文献分享

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学习树形表示实现3D冠状动脉分割

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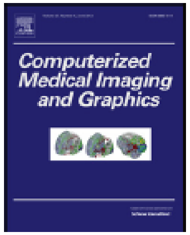

Learning tree-structured representation for 3D coronary artery segmentation

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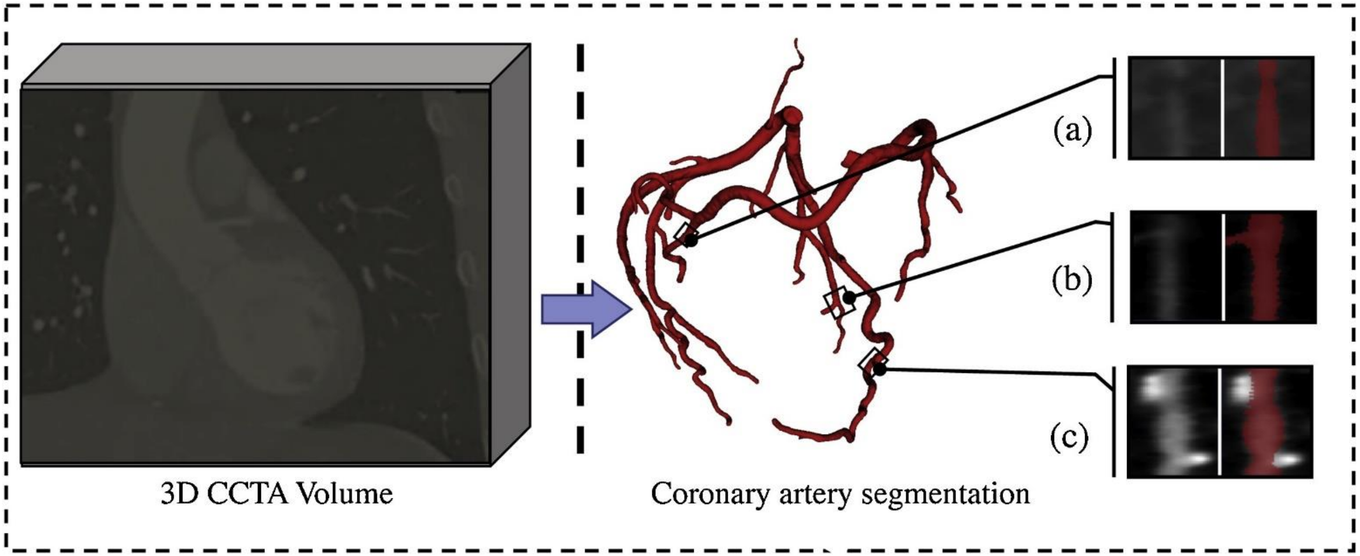
问题背景

- 冠状动脉的分割较为困难

- 边界模糊
- 分叉较多
- 钙化影响



文章亮点

- 冠状动脉的显示建模（树状结构）
- 提出新的卷积递归神经网络（CNN+RNN）
- 端到端的学习框架FCN + ConvGRU
- 经过多个大数据集验证
- 4个数据集近1000个CT

方法介绍

清華大學
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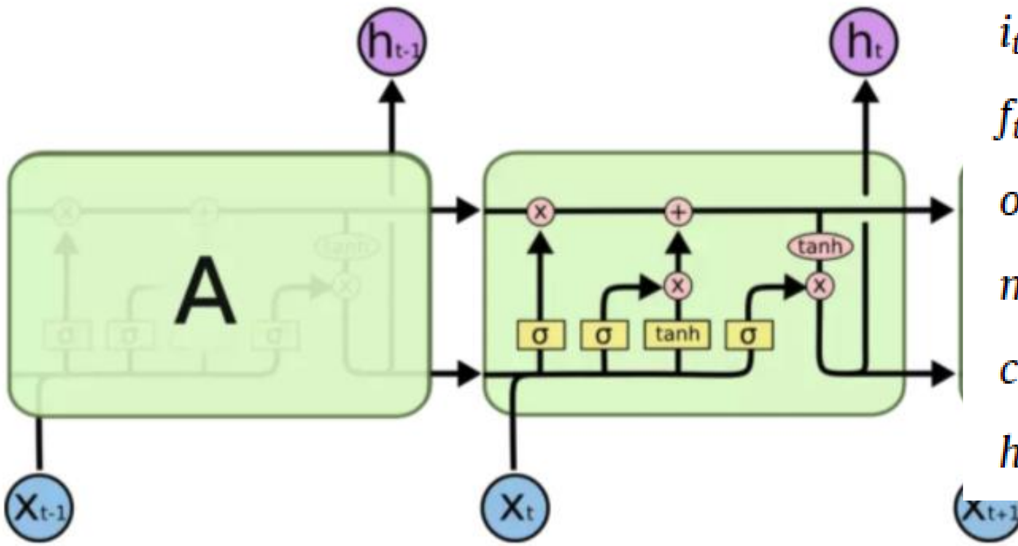
RNN和LSTM

- RNN 是包含循环的网络，可以把信息从上一步传递到下一步。



$$i_t = \sigma(W_i x_t + U_i h_{t-1}),$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1}),$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1}),$$

$$m_t = \tanh(W_m x_t + U_m h_{t-1}),$$

$$c_t = f_t \odot c_{t-1} + i_t \odot m_t,$$

$$h_t = o_t \odot \tanh(c_t),$$

LSTM的重复结构A有四层

方法介绍

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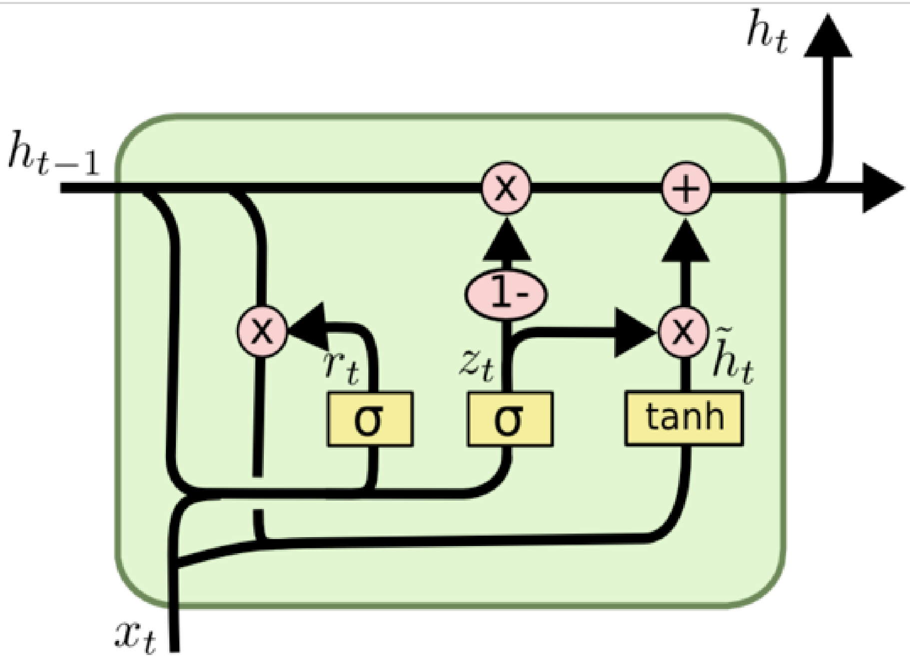
- LSTM的变形GRU



$$u_t = \sigma(W_z x_t + U_z h_{t-1}),$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}),$$

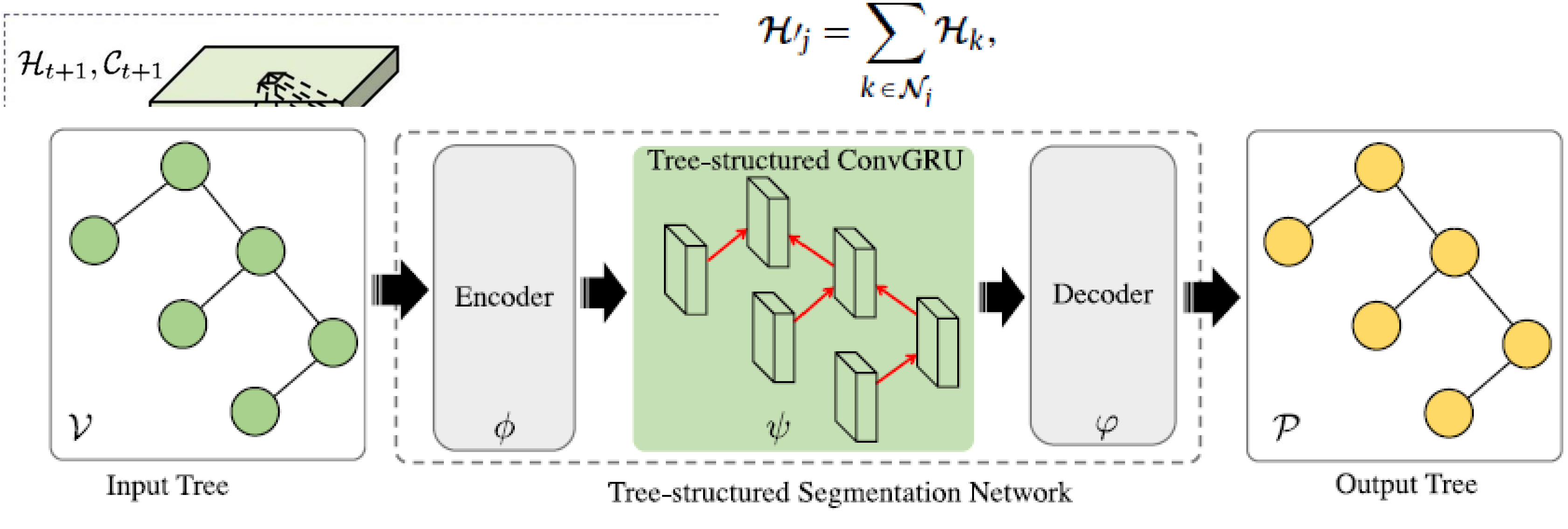
$$\tilde{h}_t = \tanh(W x_t + r_t \odot U h_{t-1}),$$

$$h_t = (1 - u_t) \odot \tilde{h}_t + u_t \odot h_{t-1},$$

方法介绍

- 向量乘法变成图像卷积
- 单一序列变成树状结构
- 顺序由下到上

$$\mathcal{H'}_j = \sum_{k \in \mathcal{N}_j} \mathcal{H}_k,$$



具体实现

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- 冠脉树的构建，即中心线的提取

DeepCenterline: A Multi-task Fully Convolutional Network for Centerline Extraction

Zhihui Guo[1], Junjie Bai[2(✉)], Yi Lu[2], Xin Wang[2], Kunlin Cao[2], Qi Song[2], Milan Sonka[1], and Youbing Yin[2]

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问题背景

- 已有冠脉的二值分割，未必完全正确
- 解决思路是获得起点和分支端点，利用最小路径算法
- Baseline是对分割图直接做距离变换，得到代价函数
- 文章工作是利用深度学习算法输出标准距离图和分支端点

文章思路

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多任务网络结构

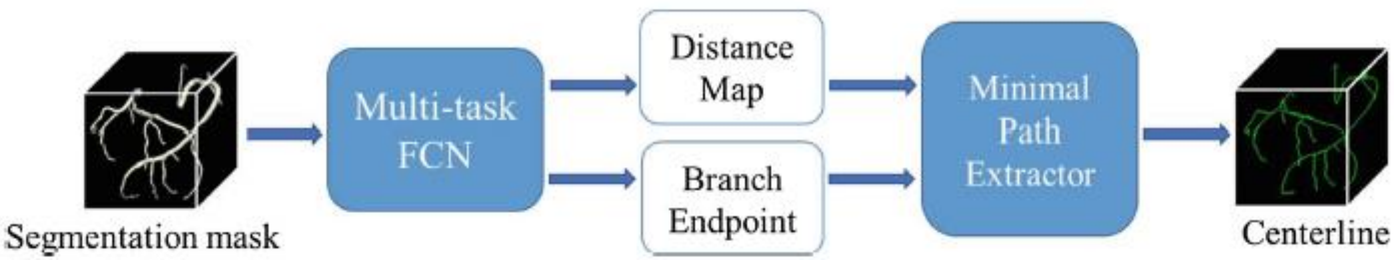
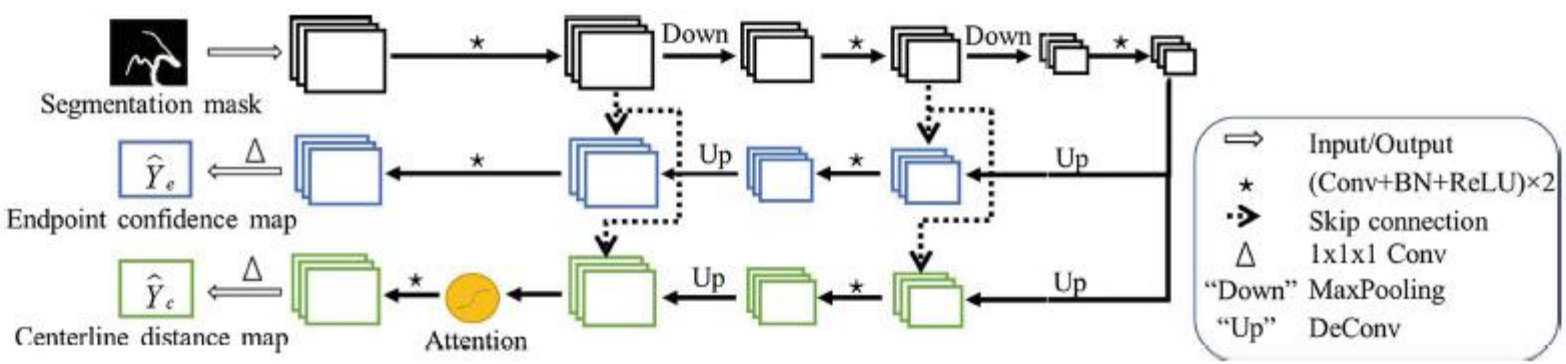


Fig. 1. Schematic workflow of DeepCenterline



方法介绍

- 中心线距离图

- 注意力机制
- GT的构建

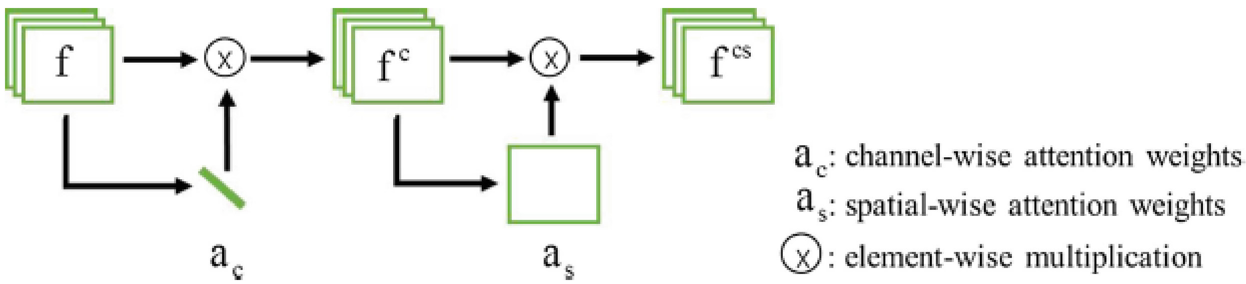


Fig. 3. Spatial-wise and channel-wise attention

作用：中心线占比小，提高局部准确度

方法介绍

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中心线距离图

- 注意力机制
- GT的构建

- 基于中心线的距离变换
- 考虑血管粗细，做局部归一化
- 在中心线横截面上，根据最大值做归一化处理
- 取log函数提高局部对比度

$$d_i = \frac{d_i^{Euc}}{\max_{i \in \mathcal{S}} d_i^{Euc}} \qquad \mathbf{Y_c} = \log(\mathbf{D_c} + \delta)$$

方法介绍

清華大學 Tsinghua University

- 分支端点检测
- 回归高斯热图

$$\mathbf{Y_e}(i) = \frac{1}{\sqrt{2\pi\Delta}} e^{-\frac{\mathbf{D_e}(i)^2}{\Delta^2}}, \quad i \in \mathcal{I}$$

- 置信图GT只有一个通道
- 原因是冠脉的分支数目不定
- 测试集上对结果取阈值，获取连通域
- 连通域个数是分支数目，连通域中心是分支端点

$$L = \gamma \| \Lambda \odot (\mathbf{Y_c} - \widehat{\mathbf{Y}}_\mathbf{c}) \|^2 + (1-\gamma) \| \Lambda \odot (\mathbf{Y_e} - \widehat{\mathbf{Y}}_\mathbf{e}) \|^2$$

实验结果

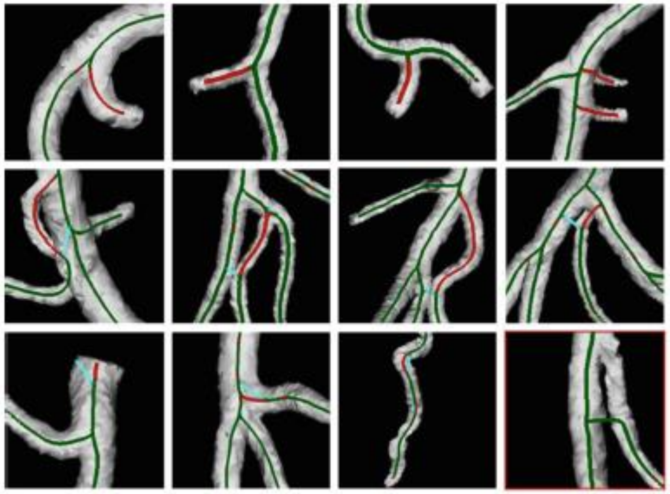
- 数据集620个CT
- 200训练，20验证，400测试

- 中心线标注困难，无人工标注
- 采用baseline的结果作为GT
- 直接对分割图做距离变换得到代价函数
- 调参适应不同尺度血管

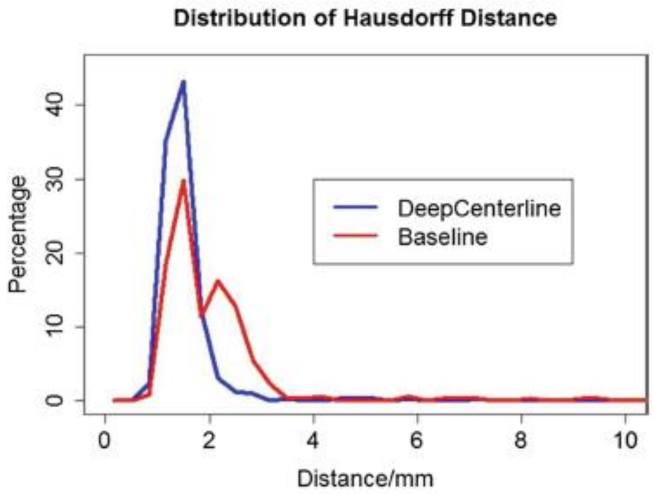
$$\mathrm{D}^{\mathrm{Sig}} = \sum_{i=1}^{3} \frac{1}{1 + \exp(-\frac{\mathrm{D}^{\mathrm{Euc}} - \beta_i}{\alpha_i})}$$

实验结果

Metrics		Raw number #/#		Ratio %	
		Baseline	DeepCL	Baseline	DeepCL
Missing endpoint	Patient-level	170/400	**34/400**	42.5%	**8.5%**
	Branch-level	233/6048	**35/6048**	3.9%	**0.6%**
Scans with wrong bifurcation		28/400	**11/400**	7.0%	**2.8%**
CL length (mm)		308.9	**314.3**	-	-
Overall success rate		217/400	**355/400**	54.3%	**88.8%**



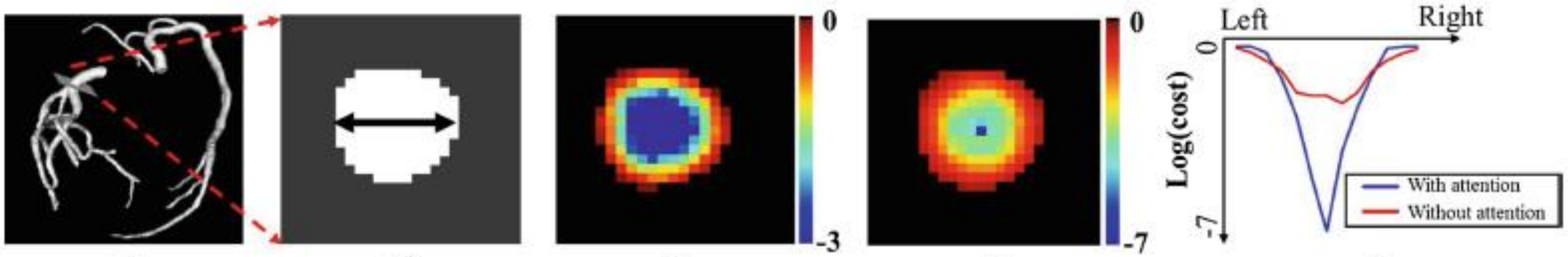
a)



b)

实验结果

- 注意力模块的必要性



a) b) c) d) e)

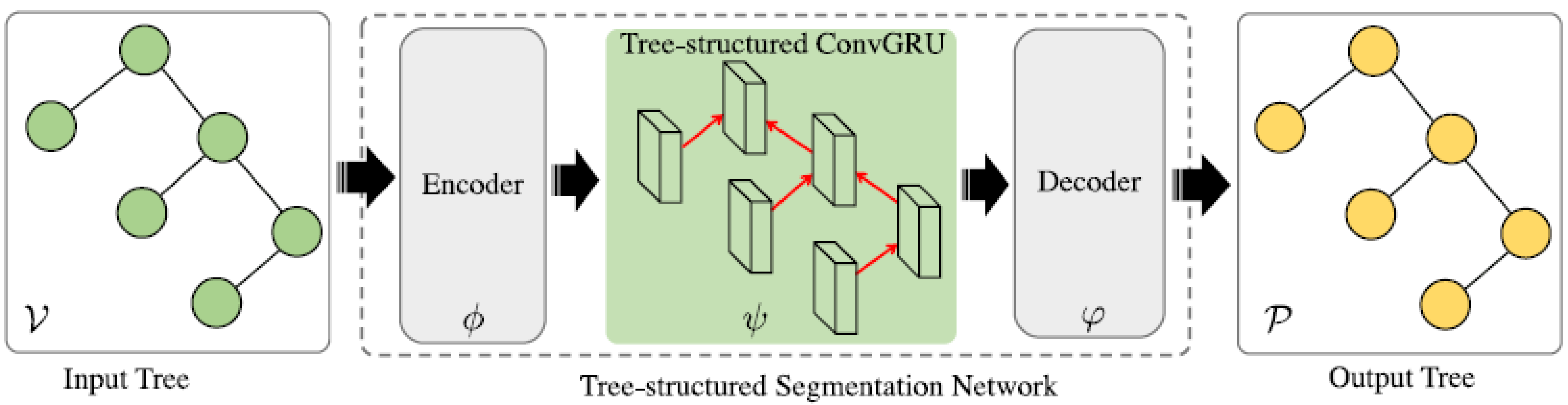
总结：
解决中心线自动提取问题
用有缺陷的GT训练，可以得到较好的结果

具体实现

清華大學 Tsinghua University

◻ 冠脉分割任务

- 利用3D-Unet分割，获得粗糙二值图
- 利用中心线提取算法，获取冠脉树
- 在每个节点取中心线横截面



具体实现

冠脉分割任务

- 利用3D-Unet分割，获得粗糙二值图
- 利用中心线提取算法，获取冠脉树
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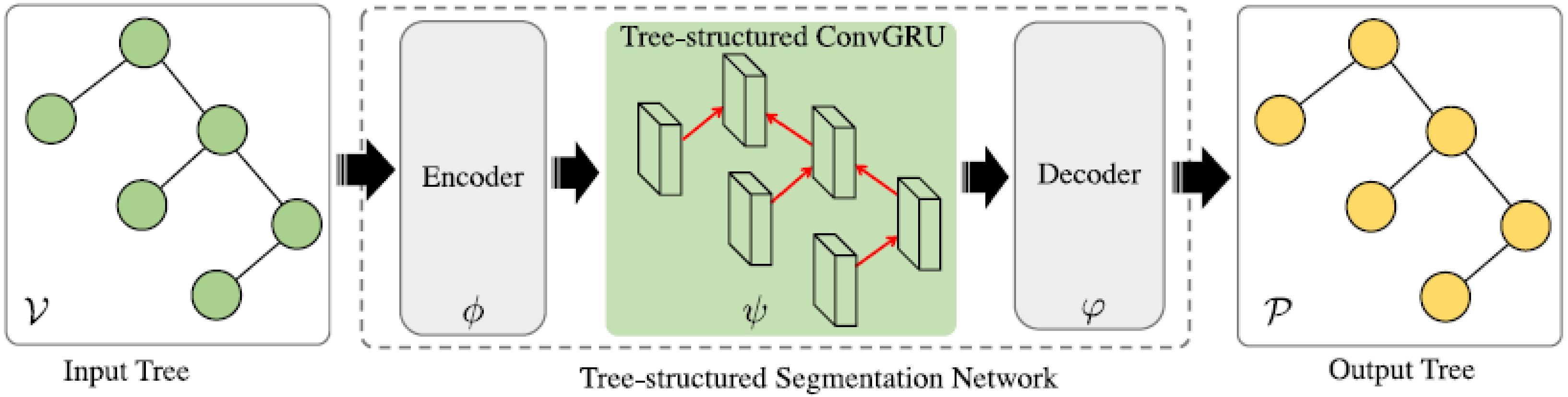
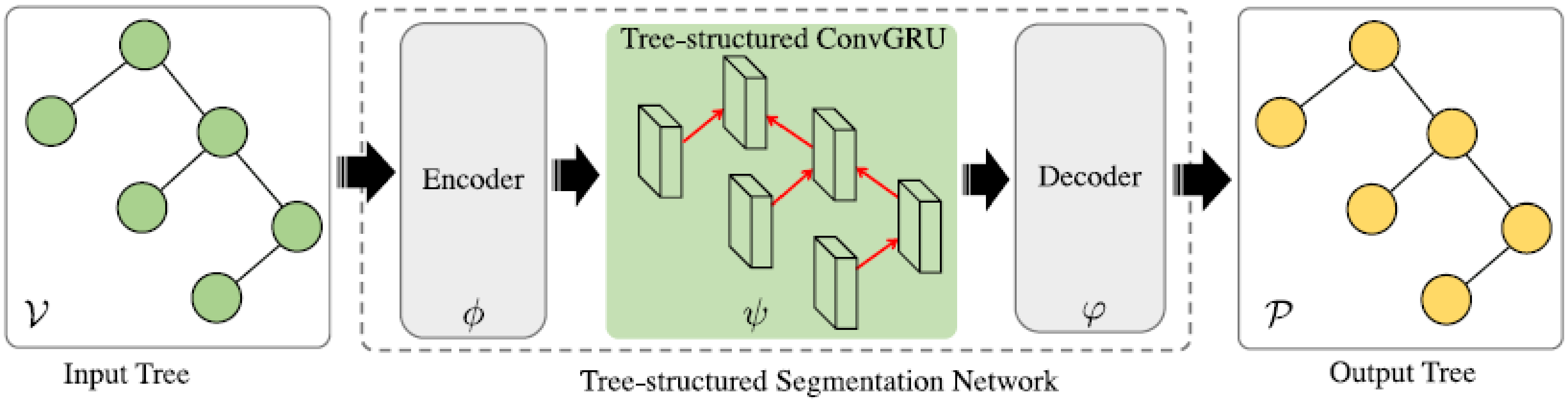
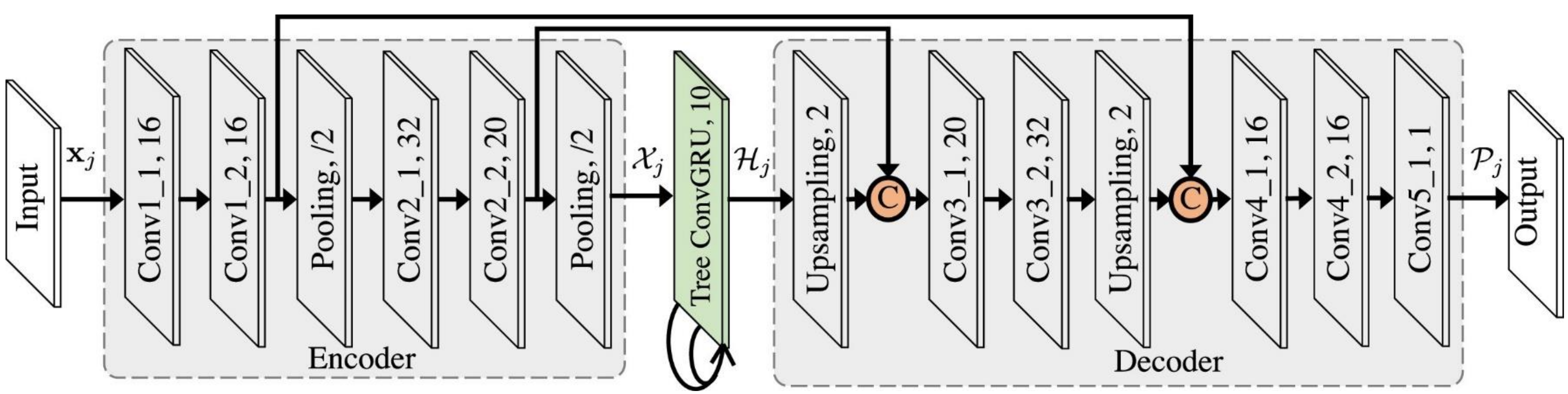


具体实现

- 冠脉分割网络



Encoder
Tree-structured ConvGRU
Decoder
$\mathcal{V}$
ϕ
ψ
φ
$\mathcal{P}$
Input Tree
Tree-structured Segmentation Network
Output Tree



Input
$\mathbf{x}_j$
Conv1_1, 16
Conv1_2, 16
Pooling, /2
Conv2_1, 32
Conv2_2, 20
Pooling, /2
Encoder
$\mathcal{X}_j$
Tree ConvGRU, 10
$\mathcal{H}_j$
Upsampling, 2
C
Conv3_1, 20
Conv3_2, 32
Upsampling, 2
C
Conv4_1, 16
Conv4_2, 16
Conv5_1, 1
Decoder
$\mathcal{P}_j$
Output

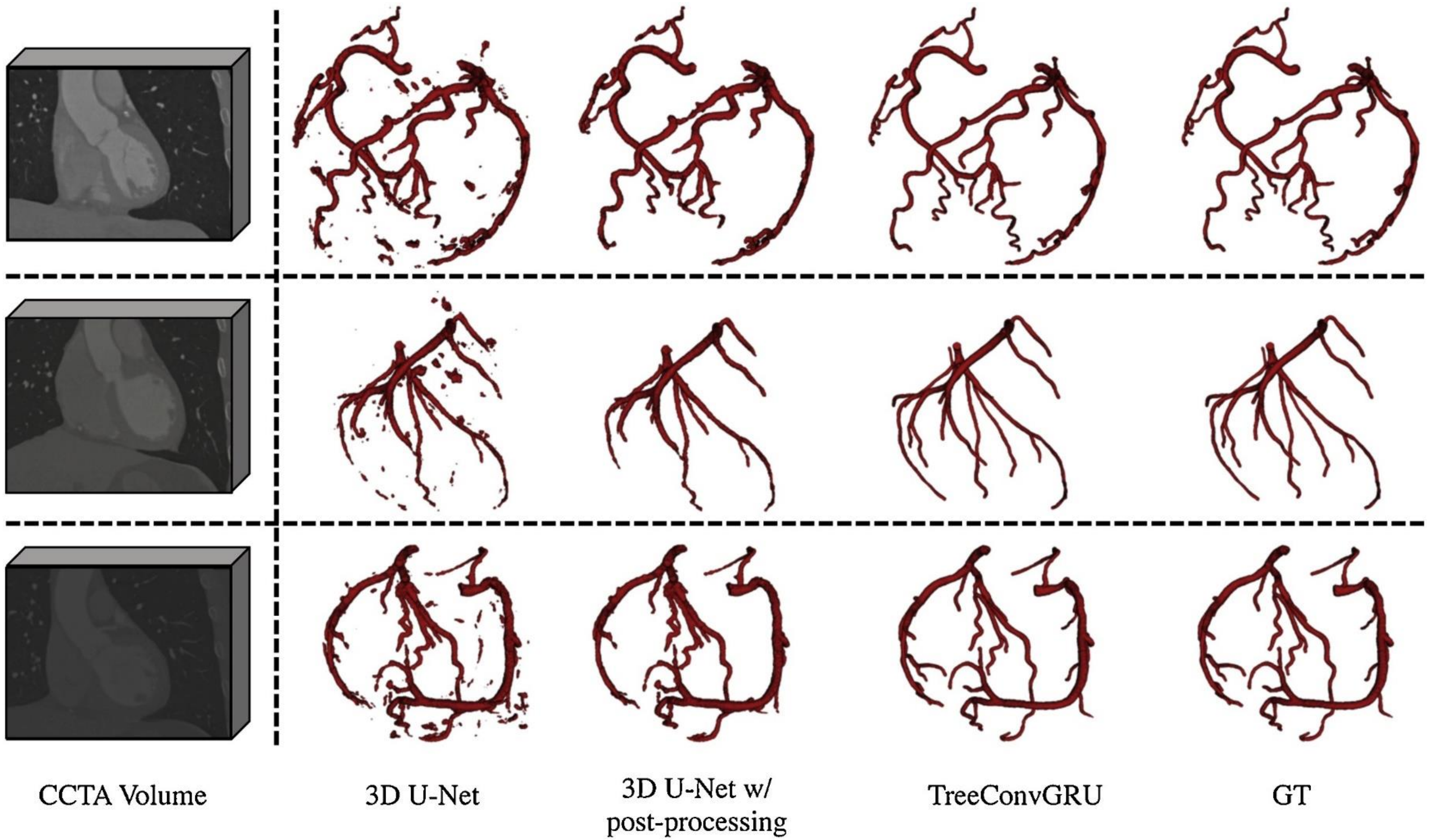
实验结果

Dataset	Number of scans	Number of nodes	Number of branches
CTA1	258	727	12.6
CTA2	273	806	11.1
CTA3	223	802	13.2
CTA4	162	694	12.9
Total	916	774	12.4

Table 2
Main comparison results. The proposed tree-structured segmentation network (TreeConvGRU) is compared with the recently proposed 3D densely-connected volumetric convnets (DenseVox) (Yu et al., 2017), sequential version of our tree-structured segmentation network (ConvGRU). All these methods are evaluated by the average dice loss.

Methods	DenseVox (Yu et al., 2017)	ConvGRU	TreeConvGRU
CTA1	0.8370	0.8399	0.8494
CTA2	0.8405	0.8427	0.8503
CTA3	0.8433	0.8436	0.8545
CTA4	0.8182	0.8237	0.8283
Total	0.8518	0.8614	0.8683

实验结果



CCTA Volume
3D U-Net
3D U-Net w/
post-processing
TreeConvGRU
GT

总结

- 方法的本质是基于中心线的2D横截面分割
- 先利用粗糙的分割获得较为准确的中心线
- 更多的利用中心线的连续性信息
- 利用RNN把整个冠脉中心线的横截面串到一起

◆ 存在问题

- 中心线的不稳定性
- 分叉处的还原算法（树节点是密集的）

总结

- 可以利用的思路
- 中心线提取的baseline
- 中心线任务中的关键点检测
- 关键点数目不确定时，GT可以是单张热图