Abstract—Training convolutional neural networks (CNNs) for segmentation of pulmonary airway, artery, and vein is challenging due to sparse supervisory signals caused by the severe class imbalance between tubular targets and background. We present a CNNs-based method for accurate airway and artery-vein segmentation in non-contrast computed tomography. It enjoys superior sensitivity to tenous peripheral bronchioles, arterioles, and venules. The method first uses a feature recalibration module to make the best use of features learned from the neural networks. Spatial information of features is properly integrated to retain relative priority of activated regions, which benefits the subsequent channel-wise recalibration. Then, attention distillation module is introduced to reinforce representation learning of tubular objects. Fine-grained details in high-resolution attention maps are passing down from one layer to its previous layer recursively to enrich context. Anatomy prior of lung context map and distance transform map is designed and incorporated for better artery-vein differentiation capacity. Extensive experiments demonstrated considerable performance gains brought by these components. Compared with state-of-the-art methods, our method extracted much more branches while maintaining competitive overall segmentation performance. Codes and models will be available later at http://www.pami.sjtu.edu.cn.

Index Terms—Computed tomography, lung, image segmentation, convolutional neural networks

I. INTRODUCTION

PULMONARY diseases pose high risks to human health. As a diagnostic tool, computed tomography (CT) has been widely adopted to reveal tomographic patterns of pulmonary diseases. It is of significant clinical interest to study pulmonary structures in volume-of-interest (VOI). One prerequisite step is to extract pulmonary airways from CT. The modeling of airway tree benefits the quantification of its morphological changes for diagnosis of bronchial stenosis, acute respiratory distress syndrome, idiopathic pulmonary fibrosis, chronic obstructive pulmonary diseases (COPD), obliterator bronchiolitis, and pulmonary contusion [11]–[15]. Combined with photo-realistic rendering and projection, the segmented airways play an important role in virtual bronchoscopy and endobronchial navigation for surgery [6]–[9]. Another essential step is to extract pulmonary arteries and veins from CT. Pulmonary diseases may affect artery or vein, or both but in different ways [10], [11]. Morphological changes of arteries are measured in diagnosing pulmonary embolism, arteriovenous malformations, and COPD [12]–[15]. The arterial alterations also serve as an imaging biomarker in chronic thromboembolic pulmonary hypertension [16]. Accurate separation of veins from arteries may improve computer-aided diagnosis of embolism because most false positive lesions were found in veins [13]. The imaging features of veins are found useful in diagnosis of vein diseases [17]. Despite the benefits of airway and artery-vein segmentation, it requires heavy workloads for manual delineation due to the complexity of tubular structures. Consequently, automatic segmentation methods were developed to reduce burden and improve accuracy. Especially if arteries and veins can be extracted from non-contrast CT (i.e. CT without the use of contrast agents), CT pulmonary angiogram may not be needed in certain cases to avoid adverse reactions to contrast agents [18], [19].

A. Related Work

Over the past decades, several methods have been proposed for airway segmentation [6], [20], [21]. Most of them employed techniques such as adaptive thresholding, region growing and filtering-based enhancement. These methods successfully segmented thick bronchi, but often failed to extract peripheral bronchioles due to the fact that the intensity contrast between airway lumen and wall weakens as airways bifurcate into thinner branches. Recent progress of convolutional neural networks (CNNs) has spawned research on airway segmentation using CNNs [22]–[31]. Two-dimensional (2-D) and 2.5-D CNNs [26], [27] were respectively applied on the...
initial coarsely segmented bronchi to reduce false positives and increase length of the detected airway tree. Three-dimensional (3-D) CNNs were developed for direct airway segmentation in either a dynamic VOI-based tracking way [28] or a fixed-stride sliding window way [30]. The spatial recurrent convolution layer and radial distance loss were proposed by [24] for tubular topology perception. In [25], the airway segmentation task was transformed into 26-neighbor connectivity prediction task for inherent structure comprehension. Both 2-D and 3-D CNNs were combined with linear programming-based tracking in [31]. Graph neural networks [22], [23] were explored to incorporate neighborhood knowledge in feature utilization.

Previous methods on artery-vein separation relied on the enhanced or segmented vessels as premise [11], [32]–[37]. To tackle the variety of vessels, combination of techniques such as local filtering and anatomical guidance is employed in the literature. Specifically, they utilized the proximity of airways to arteries for differentiation and suppressed airway walls to reduce false positives. Buelow et al. [32] proposed a measure of “arterialness” by identifying airway candidates in the vicinity of given vessels and assigning high value to vessels that run in parallel with bronchi. Mekada et al. [33] calculated the distance from vessels to airways and to interlobar fissures. Vessels closer to airways are arteries and those closer to fissures are veins. Both Saha et al. [34] and Gao et al. [35] combined distance transform and fuzzy connectivity with morphological opening for separation. Recently, three methods were developed to improve artery-vein segmentation [11], [36], [37]. Charbonnier et al. [11] first constructed a graph representation of the segmented vessels to extract sub-trees. These trees were grouped iteratively and the final classification was performed by comparing the volume size of the linked trees. Payer et al. [36] extracted vessel sub-trees and classified each sub-tree via integer programming. Two anatomy properties were used: 1) proximity of arteries to bronchi; 2) uniform distribution of arteries and veins. CNNs were at the first time introduced to artery-vein classification by Nardelli et al. [37]. Graph-cut was adopted as post-processing to remove spatial inconsistency.

**B. Limitations and Challenges**

Despite the improved performance of pulmonary airway and artery-vein segmentation by deep learning, there still remain limitations and challenges to be overcome.

First, for both airway and artery-vein segmentation, the severe class imbalance between tubular foreground and background poses a threat to the training of 3-D CNNs. Most CNNs heavily rely on airway and vessel ground-truth as supervisory signals. Unlike bulky or spheroid-like organs (e.g., liver and kidney), tree-like airways, arteries, and veins are thin, tenuous and divergent. The number of annotated voxels are far fewer than that of background voxels in the thoracic cavity. It is difficult to train deep models using such sparse and scattered targets. Although weighted cross-entropy loss and data sampling strategies were proposed to focus on the minority, single source of supervisory signals from deficient airway and artery-vein labels still makes optimization ineffective.

Second, the spatial distribution and branching pattern of airways and vessels require the model to utilize both global-scale and local-scale context to perceive the main body (e.g., trachea, main branches) and limbs (e.g., peripheral bronchi and vessels). Previous deep learning models used 2 or 3 pooling layers and the coarsest resolution features provide limited long-range context. If more layers are simply piled up, the increased parameters may cause over-fitting due to inadequate training data. If the width of CNNs (a.k.a. number of feature channels) is sacrificed for the depth (a.k.a. number of convolution layers) to avoid such parameter “explosion”, the model’s learning and fitting capacity may get restricted.

Third, it is more rigorous to deem pulmonary artery-vein separation methods in the literature as classification rather than segmentation. They used two-stage strategy and counted on vessel segmentation in the first stage. The subsequent artery-vein separation was treated as an independent classification task in the second stage. Different techniques were deployed in two stages and such isolation has two drawbacks: 1) It blocks the path for the second model to exploit rich context from the first one, especially when CNNs are applied as backbone. CNNs cannot take advantage of high correlation between the two tasks and have to learn from scratch. 2) The performance of artery-vein segmentation is largely affected by that of vessel extraction and errors accumulate along the whole pipeline.

Last but not least, for artery-vein separation, previous CNNs-based method [37] did not consider the relationship between airways, arteries, and veins. Auxiliary anatomy prior (e.g., close proximity of arteries to airways, intensity similarity between airway walls and vessels) was not involved in algorithm design, leaving room for further improvement.

**C. Contributions**

To address these concerns, we present a CNNs-based method for pulmonary airway and artery-vein segmentation. Since airways, arteries, and veins are all tubular structures, they are collectively referred to as tubules in the present study. With the carefully designed constituent modules, the proposed method learns to comprehend the contour shape, intensity distribution, and connectivity of bronchi and vessels in a data-driven way. It tackles the challenges of applying CNNs to recognition of long, thin tubules and enjoys high sensitivity to bronchioles, arterioles, and venules.

First, we propose a feature recalibration module to maximally utilize the features learned from CNNs. On one hand, to increase the field-of-view for large context comprehension, multiple pooling layers are applied with convolution and accordingly the number of learnable parameters increases. On the other hand, we expect the model to learn discriminative features without over-fitting the training set. Under this circumstance, feature recalibration is considered necessary as it intensifies task-related features. In the design of recalibration module, we hypothesize that spatial information of features is indispensable for channel-wise recalibration and should be treated differently from position to position and layer to layer. The average pooling used in [38], [39] for spatial compression may not well capture the location of airways and vessels in
Fig. 1. Overview of the proposed method for pulmonary airway and artery-vein segmentation. Instance normalization and ReLU activation are performed after each convolution layer except the last one. The number of convolution kernels is denoted above each layer.

different resolution scales. In contrast, we aim at prioritizing information at key positions with learnable weights, which provides appropriate spatial hints to model inter-channel dependency and thereafter improves recalibration.

Second, we introduce an attention distillation module to reinforce representation learning of tubular airway, artery, and vein. Attention maps of different scales enable us to potentially reveal the morphology and distribution pattern of airways and vessels. Inspired by knowledge distillation [40], [41], we refine the attention maps of lower resolution by mimicking those of higher resolution. Finer attention maps (teacher’s role) with richer context can cram coarser ones (student’s role) with details about airways, arteries, and veins. The model’s ability to recognize delicate branches is ameliorated after recursively focusing on the target anatomy. Dealing with insufficient supervisory signals, the distillation itself acts as an auxiliary learning task that provides extra signals to assist training.

Third, we incorporate anatomy prior into artery-vein segmentation by introducing lung context map and distance transform map. The lung context map, containing automatically segmented airway lumen, airway wall, and lung, explicitly informs the model of semantic knowledge. The distance transform map, computed using extracted airways, records the distance of each voxel to its nearest airway wall.

Finally, the proposed end-to-end method is applicable for both pulmonary airway and artery-vein segmentation. We do not perform independent vessel segmentation beforehand and require no post-refinement on the outputs of CNNs. The sliding window-based segmentation is used and each voxel’s coordinates within the thoracic cavity are fed into the model to make up for the loss of position information.

Our contributions can be briefly summarized as follows:
- We present a tubule-sensitive CNNs-based method for pulmonary airway and artery-vein segmentation. To our best knowledge, this method represents the first attempt to segment airways, arteries, and veins simultaneously.
- We propose a feature recalibration module that integrates prioritized spatial knowledge for channel-wise recalibration. It encourages discriminative feature learning.
- We introduce an attention distillation module to reinforce representation learning of tubular airway, artery, and vein. No extra annotation labor is required.
- We incorporate explicit anatomy prior into artery-vein segmentation by utilizing the lung context map and distance transform map as additional inputs.
- We respectively validate the proposed method on 110 and 55 non-contrast clinical CT scans for pulmonary airway and artery-vein segmentation. Extensive experiments show that our method achieved superior sensitivity to thin airways, arteries, and veins, with surpassing or competitive overall segmentation performance maintained.

II. METHODS

Overview of the proposed airway and artery-vein segmentation methods is illustrated in Fig. 1. To fulfill effective feature learning of tubular targets, feature recalibration and attention distillation modules are introduced into CNNs. Anatomy prior is included to provide semantic knowledge for artery-vein task.

Given an input CT volume \( X \), our segmentation process can be formulated as \( P_{\text{Target}} = F(X) \), where \( \text{Target} \) can be airway, artery, or vein and \( P_{\text{Target}} \) denotes its corresponding predicted probability. The objective is to learn an end-to-end...
mapping $F$ via CNNs to minimize the difference between $P_{\text{Target}}$ and its ground-truth label $Y_{\text{Target}}$. Assuming CNNs have $M$ convolution layers in total, we denote the activation output of the $m$-th convolution as $A_m \in R^{C_m \times D_m \times H_m \times W_m}$, $1 \leq m \leq M$. The number of its channels, depths, heights, and widths are respectively denoted as $C_m$, $D_m$, $H_m$, and $W_m$.

### A. Feature Recalibration

![Illustration of the mapping $Z(\cdot)$ for feature recalibration.](image)

Its input is the activated feature $A_m$ of the $m$-th convolution layer. First, spatial map that highlights important regions is integrated through $Z_{\text{spatial}}(\cdot)$ along three axes of depth, height, and width. Second, channel recombination is performed on the spatial map to compute the channel descriptor $U_m$. The final element-wise multiplication between $A_m$ and $U_m$ produces the recalibrated feature $\hat{A}_m$. The notations $r$, $C_m$, $D_m$, $H_m$, and $W_m$ refer to the channel compression factor, the number of channels, depths, heights, and widths of the $m$-th layer feature $A_m$. The learnable parameters $d_i$, $h_j$, $w_k$ denote the combination weights for each feature slice in depth, height, and weight dimension, respectively. During training, crucial airway and artery-vein regions are gradually preferred with higher weights while uninformative corner regions are neglected with lower weights. For the second step, we apply the excitation technique [38] on the compressed spatial map to model inter-channel dependency. Specifically, the channel descriptor $U_m$ is obtained by:

$$U_m = Z(A_m) = f_2(K_2 \ast f_1(K_1 \ast Z_{\text{spatial}}(A_m)))$$

where $K_1, K_2$ are 3-D kernels of size $1 \times 1 \times 1$ and “$\ast$” denotes convolution. Convolving with $K_1$ decreases the channel number to $C_m/r$ and that with $K_2$ recovers back to $C_m$. The ratio $r$ is the compression factor that determines reduction extent. $f_1(\cdot)$ and $f_2(\cdot)$ are non-linear activation functions. We choose Rectified Linear Unit (ReLU) as $f_1(\cdot)$ and Sigmoid as $f_2(\cdot)$ in the present study. Multiple channels are recombined through such channel reduction and increment, with informative ones emphasized and redundant ones suppressed. Given the activated convolutional feature $A_m$ and its channel descriptor $U_m$, the recalibrated feature $\hat{A}_m$ is defined as:

$$\hat{A}_m = U_m \odot A_m,$$

where $\odot$ denotes element-wise multiplication.

### B. Attention Distillation

In both airway and artery-vein segmentation tasks, the segmentation model is required to identify thin tubules like distal bronchi, arteries, and veins. It could be expected that reinforced attention on such objects during feature learning may conduce to improved performance. Recent studies [40], [41] on knowledge distillation showed that attention maps serve as valuable knowledge and can be transferred layer-by-layer from teacher networks to student networks. Motivated by knowledge transferability and self-attention mechanism, we introduce the attention distillation module into our 3-D CNNs for recognition of narrow, thin objects. The activation-based attention maps, which guide where to look at, are distilled and exploited during backward transfer process. Without separately setting two different models, later layers play the role of...
teacher and “impart” such attention to earlier layers within the same model. Besides, to tackle insufficient supervisory signals caused by the severe class imbalance, the distillation can be viewed as another source of supervision. It produces additional gradients by forcing low-resolution attention maps to resemble high-resolution ones, aiding the training of deep CNNs. Specifically, the attention distillation is performed between two consecutive features $A_m$ and $A_{m+1}$.

Firstly, the attention map is generated by $G_m = \mathcal{G}(A_m)$, $G_m \in \mathbb{R}^{1 \times D_m \times H_m \times W_m}$. Each voxel’s absolute value in $G_m$ reflects the contribution of its correspondence in $A_m$ to the entire segmentation model. One way of constructing the mapping function $\mathcal{G}(\cdot)$ is to compute the statistics of activation values $A_m$ across channel:

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

The element-wise operation $|\cdot|^p$ denotes the absolute value raised to the $p$-th power. More attention is addressed to highly activated regions if $p > 1$. Here, we adopt channel-wise summation instead of maximizing $\max_c(\cdot)$ or averaging $\frac{1}{C_m} \sum_{c=1}^{C_m} (\cdot)$ because it is relatively less biased. The sum operation retains all implied salient activation information without ignoring non-maximum elements or weakening discriminative elements. For intuitive comparison of different $\mathcal{G}(\cdot)$, visualization of 3-D attention maps on 2-D plane is presented in Fig. 3 by first choosing multiple 2-D slices that contain airways and vessels and then super-imposing them together with opacity of 30%. Visual comparison exhibits that summation with $p > 1$ intensifies most the sensitized task-related regions (e.g., lung borders, bronchi, vessels).

Secondly, trilinear interpolation $\mathcal{I}(\cdot)$ is performed to ensure that processed 3-D attention maps share the same dimension.

Then, voxel-wise Softmax $\mathcal{S}(\cdot)$ is spatially applied to normalize all elements in $[0, 1]$. Finally, we drive the distilled attention $\hat{G}_m$ closer to $\hat{G}_{m+1}$ by minimizing the loss:

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

where $\|\cdot\|_F$ is the squared Frobenius norm. With $\hat{G}_m$ recursively mimicking its successor $\hat{G}_{m+1}$, visual attention is transmitted from the deepest to the shallowest layer. Note that such distillation process does not require extra annotation labor and can work with arbitrary CNNs readily. In implementation, to prevent the latter attention $\hat{G}_{m+1}$ from approximating the previous $\hat{G}_m$, we detach $\hat{G}_{m+1}$ from the computation graph for each $m$ in loss calculation. Consequently, $\hat{G}_{m+1}$ will not be changed by back-propagating errors. The reasons why we do not down-sample $\hat{G}_{m+1}$ to the size of $G_m$ is that $\hat{G}_{m+1}$ at decoder side has higher resolution than $G_m$ by nature and down-sampling loses rich information that only exists in $G_{m+1}$. It is necessary to keep $\hat{G}_{m+1}$ unchanged so that the resultant distillation loss between $G_m$ and $\hat{G}_{m+1}$ can improve model’s attention on fine details about targets.

C. Anatomy Prior For Artery-Vein Segmentation

Fig. 4. Illustration of anatomy prior incorporation. Visual display of the generated lung context maps and distance transform maps superimposed on CT scans is given in bottom left.

In the present study, artery-vein segmentation in the lung hilum (e.g., pulmonary trunk, left and right main pulmonary veins) is excluded since recognition of these vessels in non-contrast CT is extremely difficult for both computers and medical experts [11]. Considering that the valid artery and vein targets are mainly restricted inside the two lungs, we believe it is reasonable to provide segmented lung masks as VOI hint. The lung segmentation is performed by: 1) binarization using OTSU thresholding [42]; 2) hole filling using morphological operations; 3) selection of the two largest connected components as left and right lungs; 4) convex hull computation to prevent over-segmentation. Besides, we hypothesize that proper representation of airway anatomy is beneficial for the model to distinguish between vessels and airway walls, where similar intensity distribution is shared. Therefore, automatic airway segmentation is first performed using the proposed method to obtain airway lumen. Then, assuming the thickness of airway wall is less than 2 mm [43], we extract airway wall by subtracting airway lumen from its morphological dilation result. The structuring element for dilation is a sphere with diameter of 3 voxels. Given the segmented airway lumen, wall, and lung field, we respectively label them as 1, 2 and 3 to generate the lung context map.

Since pulmonary arteries inside lungs often accompany with airways in parallel, we believe the proximity of arteries to airways might be informative for the segmentation model.
to discriminate arteries from veins [44]–[47]. Consequently, Euclidean distance transform is performed on the segmented airways to calculate the distance of each voxel to its nearest airway wall. The computed distance transform map is multiplied with lung mask to keep valid regions.

To summarize, two maps are introduced as anatomy prior for artery-vein segmentation (see Fig. 4): lung context map and distance transform map. The first map offers extra semantic knowledge of lung and the second map reflects voxels’ closeness to airway. These maps are concatenated with CT sub-volume as inputs to the artery-vein segmentation model.

D. Model Design

The proposed method employs 3-D U-Net [48] as network backbone. Such encoder-decoder CNNs first extract a condensed representation of input image and then reconstruct it in response to different tasks. To enlarge the receptive field of CNNs and facilitate feature learning of long-range relationships, four pooling layers are used with five resolution scales involved in total. At each scale, both encoders and decoders have two convolution layers (kernel size 3 × 3) followed by instance normalization and ReLU. The feature recalibration module is inserted at the end of each resolution scale. Since high-level features in decoders are also of high-resolution and high-relevance to segmented targets, we perform the decoder-side attention distillation to pass down the fine-grained details that are missing in previous low-resolution attention maps. The encoder-side distillation is not favored because low-level features are more local-scale and general. Furthermore, voxel coordinate map, which records voxels’ global position inside the thoracic cavity, is concatenated with features at decoder 4 to make the model explicitly consider location. In view of the patchwise training, such coordinate map is used to offset the loss of position information. Since both arteries and veins are vessels, we introduce an auxiliary task of vessel segmentation by adding another convolution layer with sigmoid activation to the artery-vein output. Such multi-head design takes advantage of: 1) the inclusion relationship between vessel and artery-vein; 2) the reduced difficulty of learning to recognize vessels. Preliminary ablation study on the auxiliary vessel segmentation output has confirmed its effectiveness. The probability outputs of airway and artery-vein are respectively obtained using sigmoid and softmax activation. Preliminary experiments confirmed that such model design and feature number choice are optimum for our tasks.

E. Training Loss

To deal with hard samples, we use both the Dice [49] and Focal loss [50] for training CNNs. For airway segmentation, given the binary label \( y^a(x) \) and prediction \( p^a(x) \) of each voxel \( x \) in the volume set \( X \), the combined loss is defined as:

\[
\mathcal{L}_{\text{Airway}} = -\left( \frac{2}{|X|} \sum_{x \in X} p^a(x) y^a(x) \right) + \left( \frac{1}{|X|} \sum_{x \in X} (1 - p^a_i(x))^2 \log(p^a_i(x)) \right),
\]

where \( p^a_i(x) = p^a(x) \) if \( y^a(x) = 1 \). Otherwise, \( p^a_i(x) = 1 - p^a(x) \). Parameter \( \epsilon \) is used to avoid division by zero. For multi-class artery-vein and binary vessel segmentation tasks, the losses are defined as the following:

\[
\mathcal{L}_{A-V} = -\frac{1}{3} \sum_{i=0}^{2} \left( \frac{2}{|X|} \sum_{x \in X} p_i^a(x) y_i^a(x) \right) + \left( \frac{1}{|X|} \sum_{x \in X} (1 - p_i^a(x))^2 \log(p_i^a(x)) \right) + \left( \frac{1}{|X|} \sum_{x \in X} (1 - p_i^v(x))^2 \log(p_i^v(x)) \right),
\]

\[
\mathcal{L}_{\text{Vessel}} = -\left( \frac{2}{|X|} \sum_{x \in X} p^v(x) y^v(x) \right) + \left( \frac{1}{|X|} \sum_{x \in X} (1 - p^v(x))^2 \log(p^v(x)) \right),
\]
all 20 scans of the EXACT’09 testing set were reserved as an independent evaluation set. Segmentation results on this extra dataset were evaluated by EXACT’09 organizers for fair comparison experiments.

2) Pulmonary artery-vein task: We used all 55 non-contrast chest CT scans from CARVE14 [11] for artery-vein segmentation. These scans share the same axial size of $512 \times 512$ pixels. They have the same slice spacing of 0.7 mm and the spatial resolution is 0.59–0.83 mm. The number of axial slices ranges from 349 to 498. Two kinds of artery-vein reference were available: 1) full annotations of 10 CT scans; 2) partial annotations of a small portion of vessel segments for the remaining 45 CT scans. We randomly split these 45 CT scans into the training set (40 scans) and validation set (5 scans). The 10 CT scans with full artery-vein labels were kept as the testing set. Since the number of labeled vessel segments of the 45 scans was too small to train and validate CNNs, we used semi-automatic segmentation results released by [11] as complement target labels. Due to annotation difficulty, some voxels were marked as non-determined by two observers and we excluded these voxels in training and evaluation. Vessel roots, which are large main vessels entering from the lung hilum into the lung field, were not marked as they are too difficult to delineate in non-contrast CT [11]. Disagreement between observers exists and vessel annotations in this region are unavailable. Therefore, the segmentation targets of interest are limited inside lungs.

B. Implementation Details

Since CT scans were acquired from different scanners using different parameter settings, data pre-processing is imperative before model training. The voxel intensity of all scans was truncated within the Hounsfield Unit (HU) window of $[-1000, 400]$ and normalized to $[0, 1]$. To avoid learning irrelevant marginal area outside lung, lung mask was extracted using the method mentioned in Sec. II-C. The minimum bounding box of lung was cropped as valid input region. Here, isotropic resampling is not used because it triggers off mismatch between CT images and ground-truth labels during voxel interpolation. The resampled annotations are discontinuous and incomplete, which are detrimental for CNNs to learn effective representation of long, thin, tubular targets. Due to GPU memory limit, CT scans were respectively cropped into sub-volume cubes of the size $80 \times 192 \times 304$ and $64 \times 176 \times 176$ for airway and artery-vein tasks. The size of the cropped cubes is kept the same for all phases of training, validation, and testing. In training phase, random horizontal flipping, shifting, Gaussian smoothing ($\sigma = 1$), and voxel intensity jittering were applied as on-the-fly data augmentation. The Adam optimizer was used with an initial learning rate of $3 \times 10^{-3}$. If the training loss stayed at a plateau for over 10 epochs, the learning rate was reduced by a factor of 10. With batch size of 1, training converged after 60 epochs for each model. In validation and testing phases, we performed sliding window prediction with axial stride of 64. Results were averaged on overlapping margins. Each voxel’s category of artery-vein or airway was assigned by respectively performing channel-wise $\text{arg max}$ or thresholding ($th = 0.5$) on the probability outputs. No post-processing was involved. All models were implemented in Python with PyTorch or Keras. Model training and hyper-parameter tuning were performed only on the training set. The model that achieved the best validation results was chosen and tested on the testing set for objectivity. In experiments, model training was executed on a Linux workstation with Intel Xeon Silver 4114 CPU, 192 GB RAM, and NVIDIA Tesla V100 GPU. Model inference and anatomy prior computation were carried out on a Linux PC with Intel Core i7-8700 CPU, 64 GB RAM, and NVIDIA Quadro P4000 GPU. The computational time of the proposed artery and artery-vein segmentation method is reported in Table I under the current hardware configuration. For hyper-parameter settings, we empirically chose $\alpha = 0.1$, $\epsilon = 10^{-7}$, $p = 2$ and $r = 2$. Note that current settings worked well for our tasks but are not necessarily optimum. Elaborate tuning may be conducted in specific tasks.

C. Evaluation Metrics

For airway task, only the largest connected component of the binarized segmentation output was kept in view of clinical practice. Five metrics were used: (a) Branches detected (BD); (b) Tree-length detected (TD); (c) True positive rate (TPR); (d) False positive rate (FPR); (e) Dice similarity coefficient (DSC). We referred to [21] for definitions of metrics (a)–(d). The first two metrics are centerline-based measurements. We computed the centerlines of reference annotations using the algorithm described in [54]. Then, the centerlines were multiplied with segmentation results to compute the length of the overlapped centerlines $L_{\text{seg}}$. The fraction of the correctly segmented tree’s length relative to the total tree length of the reference centerlines $L_{\text{ref}}$ is defined as TD, $TD = \frac{L_{\text{seg}}}{L_{\text{ref}}} \times 100\%$. For any branch segment between two nodes (bifurcation node or terminal node) on the reference centerlines, if the segmentation results and this segment overlap with over 1 voxel, then this branch is counted as “detected”. The number of branches that are successfully detected $N_{\text{seg}}$ with respect to the total number of branches in reference $N_{\text{ref}}$ is defined as BD, $BD = \frac{N_{\text{seg}}}{N_{\text{ref}}} \times 100\%$. The metrics of TPR, FPR, and DSC are voxel-based measurements. TPR is defined as the number of true airway voxels in segmentation results $N_{TP}$ divided by the total number of airway voxels in reference

| Item Name | Pulmonary Airway Segmentation | Pulmonary Artery-Vein Segmentation |
|-----------|-------------------------------|-----------------------------------|
| Training | (# Epoch $\times$ Time Per Epoch) | (# Epoch $\times$ Time Per Epoch) |
| Inference | (Per CT Volume) | (Per CT Volume) |
| $L_{\text{seg}}$ | 115.9 $\pm$ 95.8 | 115.9 $\pm$ 95.8 |
| $L_{\text{ref}}$ | 176 $\pm$ 9.9 | 176 $\pm$ 9.9 |
| $L_{\text{seg}}$ | 7.2 $\pm$ 0.4 | 7.2 $\pm$ 0.4 |
| Distance Transform Map | 9.2 $\pm$ 1.1 | 9.2 $\pm$ 1.1 |

TABLE I

Computational time of the proposed pulmonary airway and artery-vein segmentation method.
$N_p$, $TPR = \frac{N_{FP}}{N_p} \times 100\%$. FPR is defined as the number of false airway voxels in segmentation results $N_{FP}$ divided by the total number of background voxels in reference $N_N$, $FPR = \frac{N_{FP}}{N_N} \times 100\%$. With the categorized $N_{TP}$, $N_{FP}$, and $N_p$, DSC is given by: $DSC = \frac{2 \times N_{TP}}{N_{TP} + N_{FP} + N_{seg}} \times 100\%$. Note that trachea region is excluded in calculating BD, TD, TPR, and FPR to reflect model’s ability to extract peripheral airways. However, trachea is included in DSC computation as it measures overall segmentation quality.

For artery-vein task, six metrics were used: (a) Accuracy (ACC); (b) TPR; (c) FPR; (d) DSC; (e) BD; (f) TD. All connected components of artery and vein subtrees were involved in measurements. We followed [11] to report both mean and median ACC of artery-vein separation, with 95% confidence interval (CI) estimated. Other metrics were reported in mean ± standard deviation. The definitions of BD and TD are the same as those in airway tasks except that arteries and veins are first measured respectively to obtain the number of detected branches ($N_{seg_{artery}}, N_{seg_{vein}}$) and the total length of segmented sub trees ($L_{seg_{artery}}, L_{seg_{vein}}$). Then, BD and TD are given as the averaged artery and vein results over their corresponding ground-truth: $BD = \frac{1}{2} \times (\frac{L_{seg_{artery}}}{L_{seg_{ref}}} + \frac{L_{seg_{vein}}}{L_{seg_{ref}}}) \times 100\%$, $TD = \frac{1}{2} \times (\frac{N_{seg_{artery}}}{N_{seg_{ref}}} + \frac{N_{seg_{vein}}}{N_{seg_{ref}}}) \times 100\%$.

IV. RESULTS

Evaluation of the proposed method is structured as follows. First, we provide quantitative results of pulmonary airway and artery-vein segmentation in comparison with state-of-the-art methods. Second, ablation study is conducted to validate each constituting component of our method. Third, qualitative segmentation results are presented for visual analysis.

A. Comparison with State-Of-The-Art Methods

1) Pulmonary Airway Segmentation: Table II reports comparison results with state-of-the-art pulmonary airway segmentation methods. Since we adopted U-Net as network backbone, comparison experiments were performed with other encoder-decoder CNNs: the original 3-D U-Net [48], its variants V-Net [49], VoxResNet [55], and Attention-Gated (AG) U-Net [56]. The network architecture of these methods has similar encoding path but varied decoding path. We also compared our method with five state-of-the-art methods: Wang et al. [24], Juarez et al. [23], Qin et al. [25], Juarez et al. [30] and Jin et al. [29]. These methods were re-implemented by ourselves and fine-tuned on the same dataset. Only methods in [24], [25], [29], [30] were reproduced with Keras. Other pulmonary airway or artery-vein segmentation methods were implemented with PyTorch. Furthermore, we evaluated our method on the independent testing set of EXACT’09 [21]. These 20 testing cases were not used for training or fine-tuning. For a fair comparison, results of three available metrics (BD, TD, and FPR) were given by EXACT’09 organizers and shown in Table III.

Table II shows that under the same thresholding value ($th = 0.5$), the proposed method achieved the highest BD of 96.2%, TD of 90.7%, and TPR of 93.6% with a compelling DSC of 92.5%. Such high sensitivity was accompanied with an inferior FPR of 0.035%. Since the threshold $th$ directly affects airway segmentation results, we adjusted $th$ to enforce the same FPR for all methods. The FPR of 3-D U-Net [48] under $th = 0.5$ was chosen as the “anchor” FPR for alignment. Except V-Net [49] and the proposed method, all methods have to be thresholded with a rather low $th < 0.5$ to control FPR. Under the same FPR, results of state-of-the-art methods are closer to each other than those under the same $th = 0.5$. In that case, the proposed method still achieved the highest BD of 94.3%, TPR of 90.6%, and DSC of 93.5% with a competitive TD of 86.7%.

In Table III, results of recent participants are reported by EXACT’09 organizers and are not publicly accessible. It is impossible to control all FPRs to be the same. Instead, we binarized our probability results with three thresholding values ($th = 0.1, 0.5, 0.8$) and submitted them for official evaluation. Different FPR levels are presented as reference. Under $th = 0.1$, the proposed method (FPR: 9.71%) achieved a 2.4% higher BD and a comparable TD with respect to team FFJTC (FPR: 11.92%). Under $th = 0.5$, compared with teams HybAir (FPR: 6.78%) and NTNU (FPR: 3.60%), our method (FPR: 3.65%) achieved an over 25% higher BD and an over 28% higher TD. Under $th = 0.8$, we (FPR: 1.28%) obtained over 1.6 times higher BD and TD than teams Neko (FPR: 0.89%), UCCTeam (FPR: 0.71%), and MISLAB (FPR: 0.89%).

2) Pulmonary Artery-Vein Segmentation: Table IV gives comparison results with state-of-the-art pulmonary artery-vein segmentation methods. Apart from the well-known medical image segmentation models mentioned in Sec. IV-A.1, two recently proposed artery-vein classification methods were evaluated: Charbonnier et al. [11] and Nardelli et al. [37]. Both two methods were developed to recognize arteries and veins from the already segmented vessels, where vessel segmentation was performed independently in advance. The comparison of the proposed method against labels yielded a mean ACC of 90.3%, a medium ACC of 90.9%, a TPR of 90.3%, a FPR of 0.151%, a DSC of 82.4%, a BD of 85.4%, and a TD of 90.9%. It outperformed state-of-the-art segmentation CNNs by a large margin in ACC, TPR, BD, and TD with comparable FPR and DSC. Admittedly, compared with methods that adopted graph-based representation for artery-vein separation [11], [37], the proposed method has room for improvement.

B. Ablation Study

We investigated the validity of key constituents of the proposed method: 1) feature recalibration (FR); 2) attention distillation (AD); 3) anatomy prior (AP). FR and AD were employed in both airway and artery-vein segmentation while AP was only used in artery-vein task. The model trained without FR, AD, and AP was indicated as baseline. Two very recently proposed feature recalibration modules (cSE [39] and PE [38]) were introduced into our baseline for comparison. They were both adapted from the 2-D squeeze-and-excitation [57] technique for 3-D channel-wise feature recalibration. We replaced all FR with these two modules and trained models from scratch. For assessing AD, deep supervision (DS) [58]
was introduced for comparison. DS shows features of lower resolution to be supervised directly by targets. Specifically, we respectively added one convolution layer (kernel size $3 \times 3 \times 3$) and one trilinear upsampling layer to features of decoder $1$–$3$. After sigmoid or softmax activation, these features were used to reduce FPR. Although AP (AG U-Net [56]) yielded the worst results in all metrics, AP methods with different airway sources are respectively referred to as AP ($3$-D U-Net [48], AP (V-Net [49]), AP (VoxResNet [55]), AP (AG U-Net [56]), and AP (proposed)).

1) Feature Recalibration: Table V shows that under the same threshold $th = 0.5$, all three recalibration modules (cSE [39], PE [38], and FR) bring performance gains in baseline in BD, TD, and TPR. Specifically, the proposed FR leads to the highest increase of $4.5\%$ in BD, $9.5\%$ in TD, and $5.7\%$ in TPR. Meanwhile, all these modules more or less worsen FPR and DSC. Under the same FPR, results of different methods become closer than those under $th = 0.5$. All methods except baseline are binarized with $th > 0.5$ to reduce FPR. Although FPR of baseline is relaxed to be higher, it only achieved the same BD, $0.3\%$ higher TD, $1.1\%$ higher TPR, and $0.8\%$ lower DSC. The proposed FR boosted performance to a BD of $94.2\%$, a TD of $87.5\%$, a TPR of $90.1\%$, and a DSC of $93.2\%$. FR outperformed cSE [39] and PE [38] in BD, TD, TPR, and DSC, which is in line with results under $th = 0.5$.

Table VI reveals that compared with baseline (AP), all recalibration modules increase mean ACC, TPR by over $0.7\%$, and DSC by over $0.3\%$. The baseline with FR obtained a mean ACC of $89.4\%$, a median ACC of $90.2\%$, a TPR of $89.4\%$, a FPR of $0.150\%$, a DSC of $82.0\%$, a BD of $83.8\%$, and a TD of $89.9\%$. Both PE [38] and FR share similar results, surpassing cSE [39] in all metrics but FPR and DSC.

2) Attention Distillation: In Table V, under the same threshold $th = 0.5$, AD respectively improved baseline in BD, TD, and TPR by $3.3\%$, $7.0\%$, and $4.6\%$. It exceeds DS [58] in BD, TD, and TPR no matter whether FR is introduced or not. Under the same FPR, DS [58] alone performed slightly better than AD. When FR was combined, AD gained a slight advantage over DS [58] in BD and TPR.

In Table VI, consistent improvements with $1.7\%$ of mean ACC, $1.1\%$ of median ACC, $1.6\%$ of TPR, $0.003\%$ of FPR, $1.2\%$ of DSC, $1.2\%$ of BD, and $0.9\%$ of TD were observed in AD with regard to baseline + AP (proposed). DS [58] also boosted performance of baseline + AP (proposed) with $0.9\%$ of mean ACC, $0.4\%$ of median ACC, $0.9\%$ of TPR, $0.6\%$ of DSC, $0.3\%$ of BD, and $0.2\%$ of TD. Moreover, AD surpassed DS [58] in all metrics regardless of the presence of FR.

3) Anatomy Prior: Table VI shows that AP (proposed) improved baseline by $1.1\%$ of mean ACC, $2.1\%$ of median ACC, $1.4\%$ of TPR, $2.3\%$ of BD, and $1.8\%$ of TD. AP methods that were calculated using other airway results also performed better than baseline in mean and median ACC, TPR, BD, and TD. Among AP with different airway sources, although the performance variation is small, the highest increments of mean ACC, TPR, and TD were achieved by AP (proposed) whereas AP (AG U-Net [56]) yielded the worst results in all metrics.

C. Qualitative Results

Results of pulmonary airway and artery-vein segmentation are 3-D rendered in Fig. 5, illustrating the robustness of our airway segmentation method on both easy and hard cases. In line with Table II, all methods performed well on extracting thick bronchi. Compared with state-of-the-art methods, more visible tiny branches were reconstructed by the proposed method with high overall segmentation performance maintained. Some false positives were actually true airway branches. Fig. 6 reveals that the proposed artery-vein segmentation method successfully extracted multiple arteries and veins. After close inspection of wrong predictions, we noticed that our method may fail to correctly classify some isolated vessel segments. Spatial inconsistency was also observed at terminal ends of arteries and veins (e.g., top and bottom area).
TABLE IV

| Method                  | Params (×10^3) | ACC-mean [95%-CL] (%) | ACC-median [95%-CL] (%) | TPR (%) | FPR (%) | DSC (%) |
|-------------------------|---------------|-----------------------|-------------------------|---------|---------|---------|
| Baseline                | 401.8         | 91.6 ± 2.9            | 87.0 ± 1.3              | 92.4 ± 2.6 | 91.4 ± 1.9 | 0.041 ± 0.008 |
| + cSE [58]              | 421.8         | 95.2 ± 2.6            | 90.8 ± 2.3              | 94.2 ± 2.5 | 92.4 ± 1.9 | 0.034 ± 0.005 |
| + FR                    | 421.1         | 96.2 ± 1.5            | 96.0 ± 1.2              | 96.2 ± 1.5 | 96.2 ± 1.4 | 0.019 ± 0.003 |
| + U-Net                 | 419.1         | 94.8 ± 2.5            | 91.8 ± 2.6              | 94.2 ± 1.9 | 94.2 ± 1.8 | 0.020 ± 0.012 |
| + DS [51] + FR          | 431.7         | 96.2 ± 2.4            | 97.2 ± 2.7              | 94.2 ± 1.6 | 96.2 ± 1.7 | 0.022 ± 0.012 |
| + DS [51] + cSE [58]    | 423.7         | 96.0 ± 1.5            | 98.9 ± 1.3              | 94.2 ± 1.6 | 96.2 ± 1.8 | 0.022 ± 0.012 |
| + DS [51] + FR + cSE    | 425.7         | 96.2 ± 2.5            | 97.2 ± 2.7              | 94.2 ± 1.6 | 96.2 ± 1.8 | 0.022 ± 0.012 |
| Our proposed            | 423.7         | 96.2 ± 2.4            | 97.2 ± 2.7              | 94.2 ± 1.6 | 96.2 ± 1.8 | 0.022 ± 0.012 |

TABLE V

| Method                  | Params (×10^3) | ACC-mean [95%-CL] (%) | ACC-median [95%-CL] (%) | TPR (%) | FPR (%) | DSC (%) |
|-------------------------|---------------|-----------------------|-------------------------|---------|---------|---------|
| Baseline                | 401.8         | 91.6 ± 2.9            | 87.0 ± 1.3              | 92.4 ± 2.6 | 91.4 ± 1.9 | 0.041 ± 0.008 |
| + cSE [58]              | 421.8         | 95.2 ± 2.6            | 90.8 ± 2.3              | 94.2 ± 2.5 | 92.4 ± 1.9 | 0.034 ± 0.005 |
| + FR                    | 421.1         | 96.2 ± 1.5            | 96.0 ± 1.2              | 96.2 ± 1.5 | 96.2 ± 1.4 | 0.019 ± 0.003 |
| + U-Net                 | 419.1         | 94.8 ± 2.5            | 91.8 ± 2.6              | 94.2 ± 1.9 | 94.2 ± 1.8 | 0.020 ± 0.012 |
| + DS [51] + FR          | 431.7         | 96.2 ± 2.4            | 97.2 ± 2.7              | 94.2 ± 1.6 | 96.2 ± 1.7 | 0.022 ± 0.012 |
| + DS [51] + cSE [58]    | 423.7         | 96.0 ± 1.5            | 98.9 ± 1.3              | 94.2 ± 1.6 | 96.2 ± 1.8 | 0.022 ± 0.012 |
| + DS [51] + FR + cSE    | 425.7         | 96.2 ± 2.5            | 97.2 ± 2.7              | 94.2 ± 1.6 | 96.2 ± 1.8 | 0.022 ± 0.012 |
| Our proposed            | 423.7         | 96.2 ± 2.4            | 97.2 ± 2.7              | 94.2 ± 1.6 | 96.2 ± 1.8 | 0.022 ± 0.012 |

Fig. 5. Rendering of pulmonary artery segmentation results on (a) easy and (b) hard testing cases. Best viewed magnified.
V. Discussion

From results in Table II, it is conclusive that our method outperformed the others in airway segmentation, especially distal thin branches. This can be ascribed to the recalibrated features and reinforced attention on hard, tiny, peripheral branches. Although CNNs possess strong fitting ability, it is necessary to suppress redundant, irrelevant features and strengthen task-related ones. Under the same threshold, two reasons are responsible for our relatively inferior FPR and DSC: 1) Our model successfully detected some true thin airways that were too indistinct to be annotated properly by experts. After careful examination of segmented airways and retrospective evaluation of labels, some branches were unintentionally neglected due to annotation difficulty. When calculating the evaluation metrics, these actually existing branches were counted as false positives and caused higher FPR with lower DSC. 2) A little leakage was produced at bifurcations when the contrast between airway lumen and wall was fairly low. In this situation, the proposed method was inclined to predict voxels as airway while other methods were relatively conservative. Some leakage regions do resemble airway in appearance, where tubular parenchyma with high-intensity circular boundary and low-intensity hollow was observed. Under the same FPR, the superior BD, TPR, and DSC of the proposed method demonstrated its sensitivity and robustness on extracting small airways. Since our threshold $th$ was increased to 0.77, airway predictions in low confidence were excluded and false positives were suppressed. The overall performance indicator DSC was consequently improved. By considering results both under the same threshold and FPR, we believe the superiority of the proposed method is well revealed.

An additional evaluation on the EXACT’09 testing set verified that under different FPR levels, our method did extract much more branches than previous methods. Besides, there exists a gap between results on our testing set and results on EXACT’09 testing set. The reasons behind are 3-fold: 1) difference in quality between our labels and EXACT’09 labels (e.g., inter-observer variation in labeling the 5-th and 6-th order bronchi); 2) difference in implementation of metrics calculation (e.g., centerline extraction); 3) difference in data distribution between the training set and EXACT’09 testing set (e.g., multi-center CT scans, dissimilar lung diseases).

Table IV shows that state-of-the-art CNNs may not be effective to segment arteries and veins if no “customization” was involved for this task. It is undeniable that two state-of-the-art methods [11], [37] performed well in this task. In [11], graph representation was computed and the label of artery or vein was assigned to the entire linked sub-trees. It eliminated the possibility of label inconsistency for each branch and therefore performed better than ours in terms of ACC. The two-stage CNNs-based classification method [37] achieved the highest ACC. It highly relied on graph-cuts post-processing to refine the predictions of CNNs, where over 10% performance gains were brought by graph-cuts. In contrast, our method is end-to-end and segmentation was directly fulfilled by CNNs. No vessel segmentation beforehand or post-processing afterwards was designed in the pipeline, which avoids error accumulation. It is noted that post-processing methods like graph-cuts or conditional random field are not suitable for every method in every task. They may not always improve performance. In addition, the proposed CNNs-based method is effective for both pulmonary airway and artery-vein segmentation, which is the first of its kind in literature.

To study the effectiveness of the proposed FR, we conducted extensive ablation experiments. As shown in Table V, cSE [39], PE [38], and FR all contributed to model’s capacity of peripheral bronchiole extraction. Interestingly, these modules more or less worsen FPR and DSC under the same threshold. We believe the recalibration mechanism by element-wise weighting prefers airway voxels and the model tends to identify as many branches as possible, causing an increase of FPR and a decrease of DSC. Under the same FPR, the advantage of FR over baseline and other recalibration modules is clearly revealed in BD, TD, and TPR, substantiating the importance of reasonably integrating spatial knowledge for channel-wise recalibration. Table VI reveals that all recalibration modules improved sensitivity of baseline (AP) to arteries and veins. The similar performance of PE [38] and FR might be explained by
the spatial distribution of artery-vein targets. Arteries and veins spread all over the lung and their difference in position may not be highly informative for artery-vein separation.

For completeness, we also conducted experiments to investigate the efficacy of the proposed AD. In Table V, both AD and DS [58] improved baseline, confirming our hypothesis that it is difficult for CNNs to learn effective representation of small, thin targets only with supervision from the last output layer. In Table VI, AD outperformed baseline (AP) in all metrics. Such improved sensitivity was attributed to the mechanism that features of shallower layers learned to focus on fine-grained details in features of deeper layers. To intuitively assess AD, attention maps from decoder 1–4 are visualized in Fig. 7. After distillation, activated regions become more distinct and the target tubules are enhanced. The improved attention on airway, vessel, and lung border explains that our model comprehended more context and therefore achieved higher sensitivity to intricate tubules. Another interesting finding is that although the last attention map is not refined in distillation, it still gets polished up because better representation learned at previous layers in turn affects late-layer features. Moreover, it is noted that AD surpassed DS [58] if their performance in both airway and artery-vein segmentation was comprehensively considered. It may not be optimum for earlier layers to be directly supervised by scattered and sparse targets. As shown in Fig. 7, not only segmentation targets but also lung contours are enhanced. DS [58] may hamper shallow layers from learning rich context for later comprehension.

Ablation study on AP in Table VI suggested that: 1) The lung context and distance transform maps do contribute to recognizing arteries and veins. 2) The accuracy of segmented airways was positively associated with the artery-vein segmentation performance. The more complete and precise the airway is, the more informative the calculated anatomy prior is. 3) The proposed model performed robustly to AP using different airway segmentation methods. No drastic decline was observed due to poor airway prediction results. Note that the loss of DSC by introducing AP was later offset by FR and AD. From visual analysis, we find that some true airways were neglected unintentionally in labels (see Fig. 5). Such mistake was due to the weak intensity contrast and limitation of annotating 3-D objects in 2-D planes. In Fig. 6, the reason why wrong classification was observed on isolated vessel segments and terminal ends might be explained as follows. In these regions, CNNs may not capture enough context knowledge for proper inference and no label propagation was enforced to make consistent decisions on the same vessel segment.
We further provide analysis for the artery-vein task. The confusion matrix in Fig. 8(a) shows that the proposed method performed worst on recognizing veins. Lacking anatomic relationship such as the proximity of arteries to airways, veins are a bit more difficult to segment. By dividing errors into 5 types (see Fig. 8(b)), we find that the Type 1 error of predicting background as artery or vein makes up a large proportion of all errors. In accord with Fig. 6 and Fig. 8(c), Type 1 error voxels distribute all over the lung. Besides, most errors of Type 1, 2 and 4 appear at vessel boundaries which are ambiguous for accurate and unified definition. In that case, the proposed method behaved a bit aggressively due to the reinforced learning of tubular targets.

Although the proposed method solved both pulmonary airway and artery-vein segmentation with higher sensitivity to peripheral tubular branches, there exist some limitations. First, for the current artery-vein segmentation task, only vessels inside lungs are considered as targets. The main pulmonary artery and vein vessels, including the trunk, are too difficult for human observers to delineate their boundaries in non-contrast CT. To have a broader application, CT pulmonary angiogram would be investigated in the future for segmentation of vessels in the lung hilum. Second, refinement of airway annotations might be carefully conducted to incorporate fuzzy and unclear airway branches. One efficient way of correction would be to first apply the proposed method on CT and then review both the predicted and manually labeled branches. Third, the proposed method did not enforce label compatibility in artery-vein segmentation. Spatial inconsistency was therefore observed in distal vessels. Future work includes the adoption of strategies like label propagation and majority voting. It could explicitly remove conflicting predictions that mainly caused Type 3 and 5 errors. Finally, for both airway and artery-vein tasks, more diverse clinical data might be collected to improve and examine the generalizability of our method.

VI. Conclusion

This paper presented a tubule-sensitive method for both pulmonary airway and artery-vein segmentation. It utilizes CNNs and requires no post-processing. With the proposed spatial-aware feature recalibration module and the gradually reinforced attention distillation module, feature learning of our CNNs becomes more effective and relevant to target tubule perception. The incorporated anatomy prior is also beneficial for artery-vein separation. Extensive experiments showed that our method detected much more bronchioles, arterioles, and venules while maintaining competitive overall segmentation performance, which corroborates its superior sensitivity over state-of-the-art methods and the validity of its constituents.

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