Leveraging Labeling Representations in Uncertainty-based Semi-supervised Segmentation

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Take-Home Message

Proposal: An anatomically-aware uncertainty estimate to guide segmentation models

- labeling representation to approximate new uncertainty maps
- needs a single inference, reducing computation complexity

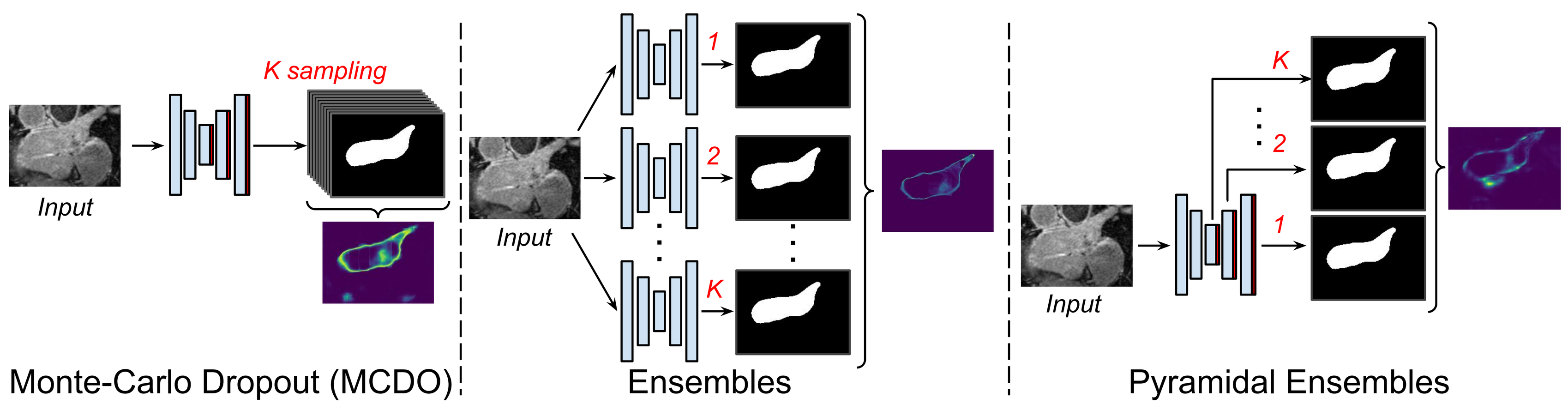
Results:

- Our method improves the segmentation performance in terms of Dice score up to 1.5% and Hausdorff Distance up to 2.5mm
- Our representation improves segmentation in uncertain regions

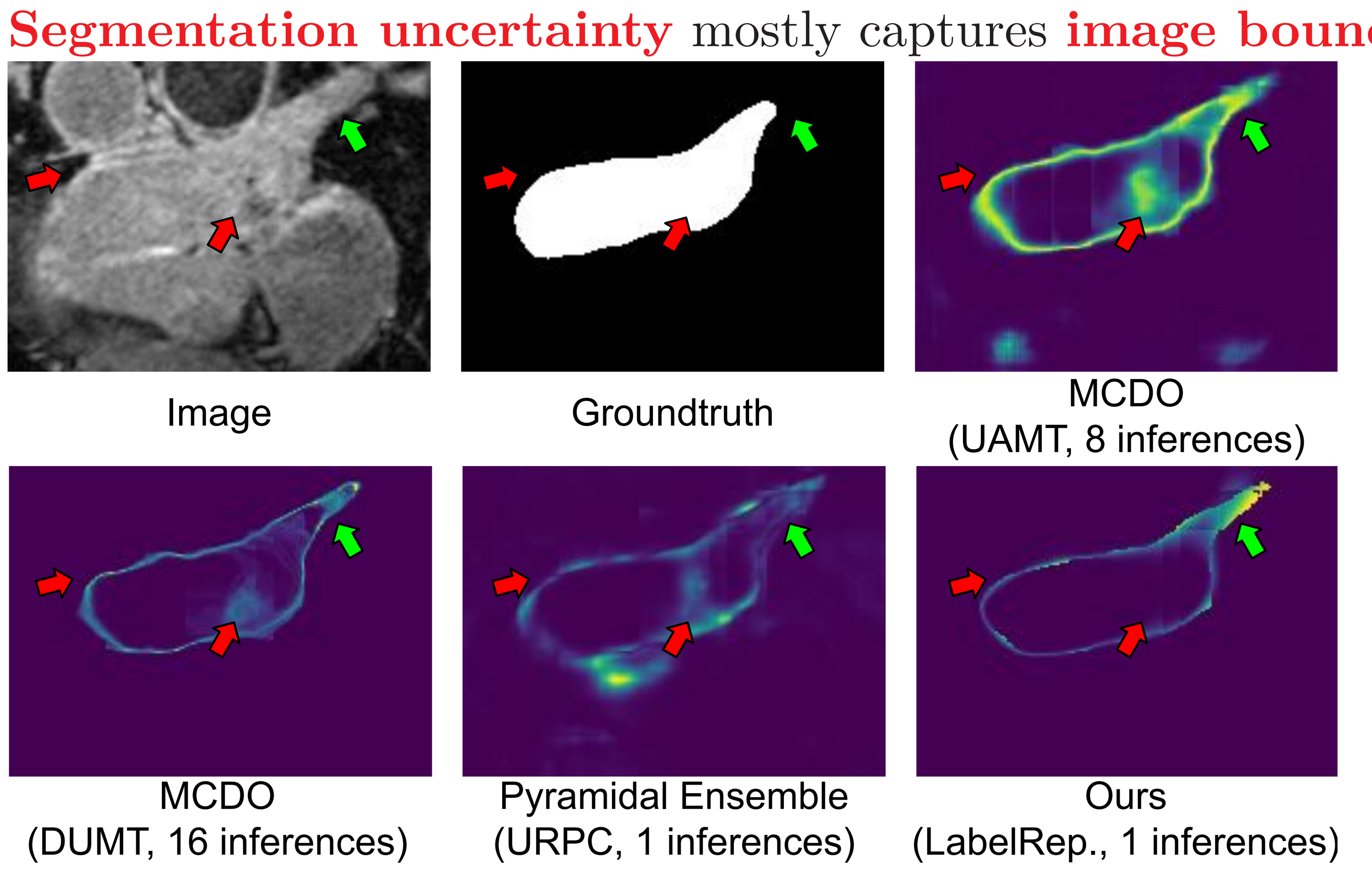
Introduction

Uncertainty in Semi-Supervision:

- **predictions** from unlabeled data can be **uncertain**
- **uncertainty-aware** methods: UAMT [1], DUMT [2], URPC [3]
- estimate uncertainty with **multiple samplings or predictions**



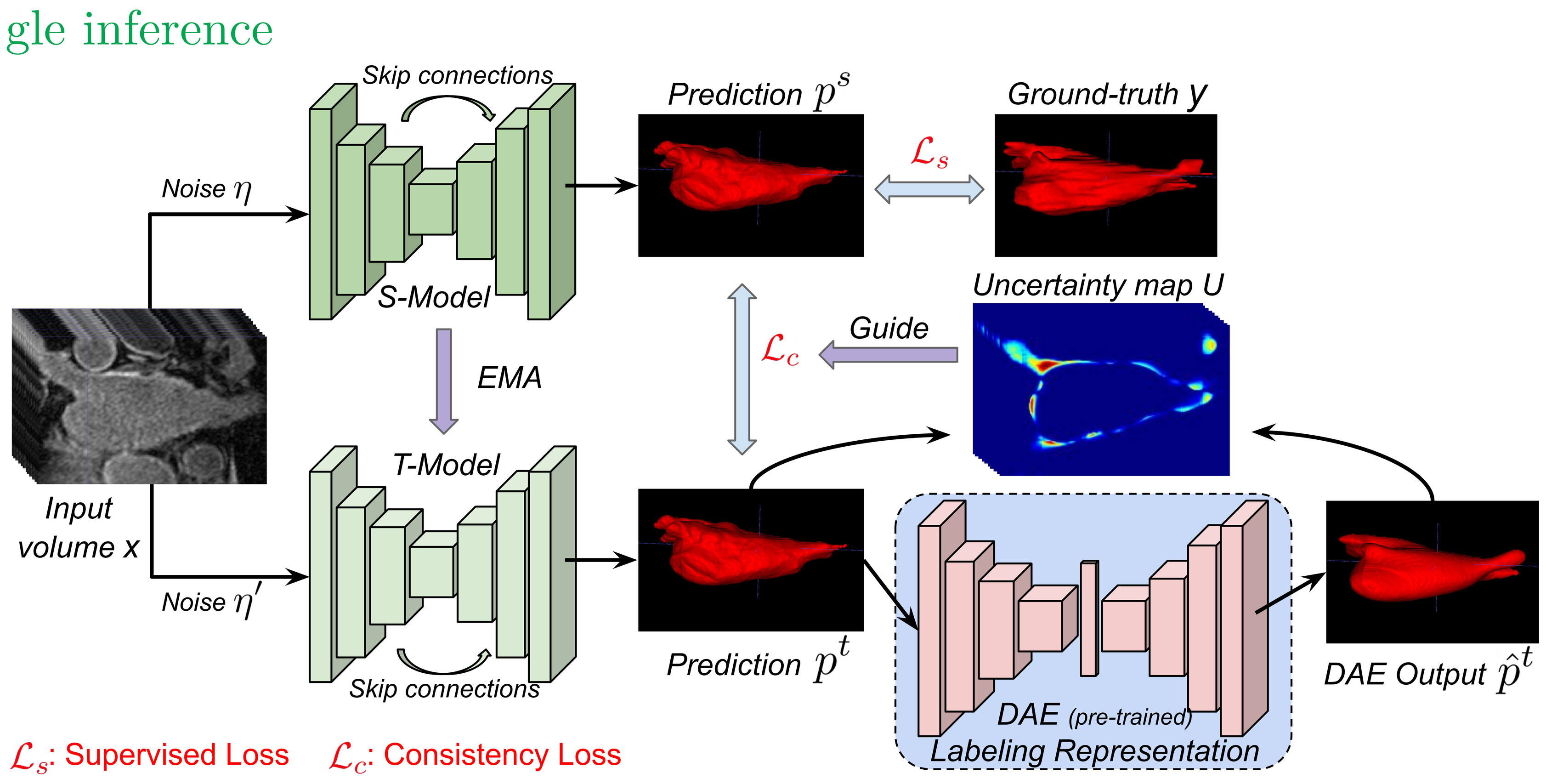
- **Problem**:
  - **High computation** from **multiple inferences**
  - **Segmentation uncertainty** mostly captures **image boundaries**



- **Idea**: Estimate uncertainty with a **single** inference that leverages an **anatomically-aware** representations
- **How**: Exploit **anatomical information** from available masks to estimate uncertainty

Method

A novel anatomically-aware representation to estimate uncertainty in a single inference



- Labeling representation is first learnt from available masks using a denoising autoencoder (DAE)
- Mask uncertainty as pixelwise difference between the DAE output and the prediction: $U_i = ||\hat{p}_i^t - p_i^t||^2$
- Our consistency loss is weighted by our mask uncertainty:

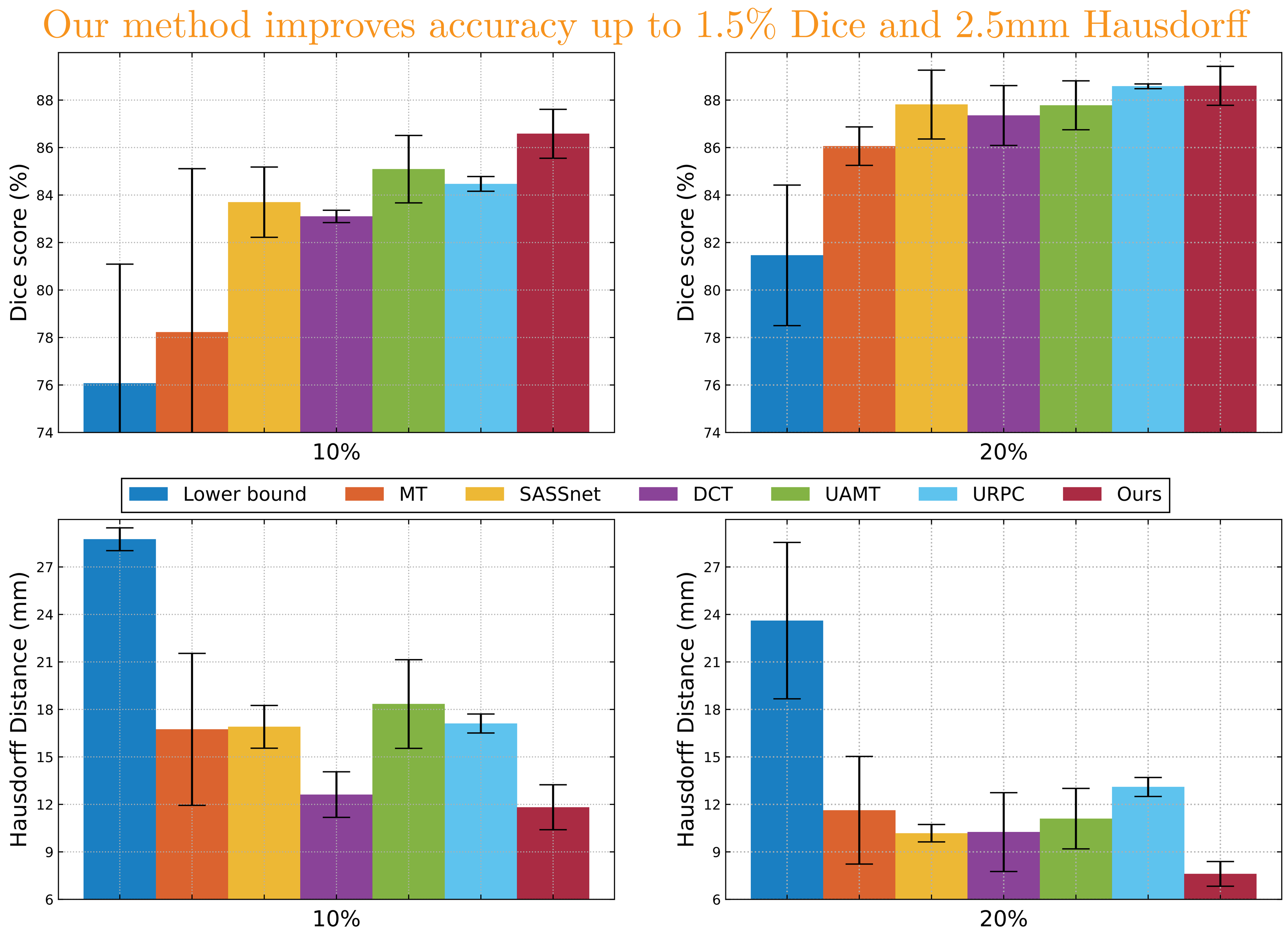
$$\mathcal{L}_c(p_i^s, p_i^t) = \frac{\sum_v e^{-\gamma U_{i,v}} ||p_{i,v}^s - p_{i,v}^t||^2}{\sum_v e^{-\gamma U_{i,v}}}$$

Results

(1) Dataset: 2018 Atrial Segmentation Challenge [4]

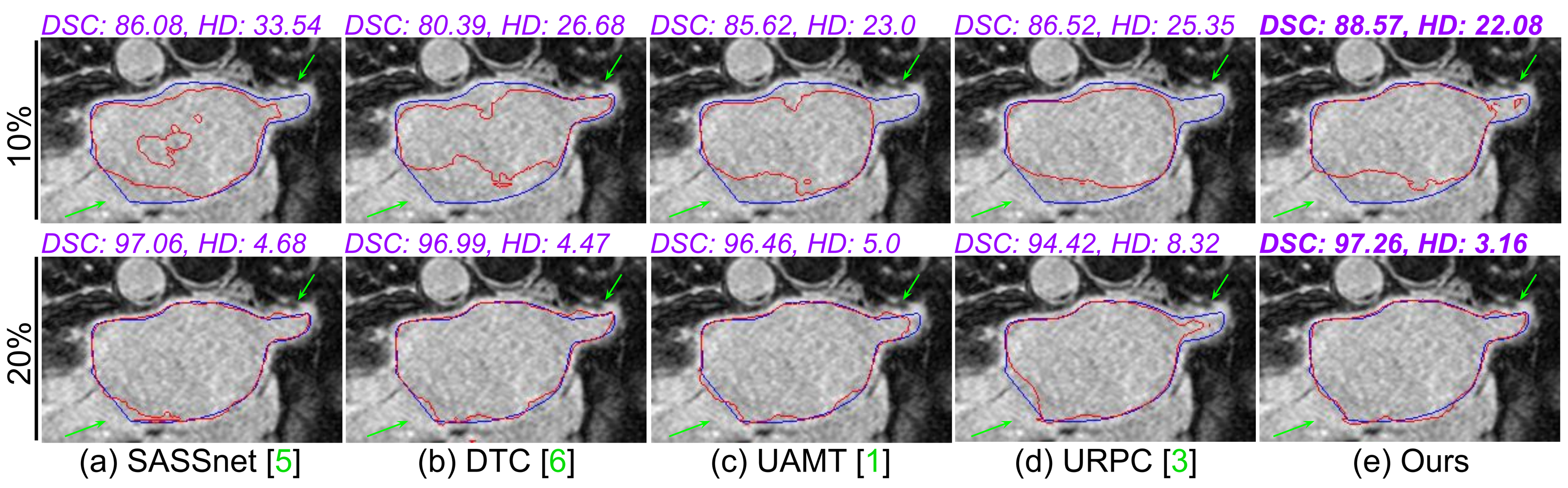
(2) Quantitative Performance

Our method improves accuracy up to 1.5% Dice and 2.5mm Hausdorff



(3) Visualization of Segmentation

Our representation improves segmentation in uncertain regions



(4) Effectiveness of proposed uncertainty estimation

Our method is robust compared to the entropy-based method

Methods	N/M	DSC (%)	HD (mm)
UAMT [1]	8/72	85.09 ± 1.42	18.34 ± 2.80
Ours (Threshold)	8/72	85.39 ± 0.91	12.96 ± 3.05
Ours (Entropy)	8/72	85.92 ± 1.52	**11.16 ± 0.82**
Ours	8/72	**86.58 ± 1.03**	11.82 ± 1.42

References

[1] L. Yu, S. Wang, X. Li, C. Fu, and P. Heng. Uncertainty-aware self-ensembling model for semi-supervised 3D left atrium segmentation. In *MICCAI*, 2019.
[2] Y. Wang, Y. Zhang, J. Tian, C. Zhong, Z. Shi, Y. Zhang, and Z. He. Double-uncertainty weighted method for semi-supervised learning. In *MICCAI*, 2020.
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[4] Z. Xiong, Q. Xia, Z. Hu, N. Ravikumar, A. Maier, X. Yang, et al. A global benchmark of algorithms for segmenting the left atrium from late gadolinium-enhanced cardiac magnetic resonance imaging. *MedIA*, 2021.
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