Pulmonary Vessel Segmentation based on Orthogonal Fused U-Net++ of Chest CT Images

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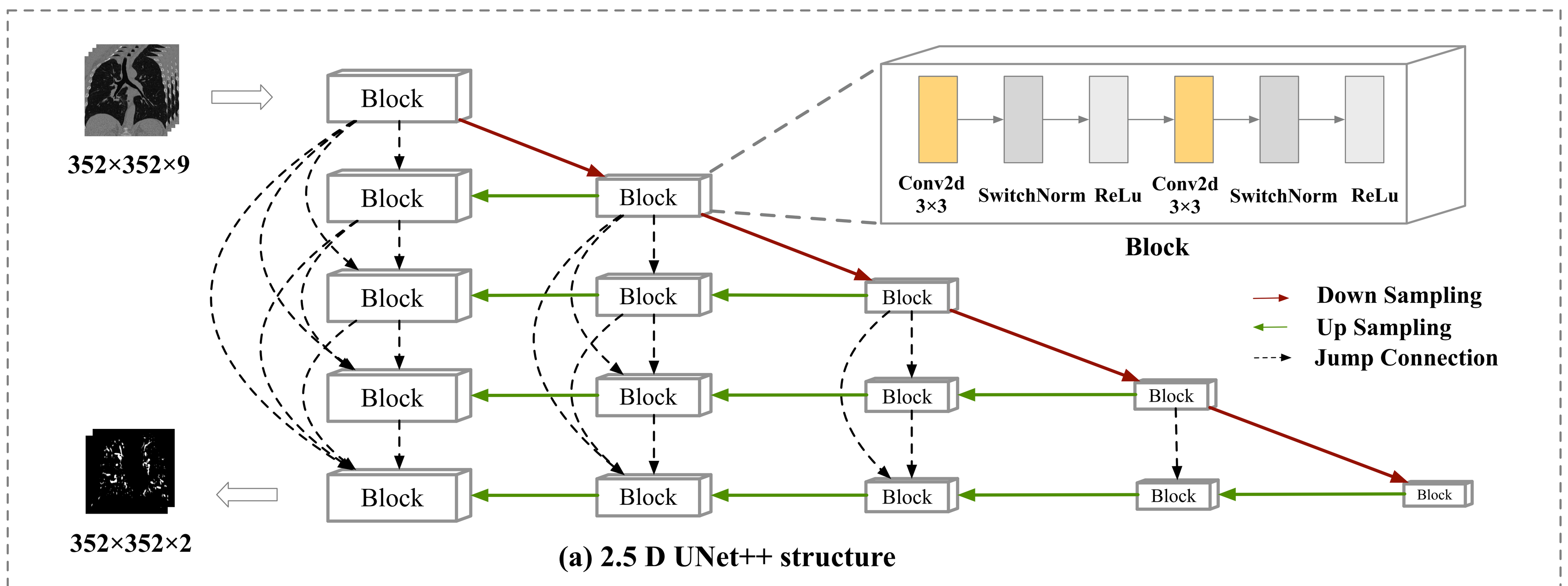
Introduction

- Pulmonary vessel segmentation is important for clinical diagnosis of pulmonary diseases, while is also challenging due to its complicated structure.
- In this work, we present an effective framework and refinement process of pulmonary vessel segmentation from chest computed tomography (CT) images.

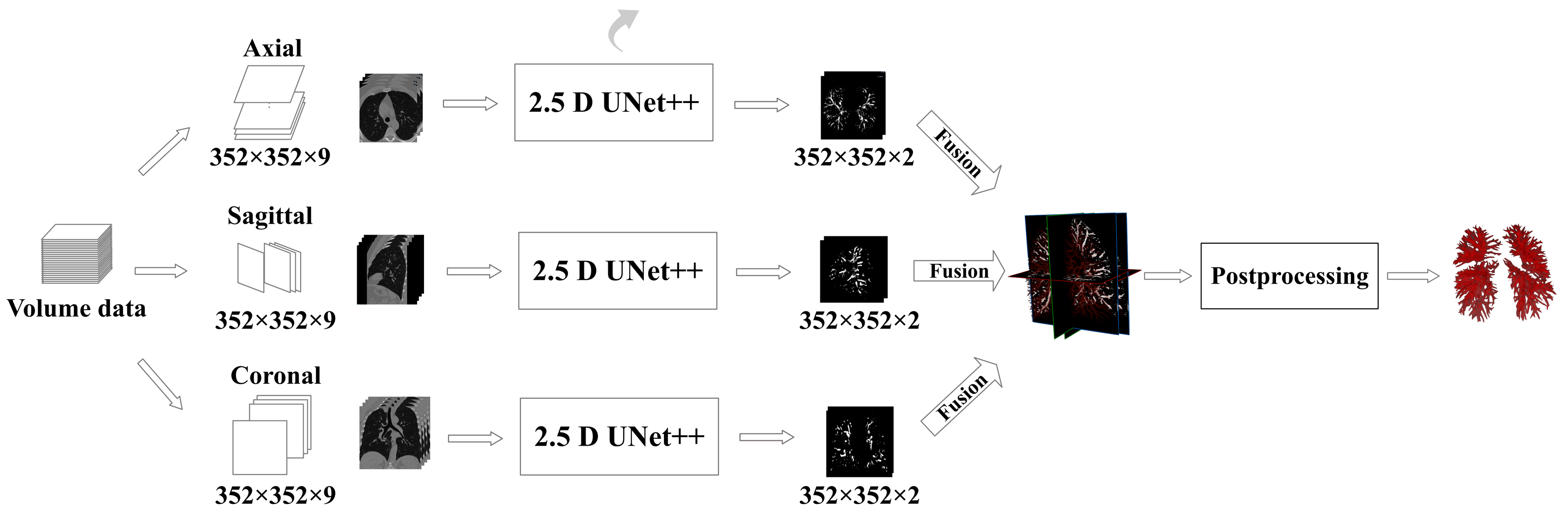
Contributions

- We propose a **2.5D convolution network**, which employs the 2D convolutional network on a stack of adjacent slices and fuses the features extracted from three orthogonal axes.
- A whole automated segmentation framework is given and the segmentation result is refined by the graph information of pulmonary vessel tree.
- Our method gives a competitive performance and ranks 1st till now on DICE Similarity Coefficient and Precision compared with other state-of-the-art methods.

Pipeline



(a) 2.5 D UNet++ structure



(b) Pipeline of the proposed pulmonary vessel segmentation framework

2.5D Network Based on U-Net++

- **Slice radius** is introduced, where slices within the radius will go through one of three separated identical up-sampling, down-sampling and convolution process, which is composed by a stack of VGG blocks.
- The input channel is 9, and the ground-truth of the middle slice will be provided. The upper and lower 4 pieces of the middle slice are used to generate the feature maps.
- The output channel of the 2.5D network is 2, indicating the voxel-wise probability of being foreground or background.

Orthogonal Fusion of Multi-planar Networks

- The slice groups along three axes are processed in parallel.
- These **three parallel results** of each direction are then fused under the comparison of different methods, including intersection, union and average value.
- By jointing together the intra and inter slice features extracted along three orthogonal axis, we optimize the description of volumetric feature representation to be more integral and comprehensive.

Two-Stage Loss Function

To alleviate the **class-imbalance problem** caused by the inequitable penalty of positive and negative voxels, we separate the training process as two stage:

$$L = L_{Y_+(W)} + L_{Y_-(W)}$$

- ❖ In the pre-trained stage, we use Negative Log Likelihood loss to get a coarse model;
- ❖ In the fine-tuned stage, we adopt a weight-balanced loss:

$$L_{Y_+(W)} = -\sum_{i \in Y_+}^{N} logP(y_i = 1|X;W)$$

$$L_{Y_-(W)} = -\sum_{j \in \tilde{Y}_-}^{N} logP(y_j = 1|X;W)$$

where $\tilde{Y}_-$ represents the top N loss value selected from the sorted list of negative samples and N is the number of elements in positive list.

Vessel Structure Generation

- We generate the morphology representation of tree-like graph from the skeleton of segmentation result.
- The **topological structure** represented by edges and nodes also indicates meaningful information for clinical practice.

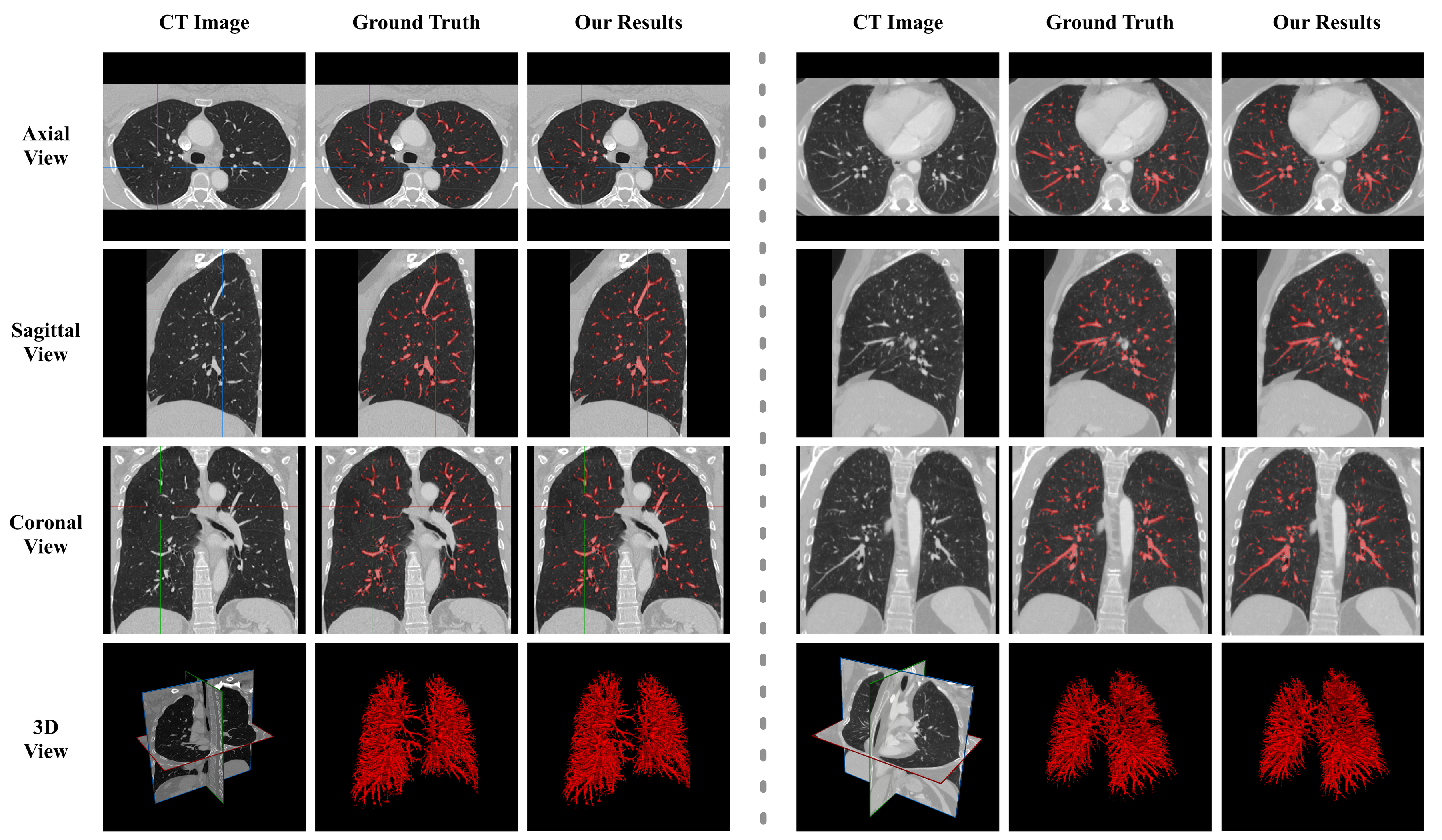
Experimental Results

- **Comparation** of the single axis model with three fusion methods, including intersection, union and average value. The average value does best one in keeping information of three axes.

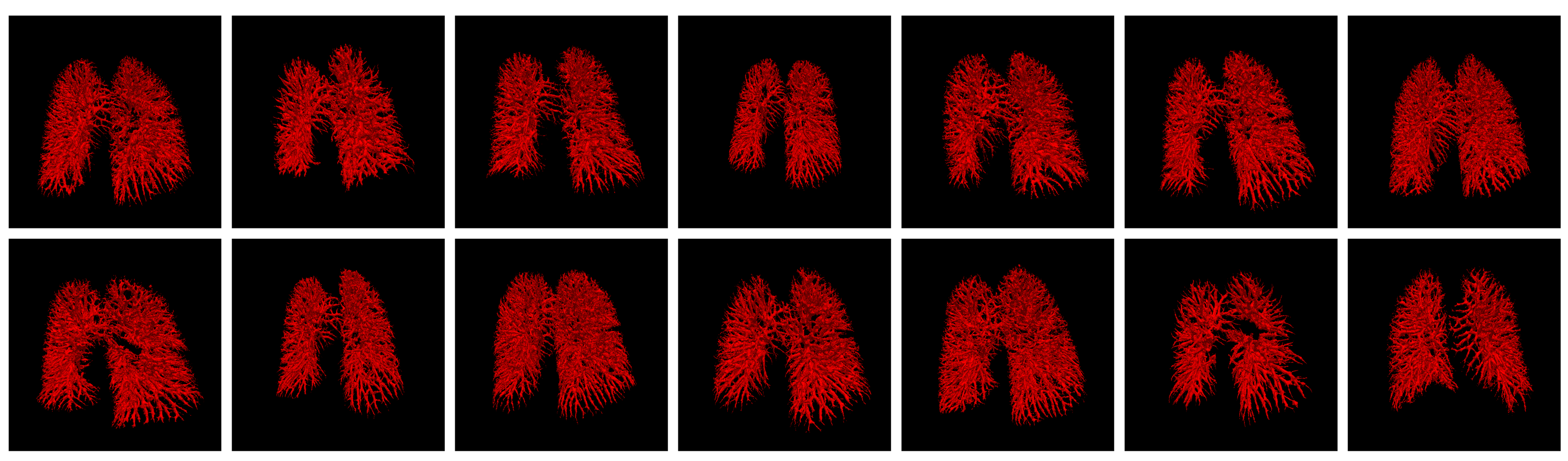
Methods	Min Dice	Max Dice	Avg. Dice	Precision/Recall
Axial	0.8618	0.9584	0.9162	0.9250/0.9144
Sagittal	0.8444	0.9575	0.9114	0.9232/0.9080
Coronal	0.7474	0.9547	0.8964	0.9024/0.9020
Union	0.8252	0.9580	0.9118	0.8714/0.9634
Intersection	0.7946	0.9555	0.9096	0.9518/0.8772
Average	**0.8779**	**0.9627**	**0.9262**	**0.9310/0.9272**

- **Comparation** of the average fused 2.5D network structure with several state-of-the-art network structures, including 2D U-Net++, 3D U-Net++ as well as several 3D FCNs.

Structures	Min Dice	Max Dice	Avg. Dice	Precision/Recall
2D U-net++	0.5201	0.7376	0.6628	0.6629/0.6767
3D U-Net++	0.4385	0.8038	0.7286	0.7425/0.7436
2.5D U-Net++	**0.8779**	**0.9627**	**0.9262**	**0.9310/0.9272**



The visual comparison between the ground truth and result of the 2.5D Average Orthogonal Fused U-Net++



Qualitative results of average fusion 2.5D U-Net++ on more CT images