Spatial CNN

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Tubular Structure Segmentation Using Spatial Fully Connected Network with Radial Distance Loss for 3D Medical Images

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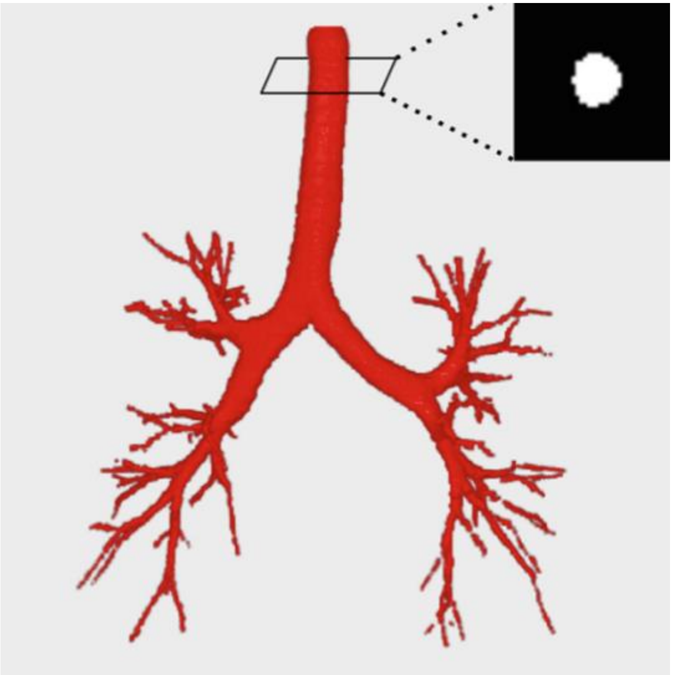
Abstract

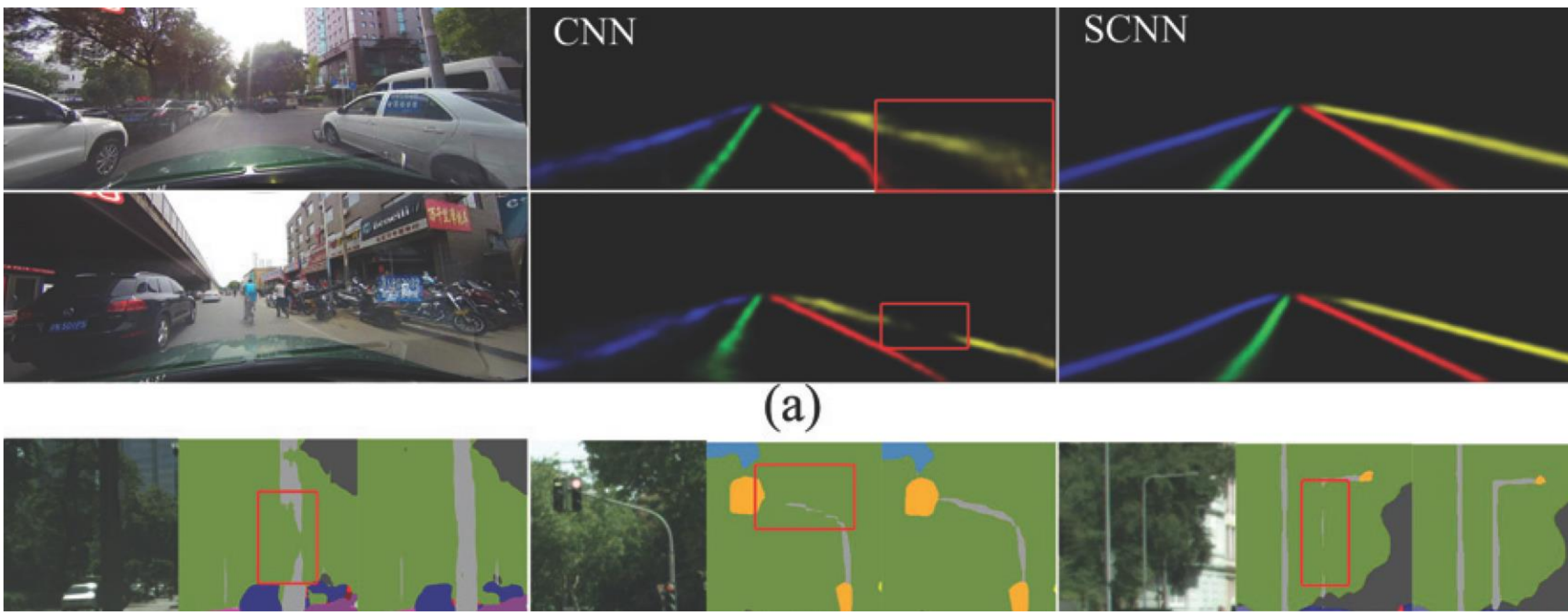
- Motivation
  - Small object size
  - Spatial information lost using 2D or 3D-patched methods
  - Unclear to learn useful context features from abundant 3D data
  - Long-range relationship and details correctness

- Contribution
  - Radial distance loss
  - 3D recurrent convolutional layers



3D Spatial-FCN

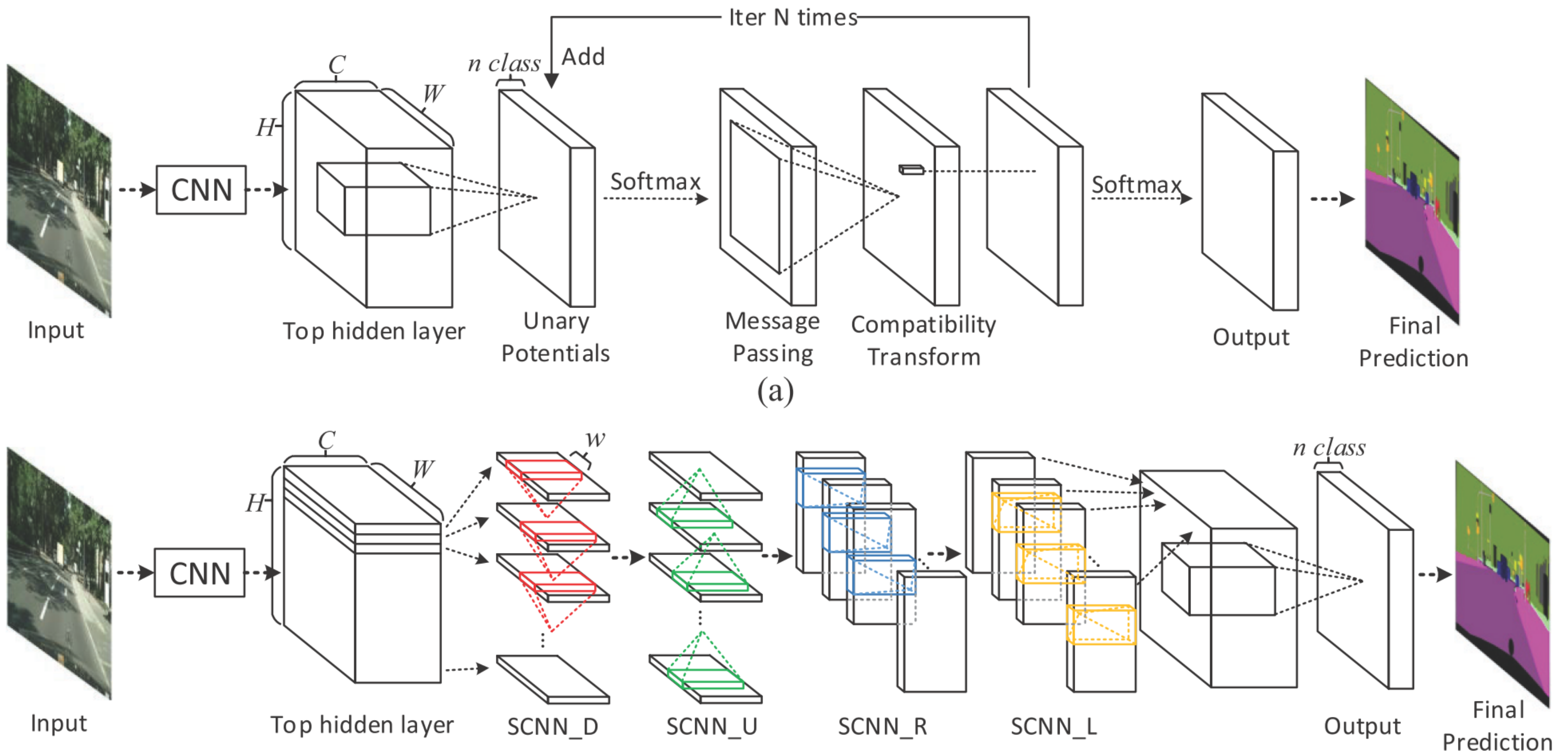
- 3D recurrent convolutional layer
  - **Spatial-CNN**: first proposed to detect traffic lane
  - Slice-by-slice convolutional layer
  - Reinforce spatial contraints



1. Spatial as Deep: Spatial CNN for Traffic Scene Understanding, AAAI 2018

3D Spatial-FCN

- Spatial-CNN
  - Capture structured object
  - Reinforce spatial information via inter-layer propagation

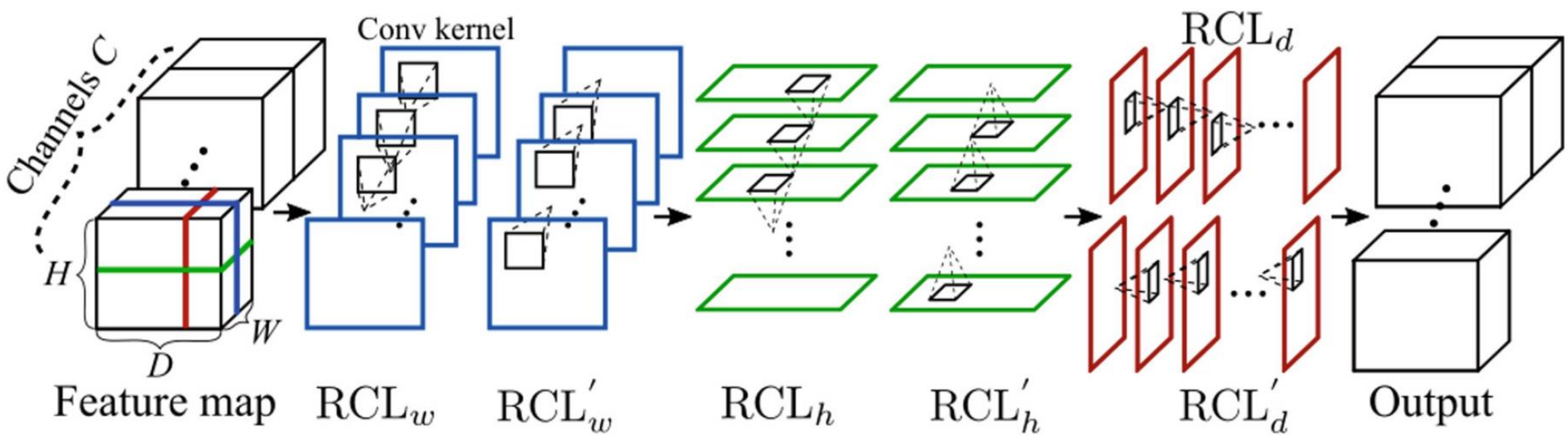


1. Spatial as Deep: Spatial CNN for Traffic Scene Understanding, AAAI 2018

3D Spatial-FCN

- 3D Spatial-FCN
  - Recurrent convolutional layers(RCLs)

$$\mathcal{Z}_{c,i,j,k} = \begin{cases} \mathcal{X}_{c,i,j,k}, & \text{if } i = 0 \\ \mathcal{X}_{c,i,j,k} + f(\mathcal{Z}_{c,i-1,j,k} * K), & \text{if } 0 < i < W, \end{cases}$$



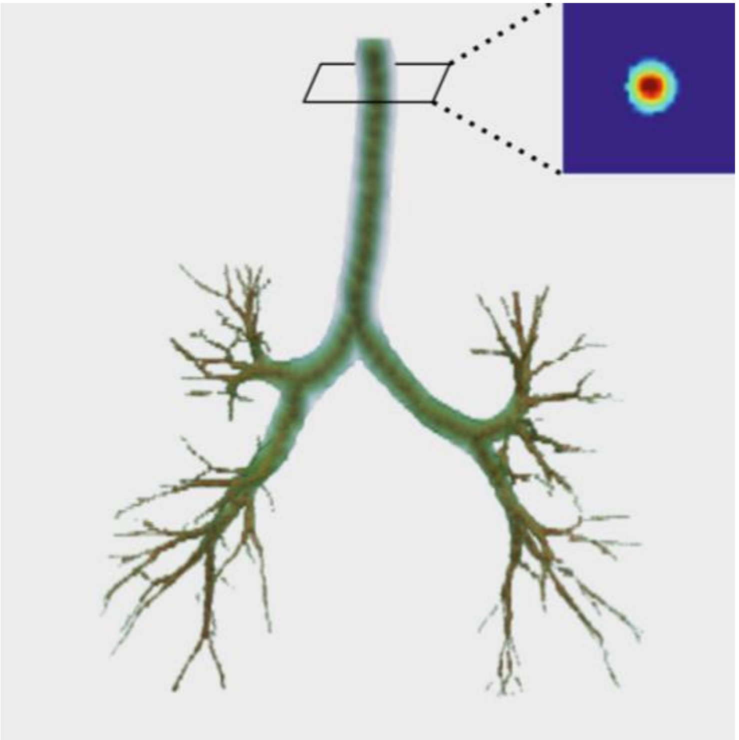
RCLs

- Radial distance map
  - Normalized distance to centerlines of airways
  - As loss function: RCLs

- Compared with centerline extraction
  - Centerline overlap (CO)

$$L = -\frac{1}{2}\sum_{k=0}^{1}\mathcal{W}_k\left(\frac{2\sum_i^N p_{i,k}d_{i,k}}{\sum_i^N p_{i,k}^2 + \sum_i^N d_{i,k}^2}\right)$$

  - Normalized: $\mathbf{D} = -\frac{1}{\max(\mathbf{F})}\mathbf{F} + 1$



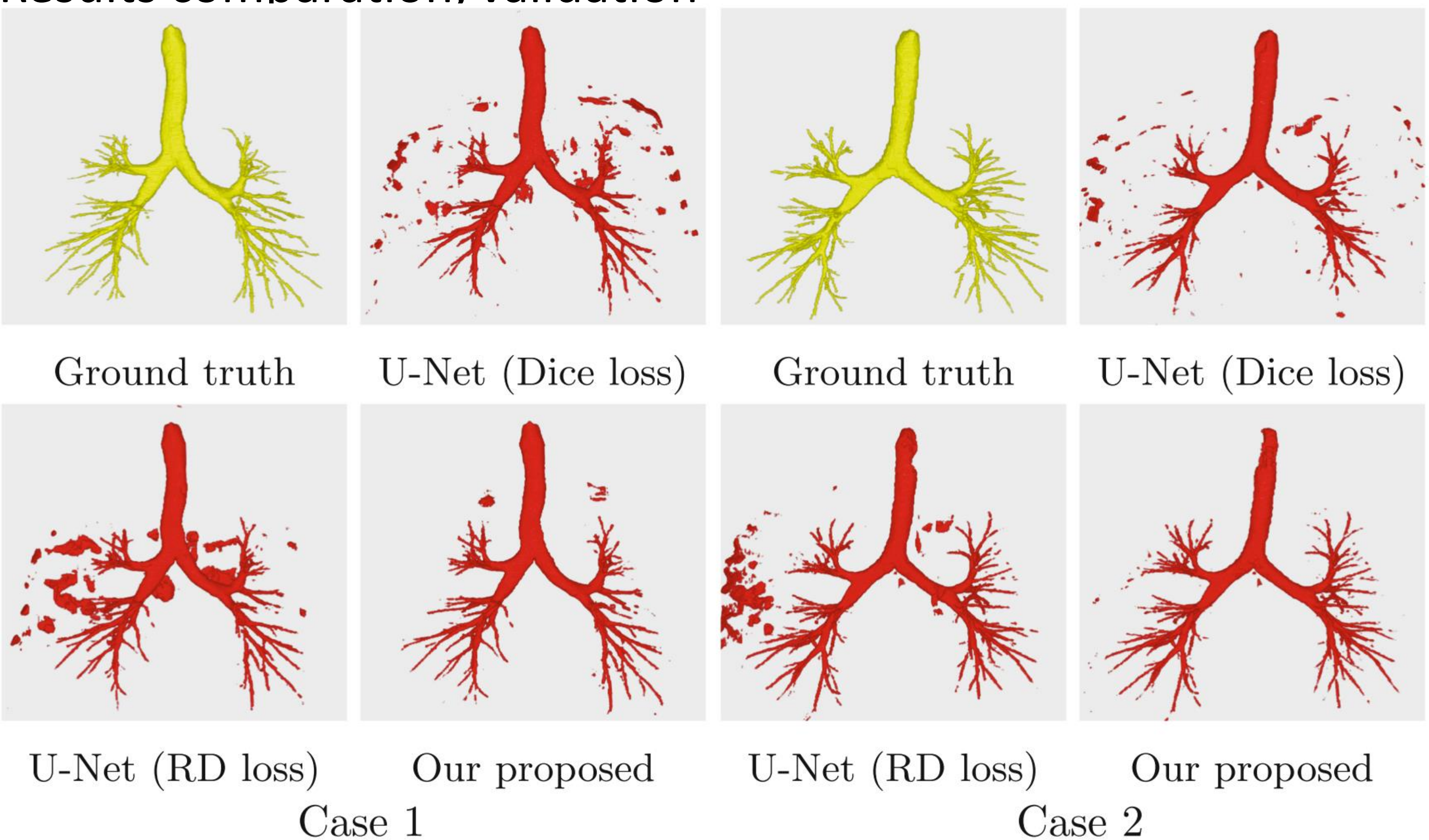
Experimetns

- Monte-Carlo cross-validation
- 35 training + 3 validation
- Test on three unseen datasets acquired in different hospital

Method	Dataset	DSC' (%)	DSC''(%)	Se (%)	CO' (%)	CO'' (%)
(1) In-house dataset						
Yun et al. [2]	Train: 59 Test:8	89.9 ± 8.9	–	–	–	–
Meng et al. [4]	Train: 30 Test:20	86.6	–	79.6	–	–
(2) Our bronchus dataset						
VoxResNet (Dice loss) [13]	MCCV Test:3	79.6 ± 3.7	90.0 ± 3.4	72.3 ± 5.0	39.2 ± 2.7	31.0 ± 2.1
V-Net (Dice loss) [9]		65.4 ± 9.9	91.0 ± 2.0	69.0 ± 2.0	28.3 ± 3.9	19.8 ± 1.1
V-Net (RD loss)		83.3 ± 2.0	88.4 ± 0.7	76.3 ± 4.6	53.8 ± 1.0	66.6 ± 4.9
U-Net (Dice loss) [8]		64.0 ± 19.5	92.4 ± 1.6	82.9 ± 5.7	47.2 ± 18.1	54.3 ± 9.0
Our proposed		88.7 ± 1.2	94.5 ± 0.8	86.5 ± 1.0	76.6 ± 6.0	80.6 ± 5.6

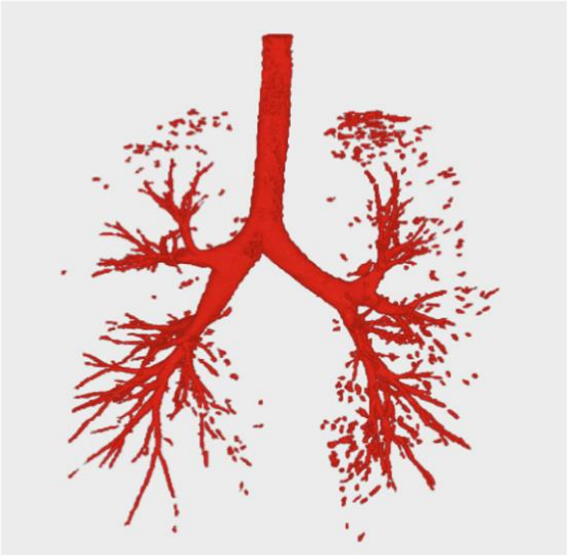
Results

- Results comparation, validation

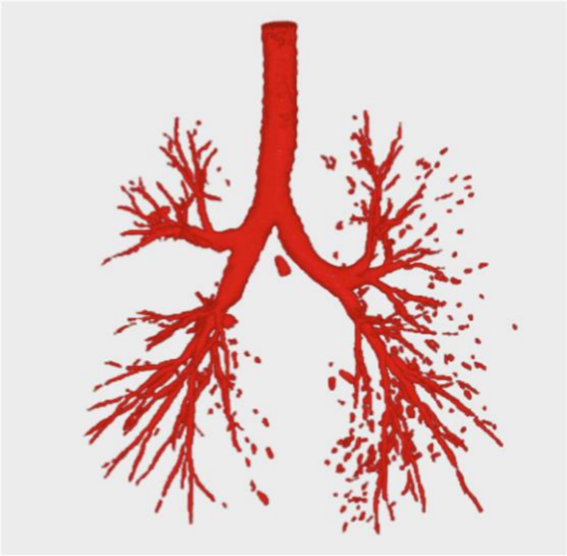


Results

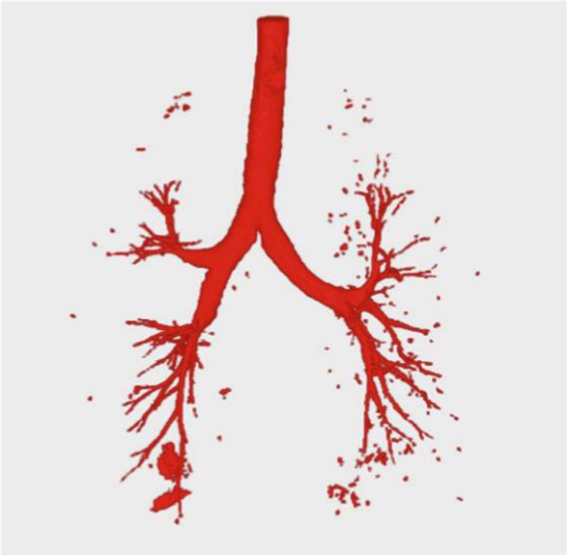
- Results comparation, test



(a) Test case 1



(b) Test case 2



(c) Test case 3

AirwayNet: A Voxel-Connectivity Aware Approach for Accurate Airway Segmentation Using Convolutional Neural Networks

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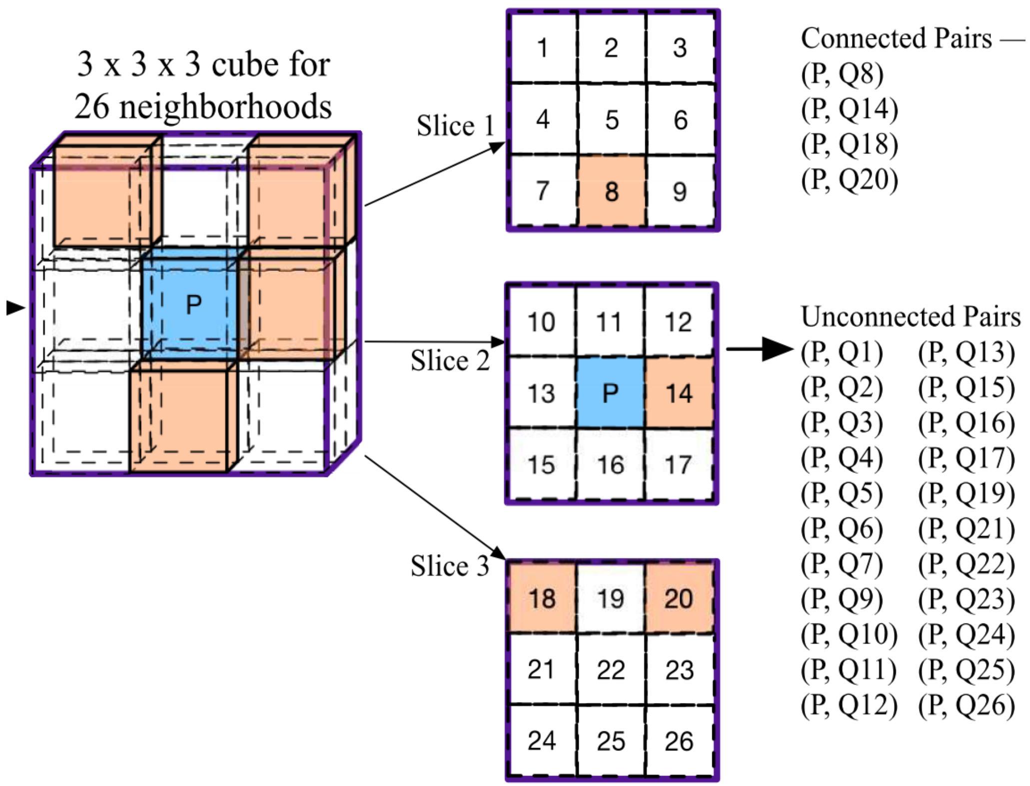
Abstract

- Motivation
  - Put emphasis on the connectivity of voxels
  - Utilize wide-range context knowledge

- Contribution
  - Multi-task learning: predict voxel probability and connectivity
  - Incorporate voxel coordinates and their distance to lung borders

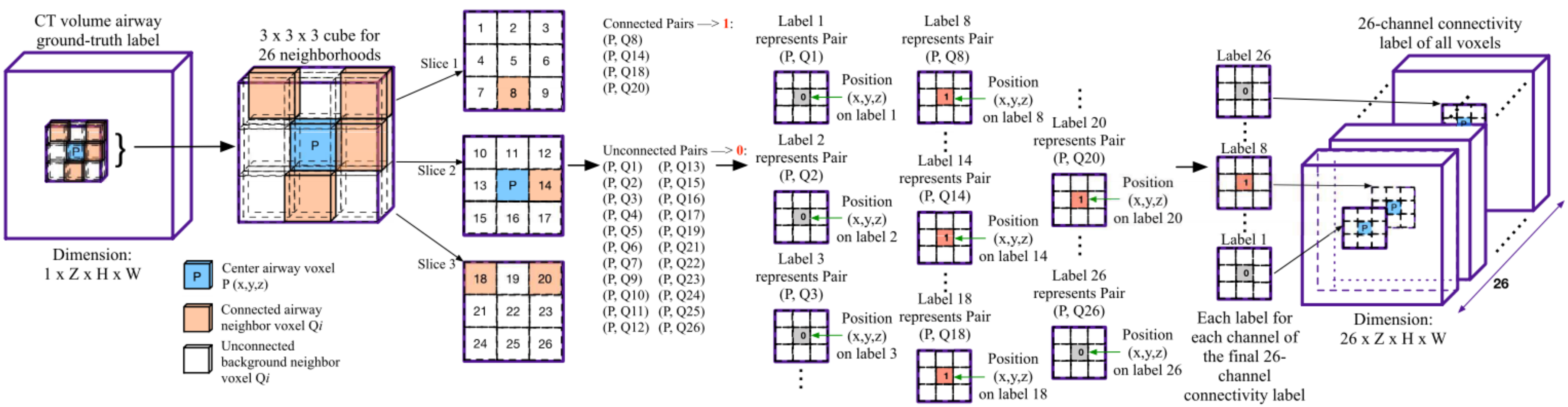
Voxel connectivity

- Voxel connectivity
  - Generate from ground truth label



Voxel connectivity

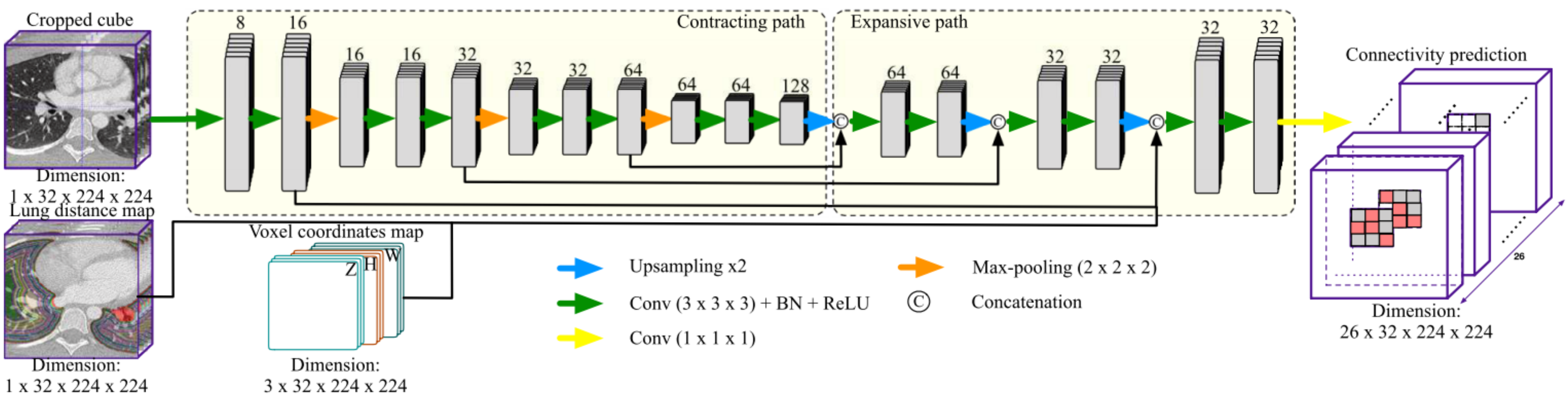
- 26-connectivity modeling
  - Decomposing one task into 26 different tasks
  - Pairwise voxels agree with each other in connectivity



$$\mathcal{L} = 1 - \frac{1}{26} \sum_{i=1}^{26} \frac{2 \sum_{x \in X} p_i(x) y_i(x)}{\sum_{x \in X} (p_i(x) + y_i(x)) + \epsilon}$$

Flow

- Architecture
  - 26-connectivity modeling
  - Lung distance map
  - Voxel coordinates map



Experiments

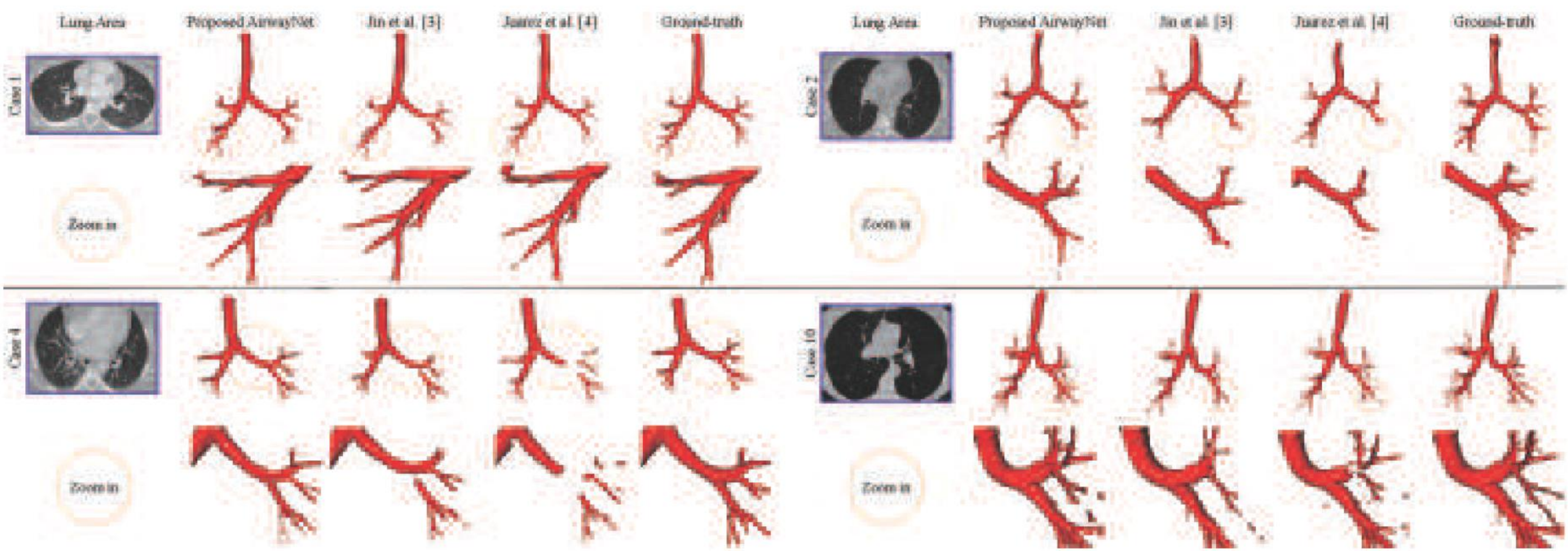
- 20 training + 10 testing

Case	AirwayNet				Jin et al. [3]				Juarez et al. [4]			
	DSC	TPR	FPR	PPV	DSC	TPR	FPR	PPV	DSC	TPR	FPR	PPV
1	92.4	86.5	0.003	99.2	90.4	84.4	0.010	97.2	91.0	83.8	0.002	99.5
2	87.5	78.5	0.003	98.8	73.8	60.8	0.011	94.0	76.9	62.6	0.000	99.8
3	91.1	85.3	0.004	97.7	88.9	83.1	0.008	95.6	91.1	84.6	0.002	98.8
4	82.9	73.1	0.009	95.7	79.6	66.5	0.002	99.1	70.8	55.6	0.004	97.4
5	90.8	86.2	0.015	95.9	90.6	85.3	0.012	96.6	89.3	81.4	0.003	99.1
6	91.5	89.2	0.025	94.0	84.5	88.3	0.091	81.0	92.3	87.9	0.012	97.1
7	90.6	87.6	0.025	93.7	88.2	85.3	0.034	91.2	90.3	85.1	0.014	96.2
8	91.7	88.9	0.017	94.7	86.4	88.1	0.054	84.8	90.2	86.5	0.018	94.2
9	93.1	88.8	0.009	97.8	90.5	84.3	0.009	97.7	85.9	75.9	0.004	98.9
10	90.4	83.2	0.003	98.9	88.2	79.3	0.002	99.4	88.3	79.4	0.001	99.5
Mean	**90.2**	**84.7**	0.011	96.6	86.1	80.5	0.023	93.7	86.6	78.3	**0.006**	**98.1**
Std.	**2.8**	**4.9**	0.008	1.9	5.2	8.9	0.027	5.9	6.7	10.3	**0.006**	**1.7**

Methods	DSC	TPR	FPR	PPV
AirwayNet w/o Conn	87.1±6.4	79.3±9.6	**0.007±0.008**	**97.6±2.5**
AirwayNet w/o D&C	88.4±5.4	81.6±8.7	0.009±0.009	97.1±2.1
AirwayNet w/o FCS	90.1±2.8	84.4±4.9	0.011±0.008	96.8±1.9
AirwayNet	**90.2±2.8**	**84.7±4.9**	0.011±0.008	96.6±1.9

Results

- Results comparation



Thanks for listening!