文献分享

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Deep vessel segmentation by learning graphical connectivity

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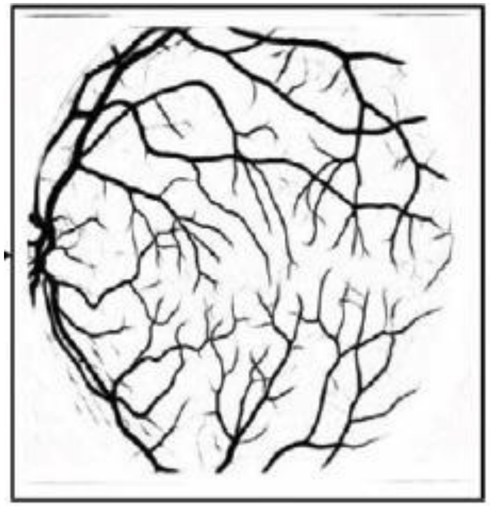
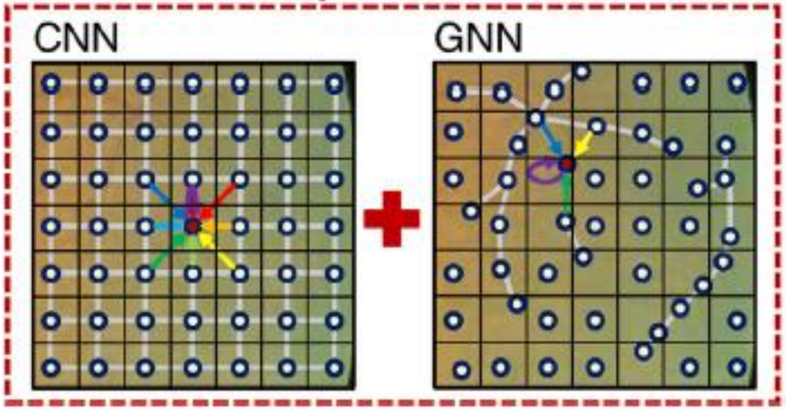
通过学习图形连接实现血管分割

问题背景

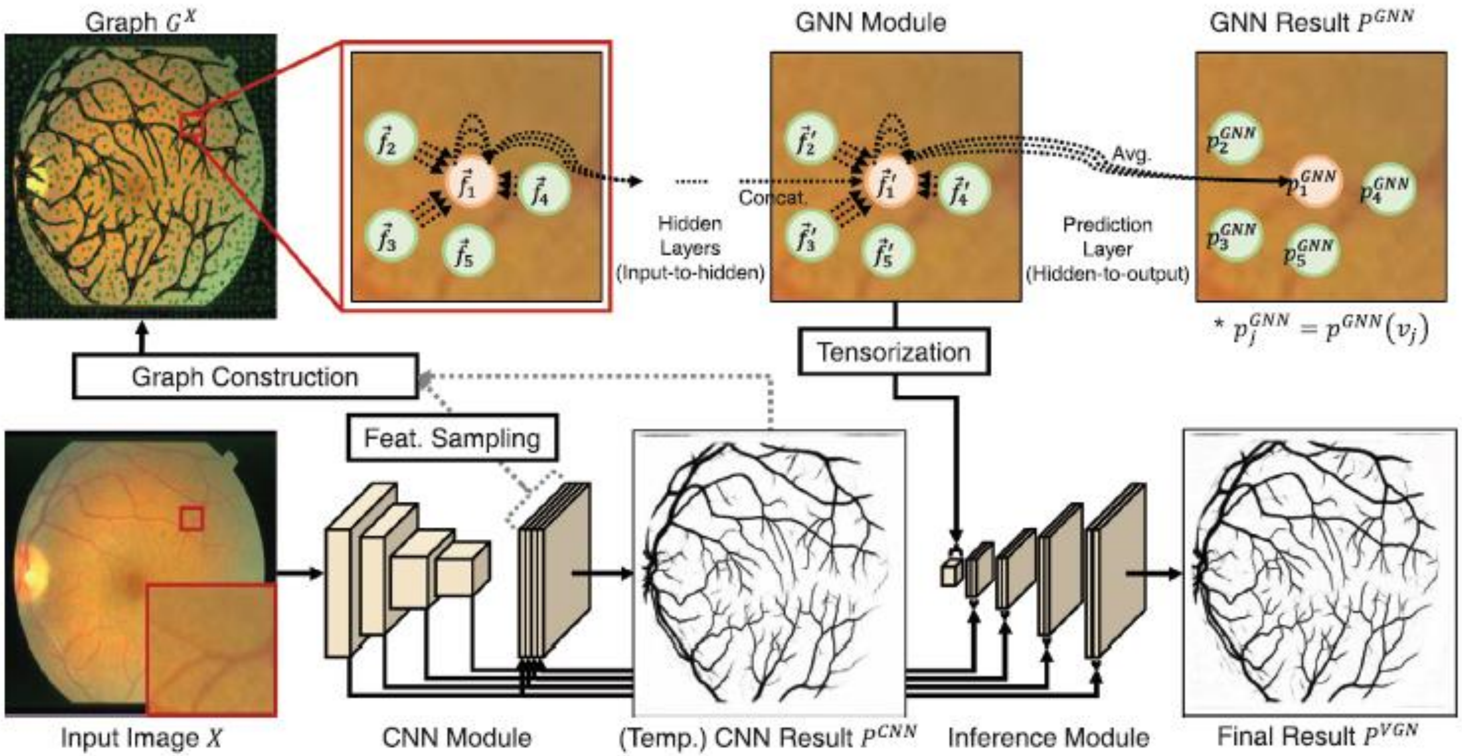
- 血管结构有其形状特殊性
- 普通CNN在欧式空间提取特征
- 图网络GNN可以在不规则空间提取特征





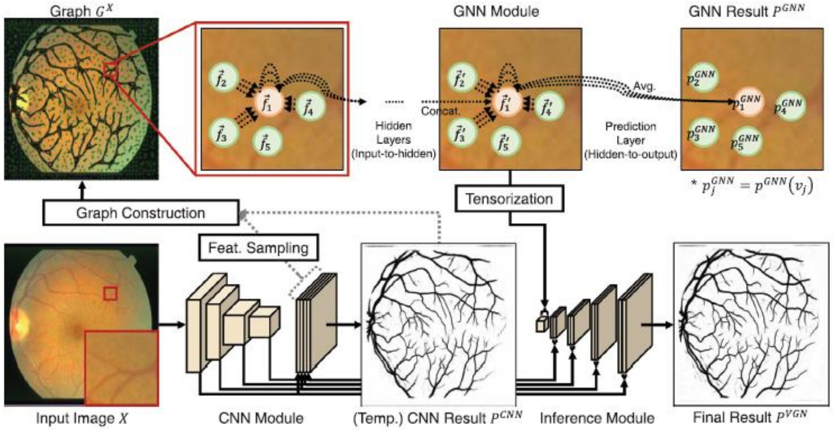
网络结构

- 融合CNN和GNN网络



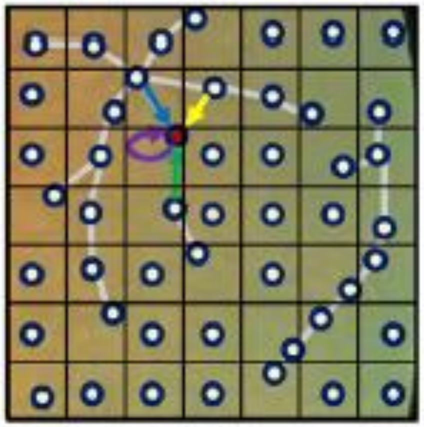
GNN网络

- Graph 初始化
  G = (V, E)



- 顶点V，特征f，边E

- 边的构造由测地距离决定
  保证这种构造方式可以保
  留血管的结构



0.9	**0.8**	**0.7**
0.1	0.8	0.1
0.4	0.7	0.9

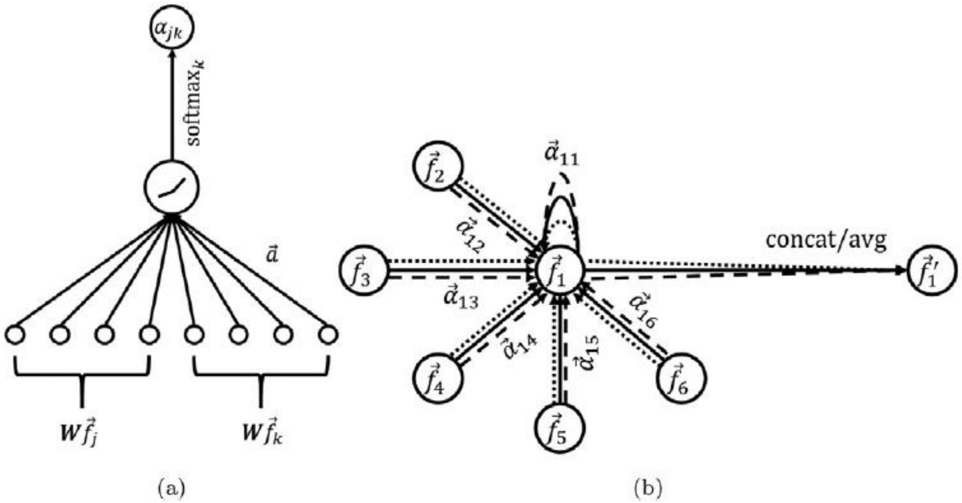
GNN网络

- 图网络的内部连接

$$e_{jk} = \mathrm{LeakyReLU}\left(\vec{a}^T \left[\mathbf{W}\vec{f}_j \| \mathbf{W}\vec{f}_k\right]\right),$$

$$\alpha_{jk} = \mathrm{softmax}_k(e_{jk}) = \frac{\exp(e_{jk})}{\sum_{m \in N_j} \exp(e_{jm})},$$

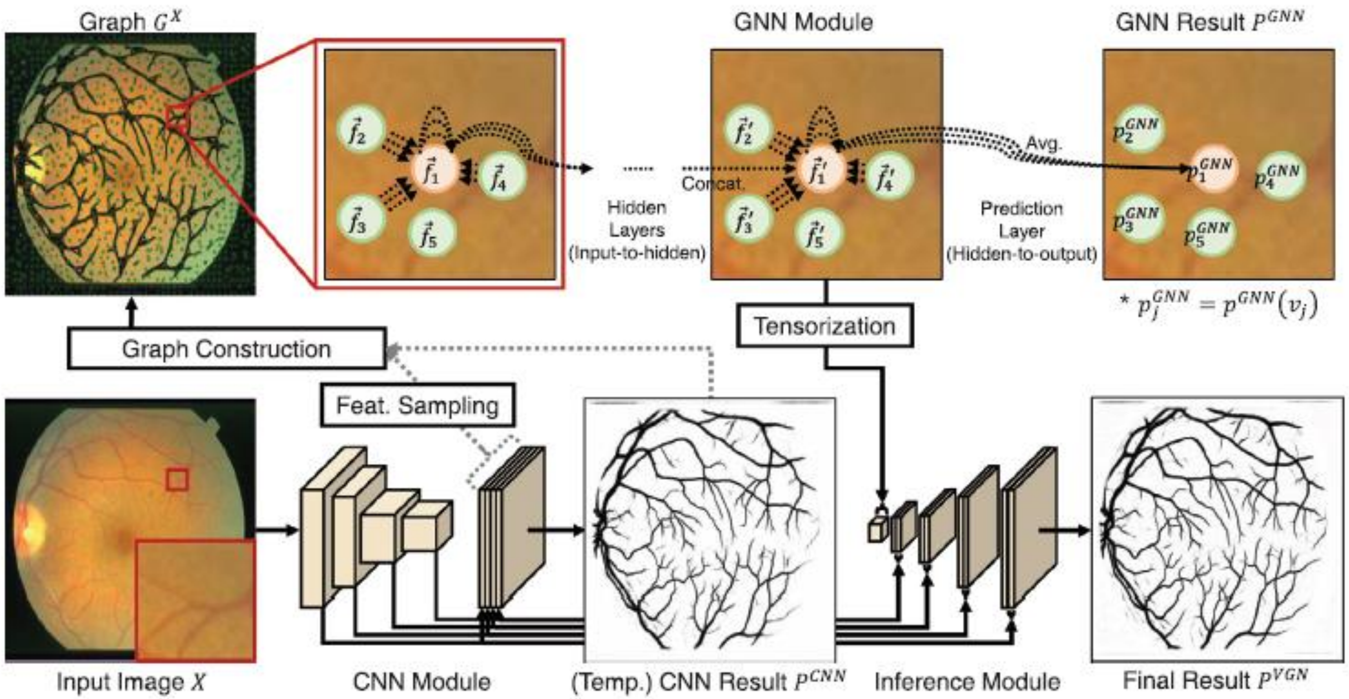
$$\vec{f}_j' = \big\|_{r=1}^{R} \mathrm{ELU}\left(\sum_{k \in N_j} \alpha_{jk}^r \mathbf{W}^r \vec{f}_k\right),$$



$$p^{GNN}(v_j) = \sigma\left(\frac{1}{R}\sum_{r=1}^{R}\sum_{k \in N_j} \alpha_{jk}^r \mathbf{W}^r \vec{f}_k\right),$$

$$L_{GNN}(G^X) = -\frac{1}{|V|}\sum_{v_j \in V}\Big(p^*(v_j)\log\, p^{GNN}(v_j) + (1 - p^*(v_j))\log\big(1 - p^{GNN}(v_j)\big)\Big),$$

网络结构



$$L_{total}(X) = L_{CNN}(X) + L_{GNN}(G^X) + L_{INFER}(X).$$

实验结果

数据集

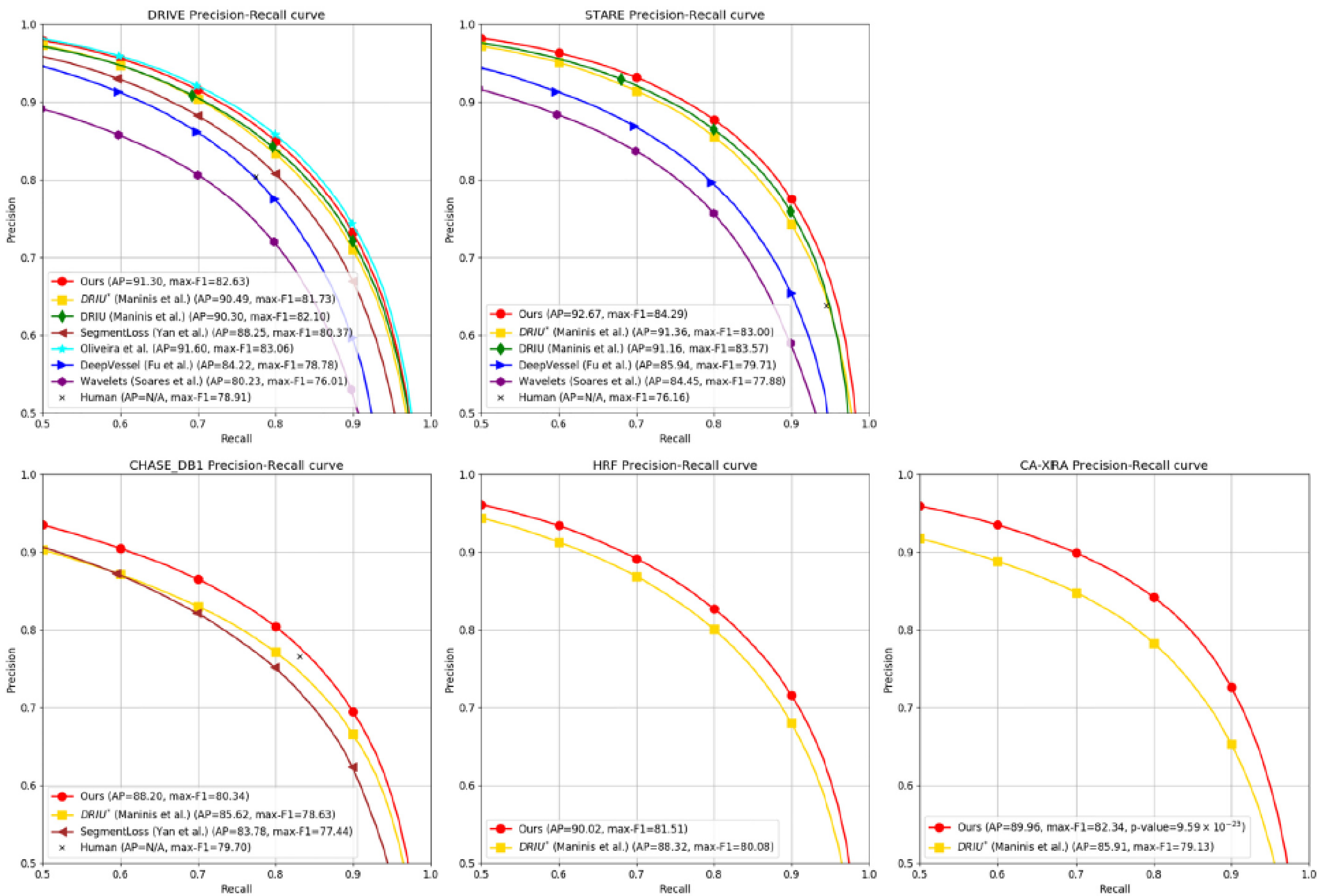
Dataset	Retinal				Coronary
	DRIVE	STARE	CHASE_DB1	HRF	CA-XRA
# of images (train/test)	40 (20/20)	20 (10/10)	28 (20/8)	45 (15/30)	3137 (2958/179)
Resolution	584 × 565	605 × 700	960 × 999	2336 × 3504	512 × 512
FoV mask	Y	Y	Y	Y	N
2nd GT	Y	Y	Y	N	N

数据增广

水平翻转，对比度调整

实验结果

VGN的CNN部分与DRIU相同



实验结果

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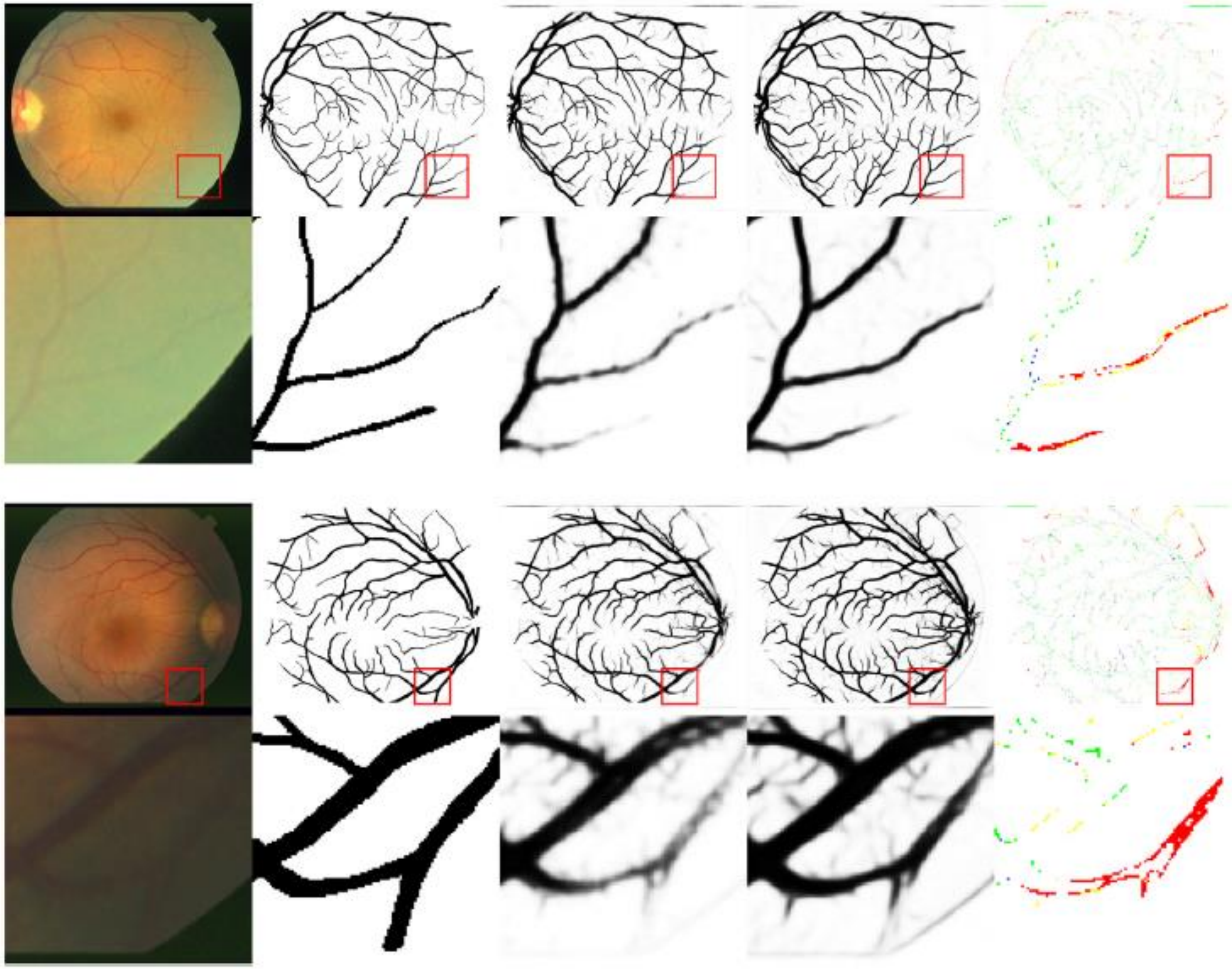
- 不同的边构造方式
  测地距离、欧式距离和全连接

Edge const. method	*DRIU** (Maninis et al., 2016)	Geodesic	Euclidean	Full CXT
Average precision (%)	91.36	**92.67**	92.56	90.34

- 与其他方法的定量对比

Network architecture	Average precision (%)	#params (million)
*DRIU** (Maninis et al., 2016)	91.36	7.86
U-Net (Ronneberger et al., 2015)	92.20	7.89
DRIU + Deformable convolution (Dai et al., 2017)	91.82	7.87
Ours	**92.67**	7.91

实验结果



GT　DRIU　OURS

文章亮点

- 结合血管特点，引入图网络
- 把图网络和CNN结合
- 精心设计了图网络的输入输出
- 图网络可以捕捉到血管的连续性