# MICCAI 2019 Paper Review

GAO Shen 高深

December 5, 2019

# Topics

- Weakly supervised segmentation
- Semi-supervised segmentation
- Unsupervised segmentation

# Content

- PseudoEdgeNet: Nuclei Segmentation only with Point Annotations
- Uncertainty-aware Self-ensembling Model for Semi-supervised 3D Left Atrium Segmentation
- Unsupervised Deep Learning for Bayesian Brain MRI Segmentation

# PseudoEdgeNet: Nuclei Segmentation only with Point Annotations

- Inwan Yoo, Donggeun Yoo, Kyunghyun Paeng
- Lunit Inc., Korea
- 用只标注了点的图像来训练。

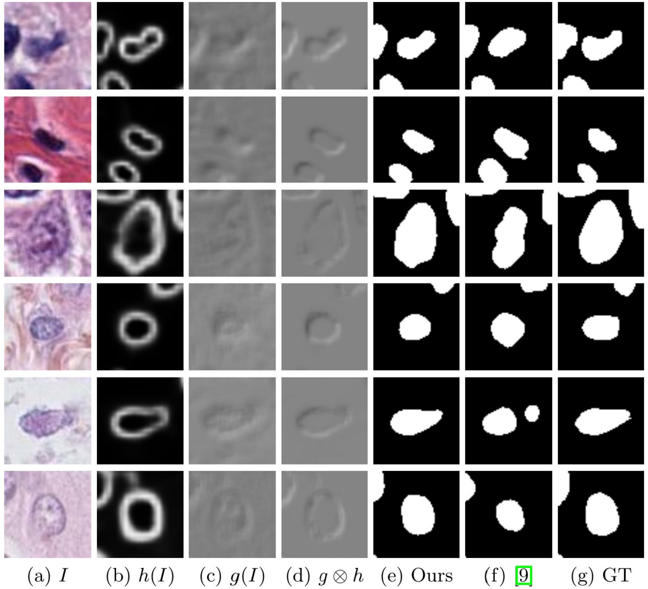


**Fig. 2.** Qualitative examples and comparisons: (a) inputs, (b) attention maps, (c) $(x, y)$-directional raw edge maps, (d) final edge maps in which attentions are multiplied, (e) final segmentation results from our segmentation network, (f) segmentation results from the baseline method [9], and (g) ground-truth masks. In (c, d), each map is averaging the $x$- and $y$-directional edge maps. The gray color represents zero while the white and black colors encode positive and negative pixel values, respectively.

# PseudoEdgeNet: Nuclei Segmentation only with Point Annotations

- 数据标注:以细胞核为中心，做Voronoi分割。
- 分割损失:分割结果与目标的binary cross-entropy loss。
- 不足之处:无法习得细胞核的边界。

# PseudoEdgeNet: Nuclei Segmentation only with Point Annotations

- 解决方法:用Edge net来习得细胞核边界
- 损失函数:
  $L = L_{ce}(f(I), P) + \lambda \cdot |(s(f(I)) - g(I) \bigotimes h(i)|$
- 分割网络:FPN

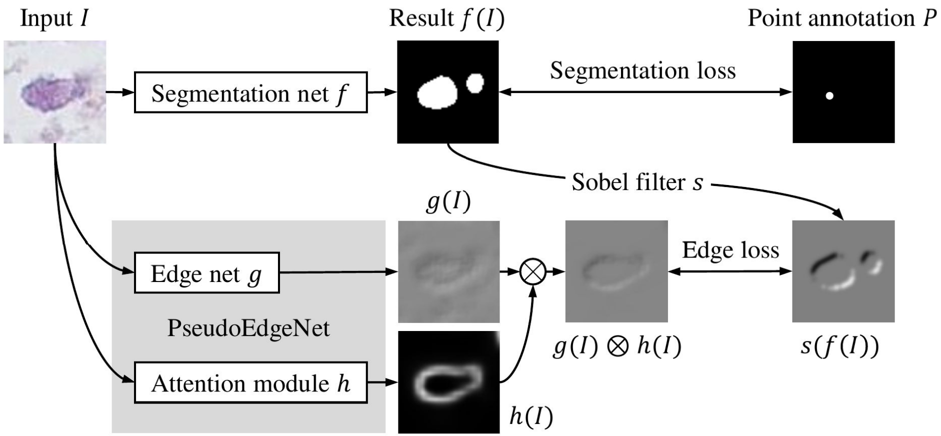


**Fig. 1.** The overall architecture for weakly-supervised nuclei segmentation. The segmentation network $f$ is jointly learned with PseudoEdgeNet $\{g, h\}$. In edge maps, the gray color represents zero while the white and black colors encode positive and negative pixel values, respectively.

# PseudoEdgeNet: Nuclei Segmentation only with Point Annotations

- 运行结果:

**Table 1.** Nuclei segmentation performance comparison between methods. The mean and standard deviation of 10-fold cross-validation results (10 IoU scores) are reported.

| Methods | MoNuSeg | TNBC |
|---|---|---|
| Baseline [9] | 0.5710 ($\pm$0.02) | 0.5504 ($\pm$0.04) |
| DenseCRF* [15] | 0.5813 ($\pm$0.03) | 0.5555 ($\pm$0.04) |
| PseudoEdgeNet with large $g$ | 0.5786 ($\pm$0.04) | 0.5787 ($\pm$0.04) |
| PseudoEdgeNet with small $g$ | 0.6059 ($\pm$0.04) | 0.5853 ($\pm$0.03) |
| PseudoEdgeNet with small $g$ and $h$ | **0.6136** ($\pm$0.04) | **0.6038** ($\pm$0.03) |
| Fully supervised (upper bound) | 0.6522 ($\pm$0.03) | 0.6619 ($\pm$0.04) |

*Authors' open source is used: https://github.com/meng-tang/rloss

# PseudoEdgeNet: Nuclei Segmentation only with Point Annotations

- 边缘识别:

**Table 2.** Nuclei segmentation performance to the size of edge networks. The mean and standard deviation of 10-fold cross-validation results (10 IoU scores) are reported.

| Edge networks ($g$) | | MoNuSeg | TNBC |
|---|---|---|---|
| Small | CNN with 2 conv layers | 0.6117 ($\pm$0.03) | 0.5928 ($\pm$0.04) |
| | CNN with 4 conv layers | **0.6136** ($\pm$0.04) | **0.6038** ($\pm$0.03) |
| | CNN with 6 conv layers | 0.6105 ($\pm$0.04) | 0.5896 ($\pm$0.03) |
| | CNN with 8 conv layers | 0.6119 ($\pm$0.02) | 0.5934 ($\pm$0.04) |
| Large | FPN-ResNet18 | 0.6005 ($\pm$0.03) | 0.5795 ($\pm$0.04) |
| | FPN-ResNet34 | 0.6069 ($\pm$0.03) | 0.5796 ($\pm$0.03) |
| | FPN-ResNet50 | 0.5786 ($\pm$0.04) | 0.5787 ($\pm$0.04) |

# Uncertainty-aware Self-ensembling Model for Semi-supervised 3D Left Atrium Segmentation


- Lequan Yu, Shujun Wang, Xiaomeng Li, Chi-Wing Fu, Pheng-Ann Heng
- The Chinese University of Hong Kong


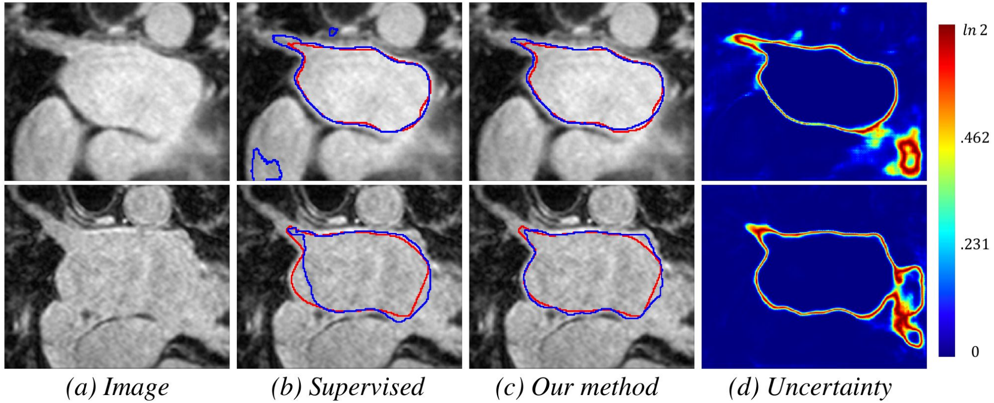


Fig. 2: Visualization of the segmentations by different methods and the uncertainty. Blue and red colors show the predictions and ground truths, respectively.

# Uncertainty-aware Self-ensembling Model for Semi-supervised 3D Left Atrium Segmentation

- 数据:只有一部分数据有标注。
- 用EMA更新Teacher Model的权重。
- 对Teacher Model的输出的每个体素计算Uncertainty，高于阈值的不计入一致性损失。
- 用监督损失和一致性损失共同训练Student Model
- https://github.com/yulequan/UA-MT/

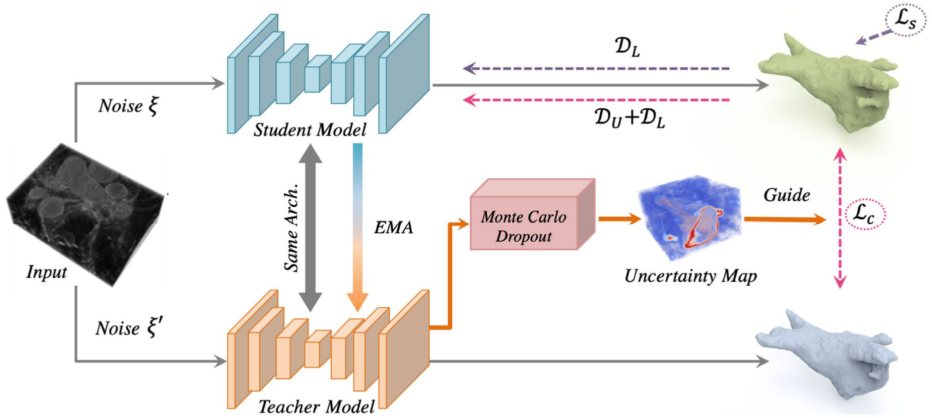


Fig. 1: The pipeline of our uncertainty-aware framework for semi-supervised segmentation. The student model is optimized by minimizing the supervised loss $\mathcal{L}_s$ on labeled data $\mathcal{D}_L$ and the consistency loss $\mathcal{L}_c$ on both unlabeled data $\mathcal{D}_U$ and labeled data $\mathcal{D}_L$. The estimated uncertainty from the teacher model guides the student to learn from the more reliable targets from the teacher.

# Uncertainty-aware Self-ensembling Model for Semi-supervised 3D Left Atrium Segmentation

- 运行结果:

Table 1: Comparison between our method and various methods.

| Method | # scans used | | Metrics | | | |
|---|---|---|---|---|---|---|
| | Labeled | Unlabeled | Dice[%] | Jaccard[%] | ASD[voxel] | 95HD[voxel] |
| Vanilla V-Net | 16 | 0 | 84.13 | 73.26 | 4.75 | 17.93 |
| Bayesian V-Net | 16 | 0 | 86.03 | 76.06 | 3.51 | 14.26 |
| Vanilla V-Net | 80 | 0 | 90.25 | 82.40 | 1.91 | 8.29 |
| Bayesian V-Net | 80 | 0 | 91.14 | 83.82 | 1.52 | 5.75 |
| Self-training [1] | 16 | 64 | 86.92 | 77.28 | 2.21 | 9.19 |
| DAN [18] | 16 | 64 | 87.52 | 78.29 | 2.42 | 9.01 |
| ASDNet [12] | 16 | 64 | 87.90 | 78.85 | **2.08** | 9.24 |
| TCSE [10] | 16 | 64 | 88.15 | 79.20 | 2.44 | 9.57 |
| **UA-MT-UN (ours)** | 16 | 64 | 88.83 | 80.13 | 3.12 | 10.04 |
| **UA-MT (ours)** | 16 | 64 | **88.88** | **80.21** | 2.26 | **7.32** |

# Uncertainty-aware Self-ensembling Model for Semi-supervised 3D Left Atrium Segmentation

- 运行结果:

Table 2: Quantitative analysis of our method.

| Method | # scans used | | Metrics | | | |
|---|---|---|---|---|---|---|
| | Labeled | Unlabeled | Dice[%] | Jaccard[%] | ASD[voxel] | 95HD[voxel] |
| MT | 16 | 64 | 88.23 | 79.29 | 2.73 | 10.64 |
| MT-Dice [5] | 16 | 64 | 88.32 | 79.37 | 2.76 | 10.50 |
| Our UA-MT | 16 | 64 | 88.88 | 80.21 | 2.26 | 7.32 |
| Bayesian V-Net | 8 | 0 | 79.99 | 68.12 | 5.48 | 21.11 |
| Our UA-MT | 8 | 72 | 84.25 | 73.48 | 3.36 | 13.84 |
| Bayesian V-Net | 24 | 0 | 88.52 | 79.70 | 2.60 | 10.45 |
| Our UA-MT | 24 | 56 | 90.16 | 82.18 | 2.73 | 8.90 |

# Unsupervised Deep Learning for Bayesian Brain MRI Segmentation


- Adrian V. Dalca, Evan Yu, Polina Golland, Bruce Fischl, Mert R. Sabuncu, Juan Eugenio Iglesias
- Harvard Medical School, Massachusetts Institute of Technology, Cornell University, University College London


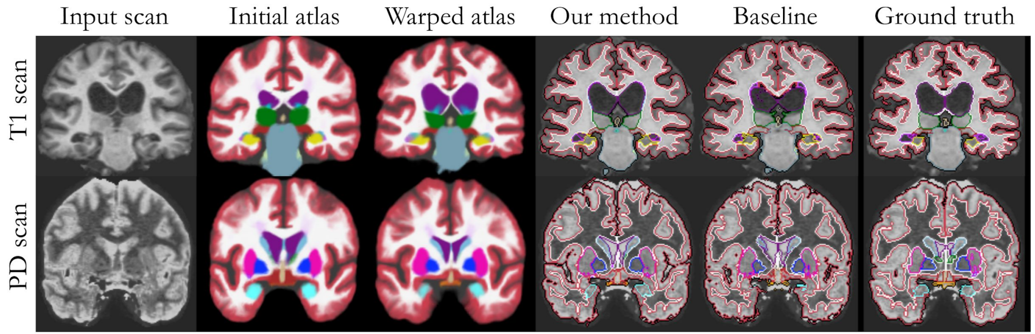


**Fig. 3. Example Results.** Coronal slices of two scans (one from each of the T1 and PD datasets), along with the initial and deformed probabilistic atlas, and corresponding segmentations. In the atlas, the color of each pixel is a combination of the colors of different labels, weighted by their probabilities. In the segmentations, we show the contour of the labels in the corresponding colors. We use the FreeSurfer color map [12].

# Unsupervised Deep Learning for Bayesian Brain MRI Segmentation

- 把分割作为贝叶斯推断问题。
- 网络输出： $\sigma, \mu, \phi$
- 用输出的参数来计算分割图。

$$\hat{S}_j = \arg\max_l \mathcal{N}(I_j; \hat{\mu}_l, \hat{\sigma}_l^2) A\Big(l, \phi_{\hat{v}}(\boldsymbol{x}_j)\Big)$$

- 用Likehood和概率图来计算Loss。

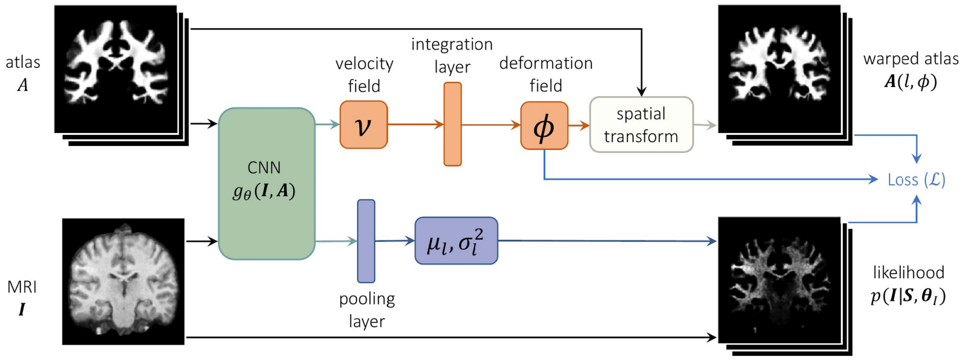


**Fig. 1. Method overview.** The network block $g_\psi(\cdot,\cdot)$ outputs a stationary velocity field $\boldsymbol{v}$, enabling alignment of the probabilistic atlas to the input volume, and likelihood Gaussian parameters $\boldsymbol{\mu}, \boldsymbol{\sigma}^2$, which yield likelihood maps for each label.

# Unsupervised Deep Learning for Bayesian Brain MRI Segmentation

- 运行结果:

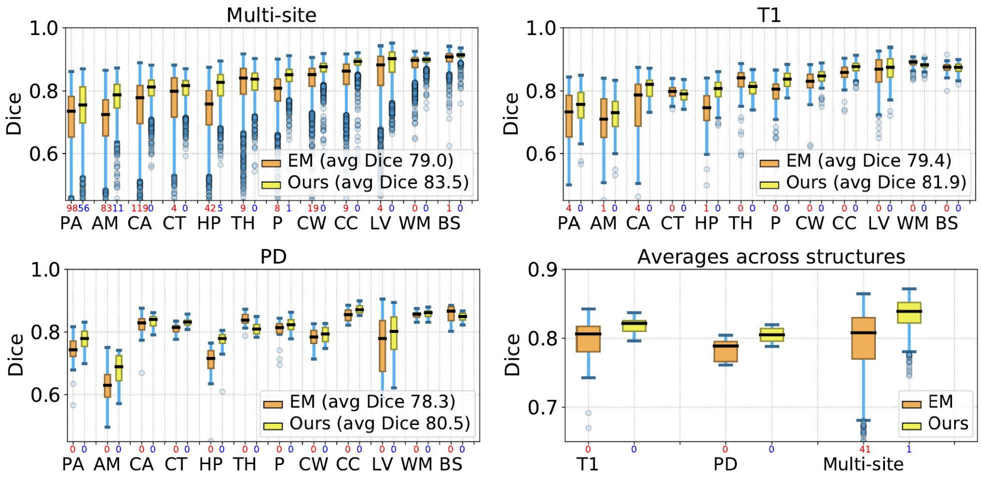


**Fig. 2. Segmentation Statistics.** Dice scores for: cerebral cortex (CT) and white matter (WM); lateral ventricle (LV); cerebellar cortex (CC) and white matter (CW); thalamus (TH); caudate (CA); putamen (P); pallidum (PA); brainstem (BS); hippocampus (HP); and amygdala (AM). Scores of contralateral structures are averaged. The number of outliers under the $x$ axis is shown in red (baseline) and blue (ours).