Medical Image Segmentation via Unsupervised Convolutional Neural Network

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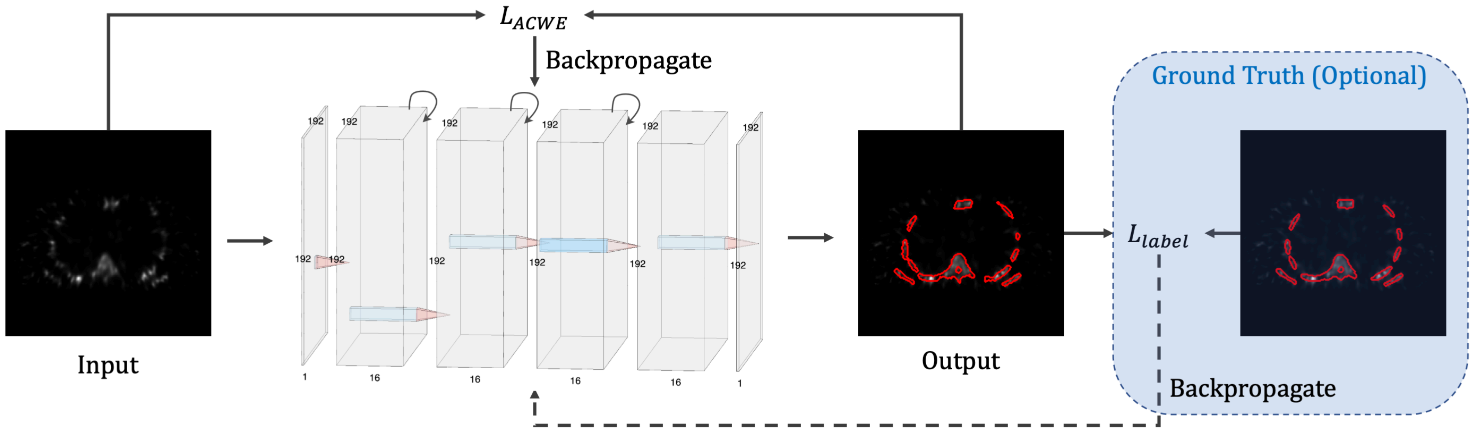
Medical Image Segmentation

- Unsupervised Methods
  - Clustering algorithms, level set methods, etc.
  - Do not depend on ground truth labels.
  - Can be computationally expensive.
- Supervised Methods
  - Deep neural networks.
  - Require a training stage but can be fast in testing phase.
  - Usually need a large amount of accurately annotated training data.
    - Especially hard for medical images.

Learning ACWE using a ConvNet

- Combine the best of both supervised and unsupervised methods.
  - We propose a self-supervised ConvNet-based segmentation method.
  - An unsupervised loss is based on the Active Contour without Edges (ACWE) [1].
  - No ground truth labels are needed during training.
  - The trained network provides fast segmentation after training.
  - Segmentation accuracy can be further improved by fine-tuning using a small set of labeled images.



Method

- ConvNet $f_\theta(g)$:
  - A 5-layer Recurrent convolutional neural network [2].
- An unsupervised loss function that is on the basis of the ACWE:
  - $\mathcal{L}_{ACWE} = v \cdot Area(f_\theta(g) > 0) + \sum_{f_\theta(g)>0} |g - c_1|^2 + \sum_{f_\theta(g)\leq 0} |g - c_2|^2$
  - g: input image, c_1: mean value inside the segmentation, c_2: mean value outside.
- An optional supervised loss function that is also based on the ACWE [3]:
  - $\mathcal{L}_{label} = \sum_{f_\theta(g)} |\nabla(f_\theta(g))| + \sum_\Omega \left(\left(\mathbf{1} - f_\theta(g)\right)^2 - \left(\mathbf{0} - f_\theta(g)\right)^2\right) \boldsymbol{u}$
  - Ω: image spatial domain, $\boldsymbol{u}$: ground truth label.
  - Can also use Dice loss or Cross-entropy loss.

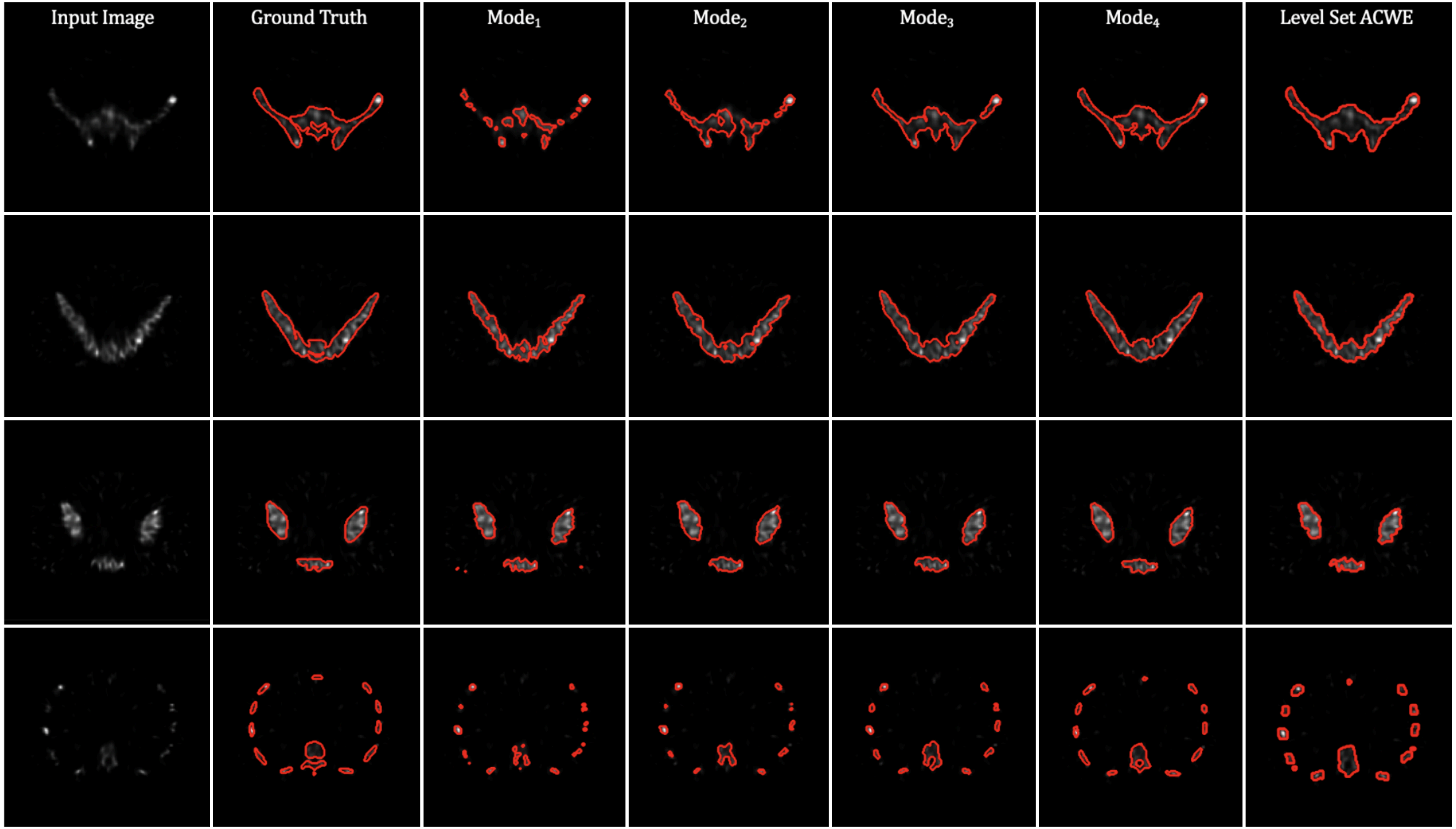
Experiments & Results

- Evaluated four modes:
  - Mode_1: Unsupervised (self-supervised) training with $\mathcal{L}_{ACWE}$.
  - Mode_2: Mode1 + fine-tuning using $\mathcal{L}_{label}$ with 10 ground truth (GT) labels.
  - Mode_3: Mode1 + fine-tuning using $\mathcal{L}_{label}$ with 80 GT labels.
  - Mode_4: Training with $\mathcal{L}_{ACWE}$ + $\mathcal{L}_{label}$.
- Tested on the task of bone segmentation in Tc-99m SPECT simulations generated based on the XCAT phantom [4-6].
- Quantitative Results:

	Mode_1	Mode_2	Mode_3	Mode_4	Level set ACWE
DSC	0.593±0.19	0.661±0.16	0.732±0.12	0.856±0.09	0.518±0.337

	Proposed Method	Level set ACWE
Time per Image (Sec.)	0.006 ± 0.022	2.698±0.085

Results


Input Image
Ground Truth
Mode$_1$
Mode$_2$
Mode$_3$
Mode$_4$
Level Set ACWE

References

1. Chan, Tony F., and Luminita A. Vese. "Active contours without edges." *IEEE Transactions on image processing* 10.2 (2001): 266-277.
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3. Chen, Xu, et al. "Learning active contour models for medical image segmentation." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2019.
4. Segars, W. Paul, et al. "4D XCAT phantom for multimodality imaging research." *Medical physics* 37.9 (2010): 4902-4915.
5. Frey, E. C., and B. M. W. Tsui. "A practical method for incorporating scatter in a projector-backprojector for accurate scatter compensation in SPECT." *IEEE Transactions on Nuclear Science* 40.4 (1993): 1107-1116.
6. Kadrmas, Dan J., Eric C. Frey, and Benjamin MW Tsui. "An SVD investigation of modeling scatter in multiple energy windows for improved SPECT images." *IEEE transactions on nuclear science* 43.4 (1996): 2275-2284.