Paper ID: CS840 2024 International Conference on Applied Mathematics, Modeling and Computer Simulation (AMMCS 2024)

Jointly Model-level and Task-level Learning for Semi-supervised Medical Image Segmentation with Low Sample Size

Bin Xu[a], Zhenjie Zhao[a],*

[a]School of Computer Science, Nanjing University of Information Science & Technology, Nanjing 210044, China

*Corresponding author's email: zzhaoao@nuist.edu.cn

Supported by the National Natural Science Foundation of China [Grant NO. 62106109].

Introduction

Despite existing semi-supervised learning methods utilizing a limited number of training samples, further reducing the amount of labeled data is practical in healthcare due to its high acquisition costs and potential invasiveness. In this paper, we address the challenge of low-sample-size semi-supervised medical image segmentation by proposing a joint model-level and task-level learning approach. Task-level supervision guides the model to learn shape-aware segmentation, while model-level supervision further constrains the model's uncertainty to enhance performance. With two levels of supervisions, our method can learn better segmentation results even with low sample size. On the publicly available left atrium (LA) segmentation dataset, we show that our method outperform state-of-the-art medical segmentation methods in terms of Dice, Jaccard, ASD, and 95HD, under the condition of low labeled sample size, which indicates the potential of leveraging model-level and task-level methods jointly.

Research objectives

- Explore semi-supervised medical image segmentation under low sample size conditions.
- By joint model-level and task-level learning, the supervised signals at both levels are utilized to learn better segmentation results at low sample sizes.

Methods

The overview of our model is shown in Figure 1.The backbone of our model is a Vnet.

On the task-level, we use both labeled and unlabeled samples. On the model-level, we only use unlabeled samples to calculate the model consistency loss. The labeled samples are used to calculate the distance map loss L_{dist} and dice loss L_{dice}, and both the labeled and unlabeled samples are used to calculate the task consistency lossL_{cT}. On the model-level, we only use unlabeled samples to calculate the model consistency loss L_{cM}.The overall objective is:

$$L = L_{dice} + L_{dist} + \beta_1 L_{cT} + \beta_2 L_{cM}$$

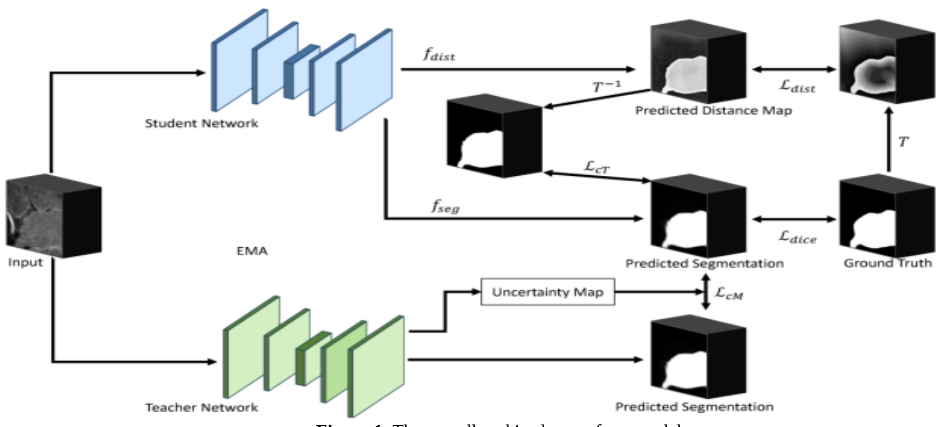

Figure 1. The overall architechture of our model.

- Task-level Loss

  Task-level losses contains dice loss, distance loss, and task consistency loss,and use both labeled and unlabeled samples. For labeled samples, we add adaptation layers to VNet to predict bothsegmentation and distance map,where distance map is used to constrain the geometry-shape of the output.
- Model-level Loss

  The model-level loss only contains one consistency loss. To calculate the model-level loss, a teacher network that has the same structure with the target network (called student network) is used to provide supervised signals for unlabeled samples. In particular, exponential moving average (EMA) is used to update parameters of the teacher network.

Experiments

- Dataset: The Atrial Segmentation Challenge dataset.
- Baselines: UA-MT, DTC.

  UA-MT is a semi-supervised medical image segmentation method that uses model-level learning.

  DTC is a semi-supervised medical image segmentation method that uses task-level learning.
- Evaluation Metrics: Dice similarity coeffiecient (Dice), Jaccard Index (Jaccard), Average Surface Distance (ASD), and 95% Hausdorff Distance (95HD) .

  Given a binary segmentation image A and the corresponding ground truth B, Dice and Jaccard are calculated as:

$$Dice = \frac{2|A \cap B|}{|A| + |B|} \qquad Jaccard = \frac{|A \cap B|}{|A \cup B|}$$

  ASD and 95HD are boundary-distance-based methods. Given the segmented object M and the ground truth object G, ASD and 95HD are calculated as:

$$ASD = \frac{\sum_{x \in \partial G} d(x, \partial M) + \sum_{y \in \partial M} d(y, \partial G)}{|\partial G| + |\partial M|}$$

$$95HD = max\{max95_{x \in \partial G} d(x, \partial M), max95_{y \in \partial M} d(y, \partial G)\}$$

- Results: The main results are shown in Table 1, where ↑ denotes the bigger the better, and ↓ denotes the smaller the better. From the results we can see that our method outperforms all baselines under the low sample size setting, which indicates the potential of adding supervision levels to improve segmentation performance under low sample size condition.

Method	Metrics			
	Dice↑	Jaccard↑	ASD↓	95HD↓
UA-MT	84.25	73.48	3.36	13.84
DTC	86.57	76.55	3.74	14.47
Ours	**86.72**	**76.99**	**2.53**	**9.34**

Table 1. Experiment results.

Conclusions

In this paper, we introduce a jointly model-level and task-level learning for semi-supervised medical image segmentation. Through the use of two levels of supervision, our method outperforms state-of-the-art methods on low sample size medical image segmentation tasks. In the future, we plan to con-sider more levels of supervision, such as data-level, and investigate extremely low sample size condition, or even without the use of labeled samples.

Acknowledgement

This work was supported by the National Natural Science Foundation of China [grant numbers 62106109].

References

[1] Yu, L., Wang, S., Li, X., Fu, C.W., Heng, P.A.: Uncertainty-aware self-ensembling model for semi-supervised 3d left atrium segmentation. In: MICCAI (2019)

[2] Luo, X., Chen, J., Song, T., Wang, G.: Semi-supervised medical image segmentation through dual-task consistency. AAAI Conference on Artificial Intelligence (2021)