UPCoL: Uncertainty-informed Prototype Consistency Learning for Semi-supervised Medical Image Segmentation

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Motivations

1. **Challenges in Uncertainty Quantification:** Defining reliable uncertainty criteria across tasks is difficult.
2. **Underutilization of Latent Features:** Existing constraints focus on decision space, neglecting the potential of latent feature space.
3. **Limitations in Prototype Learning:** Current methods relies heavily on labeled data and separate prototypes for labeled and unlabeled data.

Introduction

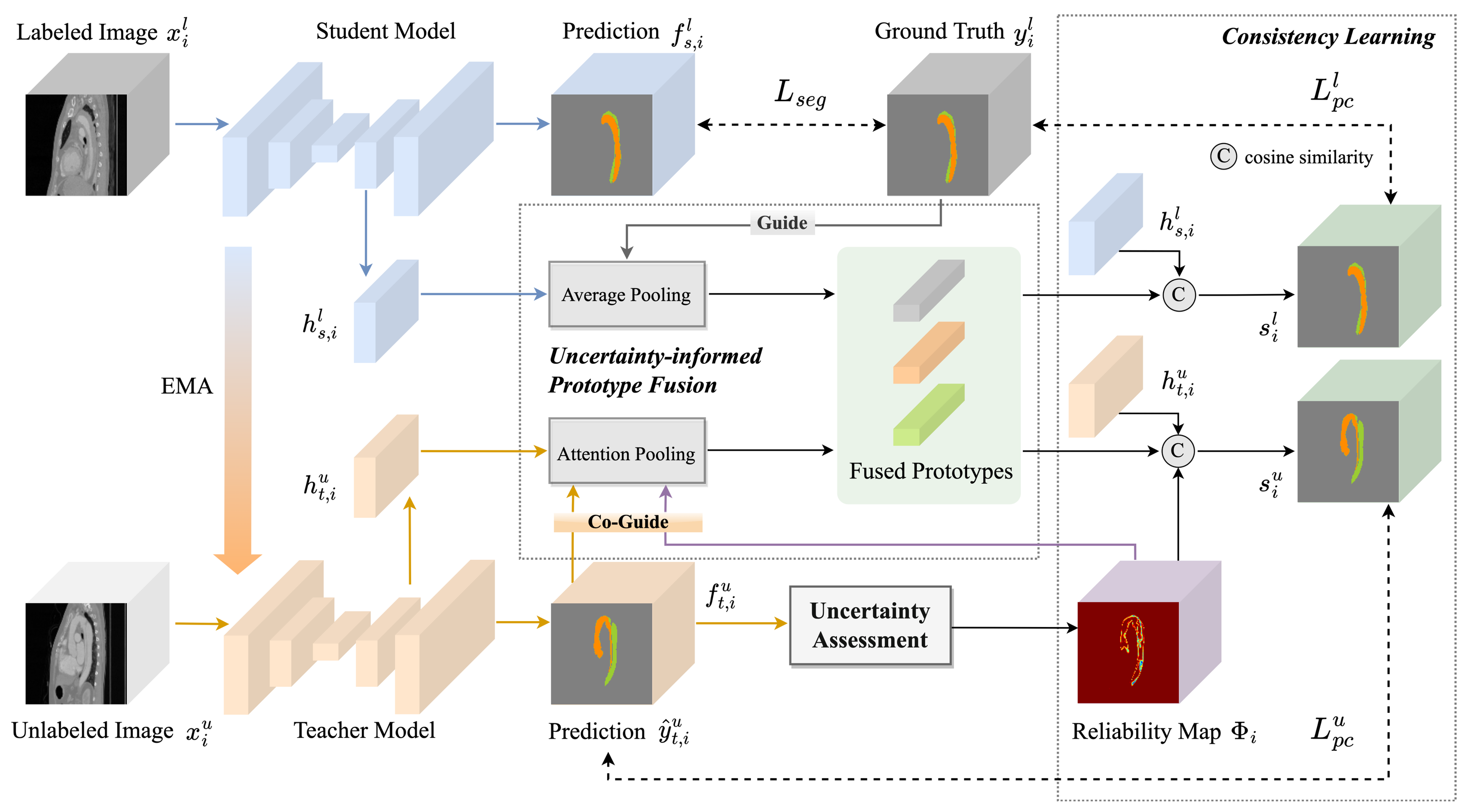

Figure 1: Overview of UPCoL (using Aortic Dissection segmentation for illustration).

- Develope UPCoL, an **uncertainty-informed prototype consistency framework** for voxel-level consistency in feature and decision spaces.
- Introduce a unique **fused prototype learning approach** that leverages both labeled and unlabeled data embeddings, setting us apart from prior research.
- Propose a novel **reliability measure** for unlabeled voxels and an **attention-weighted strategy** for fusion.
- Showcase UPCoL's outstanding performance in two-class and three-class segmentation tasks, outperforming **SOTA** semi-supervised methods.

Methodology

- **Uncertainty Assessment**
  - Entropy per voxel

$$\mathcal{H}(f_{t,i}^{(x,y,z)}) = -\sum_{c=0}^{C-1} f_{t,i}^{(x,y,z)}(c) \log f_{t,i}^{(x,y,z)}(c). \quad (1)$$

  - Reliability map

$$\Phi_i^{(x,y,z)} = \frac{1}{H \times W \times D}\left(1 - \frac{\mathcal{H}(f_{t,i}^{(x,y,z)})}{\sum_{x,y,z}\mathcal{H}(f_{t,i}^{(x,y,z)})}\right). \quad (2)$$

- **Prototype Learning**
  - Labeled prototype of class c is computed via masked average pooling

$$p_c^l = \frac{1}{\mathcal{B}_l}\sum_{i=1}^{\mathcal{B}_l} \frac{\sum_{x,y,z} h_{s,i}^{l(x,y,z)} \mathbb{1}\left[y_i^{l(x,y,z)} = c\right]}{\sum_{x,y,z} \mathbb{1}\left[y_i^{l(x,y,z)} = c\right]}. \quad (3)$$

  - Unlabeled prototype of class c is computed via masked attention pooling

$$p_c^u = \frac{1}{\mathcal{B}_u}\sum_{i=1}^{\mathcal{B}_u} \frac{\sum_{x,y,z} h_{t,i}^{u(x,y,z)} \Phi_i^{(x,y,z)} \mathbb{1}\left[\hat{y}_i^{u(x,y,z)} = c\right]}{\sum_{x,y,z} \mathbb{1}\left[\hat{y}_i^{u(x,y,z)} = c\right]}. \quad (4)$$

  - Prototype Fusion

$$p_c = \lambda_{lab} p_c^l + \lambda_{unlab} p_c^u, \qquad \lambda_{lab} = \frac{1}{1+\lambda_{con}}, \qquad \lambda_{unlab} = \frac{\lambda_{con}}{1+\lambda_{con}} \quad (5)$$

- **Consistency Learning**
  - Non-parametric metric learning: feature-to-prototype similarity

$$s_i^{(x,y,z)} = \mathrm{CosSim}\left(h_i^{(x,y,z)}, p_c\right) = \frac{h_i^{(x,y,z)} \cdot p_c}{\max(\left\|h_i^{(x,y,z)}\right\|_2 \cdot \|p_c\|_2, \epsilon)} \quad (6)$$

  - Prototype consistency losses

$$\mathcal{L}_{pc}^l = \mathcal{L}_{CE}(s_i^l, y_i^l), \qquad \mathcal{L}_{pc}^u = \sum_{x,y,z} \Phi_i^{(x,y,z)} \mathcal{L}_{CE}(s_i^{u(x,y,z)}, \hat{y}_i^{u(x,y,z)}), \quad (7)$$

  - Overall loss

$$\mathcal{L} = \mathcal{L}_{seg} + \mathcal{L}_{pc}^l + \lambda_{con}\mathcal{L}_{pc}^u. \quad (8)$$

Experimental results

- Segmentation performance of different approaches.

Table 1: Performance comparison on the Left Atrium and Pancreas datasets.

Method	Left Atrium						Pancreas-CT					
	Lb	Unlb	Dice	Jac	95HD	ASD	Lb	Unlb	Dice	Jac	95HD	ASD
V-Net	16	0	84.41	73.54	19.94	5.32	12	0	70.63	56.72	22.54	6.29
V-Net	80	0	91.42	84.27	5.15	1.50	62	0	82.60	70.81	5.61	1.33
MT [1] (NIPS'17)	16	64	86.00	76.27	9.75	2.80	12	50	75.85	61.98	12.59	3.40
UA-MT [2] (MICCAI'19)	16	64	88.88	80.21	7.32	2.26	12	50	77.26	63.28	11.90	3.06
DTC [3] (AAAI'21)	16	64	89.42	80.98	7.32	2.10	12	50	76.27	62.82	8.70	2.20
MC-Net [4] (MICCAI'21)	16	64	90.34	82.48	6.00	1.77	12	50	78.17	65.22	6.90	1.55
MC-Net+ [5] (MIA'22)	16	64	91.07	83.67	5.84	1.67	12	50	80.59	68.08	6.47	1.74
ASE-Net [6] (TMI'22)	16	64	90.29	82.76	7.18	1.64	-	-	-	-	-	-
CoraNet [7] (TMI'21)	-	-	-	-	-	-	12	50	79.49	67.10	11.10	3.06
SimCVD [8] (TMI'22)	16	64	90.85	83.80	6.03	1.86	-	-	-	-	-	-
URPC [9] (MIA'22)	-	-	-	-	-	-	12	50	80.02	67.30	8.51	1.98
UPCoL(Ours)	16	64	**91.69**	**84.69**	**4.87**	**1.56**	12	50	**81.78**	**69.66**	**3.78**	**0.63**

'Lb' and 'Unlb' denote the number of labeled samples and unlabeled samples, respectively.

Table 2: Ablation study results on the pancreas dataset.

Method		Component indication				Metric			
		MT	PL			Dice	Jaccard	95HD	ASD
			Lb	Unlb	Fuse	(%)	(%)	(voxel)	(voxel)
W/o Consistency						70.63	56.72	22.54	6.29
Prediction Consistency	MT	✓				75.85	61.98	12.59	3.40
	MT + AMC	✓				77.97	64.46	9.80	2.52
Prototype Consistency	MT + PL	✓	✓			80.50	68.11	4.49	0.74
	CPCL*	✓	✓	✓		80.08	67.29	7.68	2.08
	UPCoL	✓	✓	✓	✓	**81.78**	**69.66**	**3.78**	**0.63**

- Visualization of segmentation results.

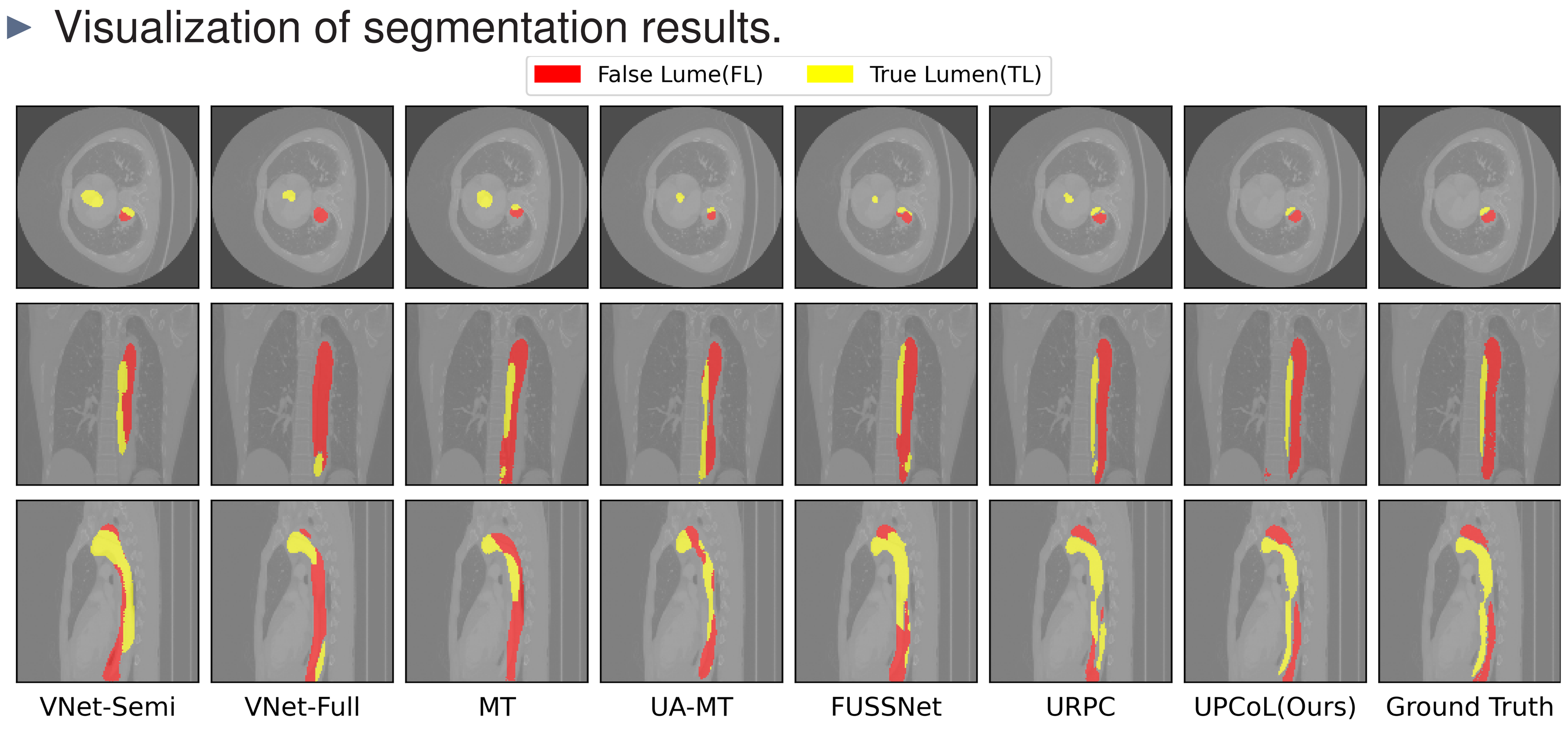

Figure 2: Visualization of segmentation results on Type B Aortic Dissection dataset.

Conclusions

- **Efficient Mitigation of Label Sparsity**
  - Address label sparsity through uncertainty-based prototype consistency learning.
- **Optimized Utilization of Unlabeled Data**
  - Employ voxel-level quantitative uncertainty measures for improved attention allocation to unlabeled data.
- **Exceptional Segmentation Performance**
  - Achieve outstanding results in 2-class and 3-class medical image segmentation, demonstrating its efficacy.
- **Future Enhancements**
  - Explore the incorporation of multiple prototypes for diverse semantic concepts.
  - Introduce memory-bank-like mechanisms for more efficient prototype learning from extensive sample pools.

References

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Code is available at: *https://github.com/VivienLu/UPCoL*