MICCAI Journal Report

QIU Liangdong 邱梁东

CUHK(SZ) SRIBD

November 28, 2019

Paper Lists

FocusNet: Imbalanced Large and Small Organ Segmentation for Head and Neck CT Images

Harnessing 2D Networks and 3D Features for Automated Pancreas Segmentation from Volumetric CT Images

FocusNet: Imbalanced Large and Small Organ Segmentation for Head and Neck CT Images (MICCAI 2019) ▸ FocusNet

- Segmentation of Head and Neck Organs

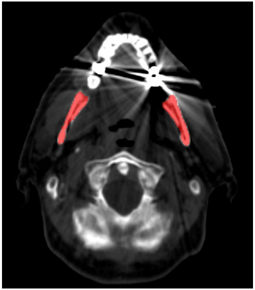

Figure 1: a CT image on axial plane

Related work

FocusNet

Related work of HaN organ segmentation

- Atlas-based methods
- CNN-based methods

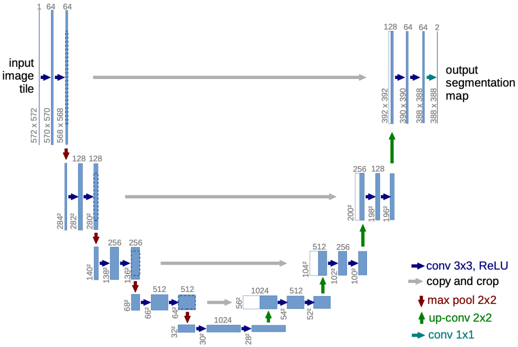

Figure 2: U-Net

Current problem

FocusNet

- The numbers of voxels of organs vary on magnitude.
- Current methods perform poorly on segmentation of small organs.

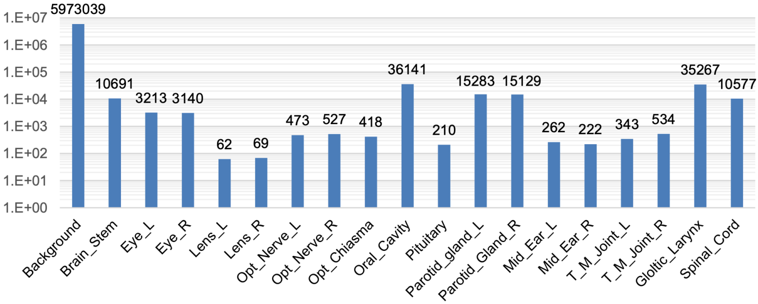

Figure 3: The numbers of voxels of organs

Network structure

FocusNet

S-Net, SOL-Net for locating and SOS-Net for fine segmentation

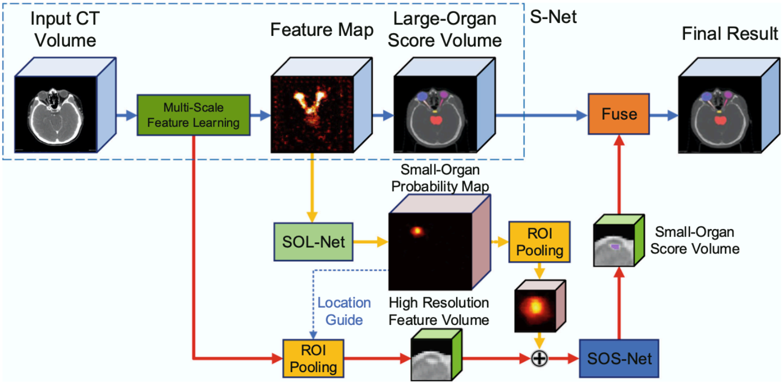

Figure 4: FocusNet structure

Network structure

FocusNet

S-Net: main segmentation network

- One time down sample
- Dense ASPP

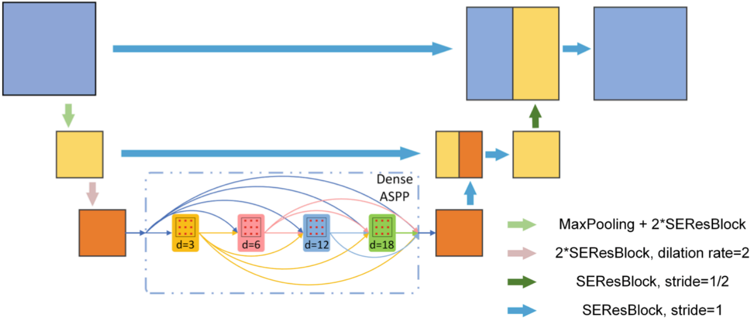

Figure 5: S-Net structure

Evaluation

FocusNet

- Their own collected data
- Contain labels of 10 small organs (below the dash line)

Organs	Atlas-based	SERes U-Net	DeepLab	Ours
Brain Stem	80.6±1.7	79.2±1.8	84.0±1.2	**85.8±1.4**
Lens L	24.0±8.3	60.8±4.2	59.2±8.4	**80.8±4.7**
Lens R	26.9±1.5	57.1±6.2	64.3±6.6	**79.0±6.4**
Opt. Ner. L	47.7±10.6	56.0±3.7	52.7±9.9	**63.9±3.9**
Opt. Ner. R	48.5±6.0	49.3±9.5	57.1±21.4	**61.7±12.1**
Opt. Chiasm	54.8±9.0	54.0±7.6	55.6±11.3	**63.8±11.4**
Pituitary	44.6±12.0	67.6±12.7	**78.1±10.8**	76.9±7.2
Mid. Ear L	56.4±9.7	55.2±15.6	51.9±25.3	**56.7±16.7**
Mid. Ear R	**56.2±14.5**	47.4±13.4	46.6±21.8	52.2±20.9
T.M.J. L	46.9±14.1	56.5±8.1	**64.7±3.9**	58.4±7.3
T.M.J. R	50.3±18.8	55.1±12.1	**66.1±8.4**	57.2±5.6
Average	62.3	66.5	69.4	**72.5**

Figure 6: Evaluation on their own data

Evaluation

FocusNet

- MICCAI 2015 HaN organs dataset
- Compared with Top 4 Teams

Organs	MICCAI 2015 [6]	Ren et al. [7]	Wang et al. [9]	Zhu et al. [11]	S-Net	FocusNet
Extra Data	×	×	×	✓	×	×
Brain Stem	88.0	N/A	**90.3±4**	86.7±2	86.8±2.9	87.5±2.6
Chiasm	55.7	58±17	N/A	53.2±15	57.4±25.1	**59.6±18.1**
Mandible	93.0	N/A	**94.4±1**	92.5±2	92.5±1.5	93.5±1.9
Opt. Ner. L	64.4	72±8	N/A	72.1±6	71.8±6.9	**73.5±9.6**
Opt. Ner. R	63.9	70±9	N/A	70.6±10	71.9±9.9	**74.4±7.2**
Parotid L	82.7	N/A	82.3±6	**88.1±2**	86.1±2.6	86.3±3.6
Parotid R	81.4	N/A	82.9±6	87.4±4	87.8±4.6	**87.9±3.1**
Subman. L	72.3	N/A	N/A	**81.4±4**	79.4±9.8	79.8±8.1
Subman. R	72.3	N/A	N/A	**81.3±4**	79.7±4.5	80.1±6.1
Average	74.9	N/A	N/A	79.25	79.24	**80.29**

Figure 7: Evaluation on MICCAI 2015 HaN dataset

Summary

FocusNet

Starting point

- Problem-oriented
- Imitate oncologists

Network detail

- Locate small organs and fine segment
- Reduce the times of down-sampling

Harnessing 2D Networks and 3D Features for Automated Pancreas Segmentation from Volumetric CT Images (MICCAI 2019) ▸ Harnessing 2D and 3D

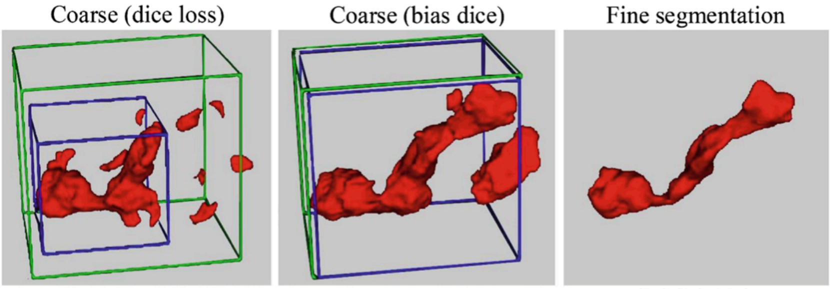

Figure 8: Pancreas Refinement

Related work

Harness 2D and 3D

- 2D network for refinement
- Tri-planar scheme (2.5D)

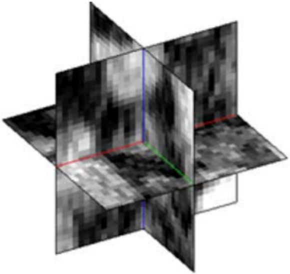

Figure 9: Tri-planar

Current problem

Harness 2D and 3D

Computational waste

- ROI refinement
- Not make good use of 2D network

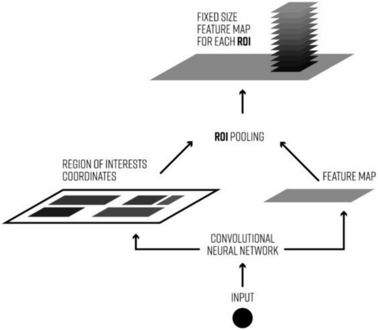

Figure 10: ROI Pooling

Coarse Network Structure

Harness 2D and 3D

- Revise loss function to emphasize "Recall"

$$Loss_{bias\_dice} = 1 - \frac{2(\sum_{i=1}^{N} p_i g_i + \epsilon)}{\sum_{i=1}^{N} p_i(1-g_i) + 2\sum_{i=1}^{N} g_i p_i + \beta \times \sum_{i=1}^{N} g_i(1-p_i) + \epsilon}$$

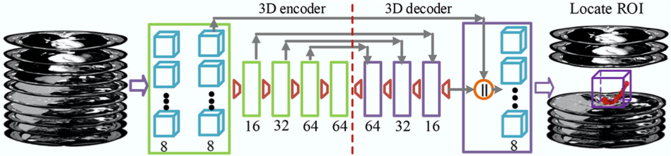

Figure 11: Coarse segmentation network

Fine Network Structure

Harness 2D and 3D

- combine 2d and 3d networks

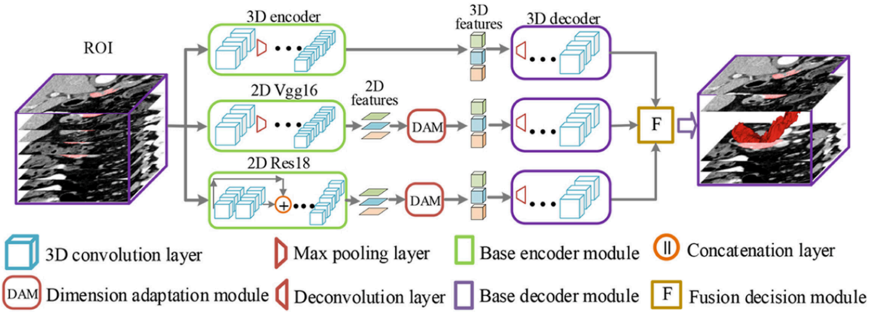

Figure 12: Fine segmentation network

Network Structure
Harness 2D and 3D

- Convert 2D slices to 3D

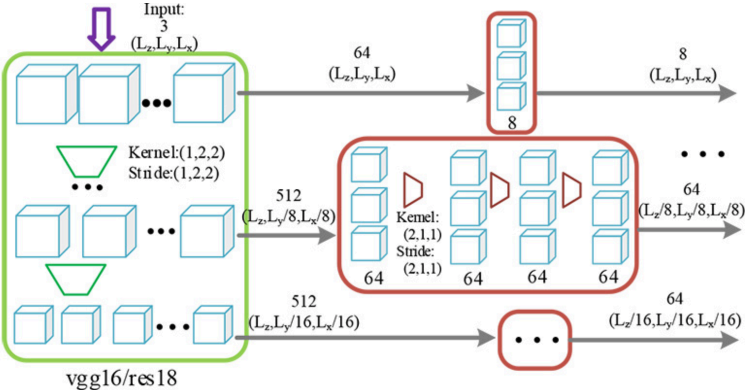

Figure 13: dimension adaptive module

Evaluation

Harness 2D and 3D

Method	Mean DSC (%)	Max DSC (%)	Min DSC (%)	Time (m)
Roth et al. [5]	71.42 ± 10.11	86.29	23.99	6–8
Roth et al. [6]	78.01 ± 8.20	88.65	34.11	2–3
Roth et al. [7]	81.27 ± 6.27	88.96	50.69	2–3
Cai et al. [1]	82.4 ± 6.7	90.10	60.00	N/A
Zhou et al. [11]	82.50 ± 6.14	89.98	56.33	0.9
Zhu et al. [12]	84.59 ± 4.86	91.45	69.62	4.1
Xia et al. [9]	84.63 ± 5.07	**91.57**	61.58	1.4
Yu et al. [10]	84.50 ± 4.97	91.02	62.81	1.3
Our proposed (no parallel training)	83.99 ± 5.34	91.41	66.62	**0.40**
Our proposed	85.09 ± 4.13	91.26	**71.42**	**0.40**
Our proposed (integrated)	$\mathbf{85.22 \pm 4.07}$	91.36	71.40	0.44

Figure 14: Evaluation on NIH dataset

Summary

Harness 2D and 3D

Method-oriented

- Bias dice loss function
- Combine 2D features in a 3D way