0.045, 0.246)

The ventilation-only method did not generate plausible LCEs due to the lack of structural features provided to the CNN. Conversely, the structural-only method generated reasonable LCEs; however, in cases where there were misalignments between the ^{129}Xe-MRI and ^{1}H-MRI scans, the structural-only method could not account for inherent registration errors. The multi-channel method, utilizing structural and functional modalities, significantly outperformed single-channel methods across all metrics tested ($p<0.001$). Previous studies used single-channel CNN-based methods to segment the lung parenchyma on ^{1}H-MRI. The inclusion of functional features present in the ^{129}Xe-MRI scans, in addition to structural features on ^{1}H-MRI, provide the network context with which to adapt the structural LCE to account for inherent registration errors.

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