Learning Bronchiole-Sensitive Airway Segmentation CNNs by Feature Recalibration and Attention Distillation

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Challenges of airway segmentation using deep learning:

- Deficient supervisory signals due to the severe class imbalance between airway and background

- Risk of over-fitting due to the design of deep CNNs that need to extract both global-scale and local-scale context knowledge

Feature recalibration

$$\mathcal{Z}_{spatial}(A_m) = \mathcal{B}(\mathcal{Z}_{spatial}^{Depth}(A_m)) + \mathcal{B}(\mathcal{Z}_{spatial}^{Height}(A_m)) + \mathcal{B}(\mathcal{Z}_{spatial}^{Width}(A_m)), \quad (1)$$

$$\mathcal{Z}_{spatial}^{Depth}(A_m) = \sum_{j=1}^{H_m} h_j \sum_{k=1}^{W_m} w_k A_m[:,:,j,k], \mathcal{Z}_{spatial}^{Depth}(A_m) \in R^{C_m \times D_m \times 1 \times 1}, \quad (2)$$

$$\mathcal{Z}_{spatial}^{Height}(A_m) = \sum_{i=1}^{D_m} d_i \sum_{k=1}^{W_m} w_k A_m[:,i,:,k], \mathcal{Z}_{spatial}^{Height}(A_m) \in R^{C_m \times 1 \times H_m \times 1}, \quad (3)$$

$$\mathcal{Z}_{spatial}^{Width}(A_m) = \sum_{i=1}^{D_m} d_i \sum_{j=1}^{H_m} h_j A_m[:,i,j,:], \mathcal{Z}_{spatial}^{Width}(A_m) \in R^{C_m \times 1 \times 1 \times W_m}, \quad (4)$$

$$U_m = \mathcal{Z}(A_m) = f_2(K_2 * f_1(K_1 * \mathcal{Z}_{spatial}(A_m))), \quad (5)$$

Attention distillation module module:

$$G_m = \sum_{c=1}^{C_m} |A_m[c,:,:,:]|^p$$

$$\mathcal{L}_{distill} = \sum_{m=1}^{M-1} \|\hat{G}_m - \hat{G}_{m+1}\|_F^2, \hat{G}_m = \mathcal{S}(\mathcal{I}(G_m)), \quad (6)$$

Input CT cube

Output Airway probability

Encoder-Decoder style CNNs for airway segmentation

Feature Recalibration

Attention Distillation

Feature-In A_m

Spatial knowledge compression

Channel-wise recombination

U_m

Feature-Out $\hat{A}_m$

Colormap Viridis 0 — 1

Colormap OrRd 0 — 1

Two modules to improve model's sensitivity to peripheral branches

Attention maps

Mimick

Lower resolution (student) — Mimick — Higher resolution (teacher)