Unsupervised Domain Adaptive Fundus Image Segmentation with Few Labeled Source Data

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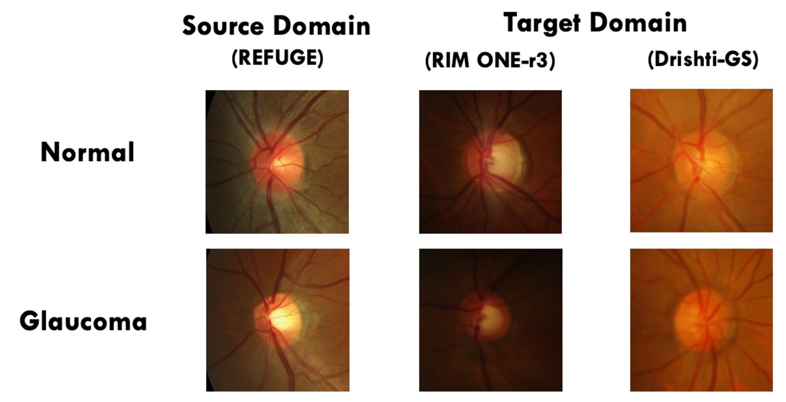
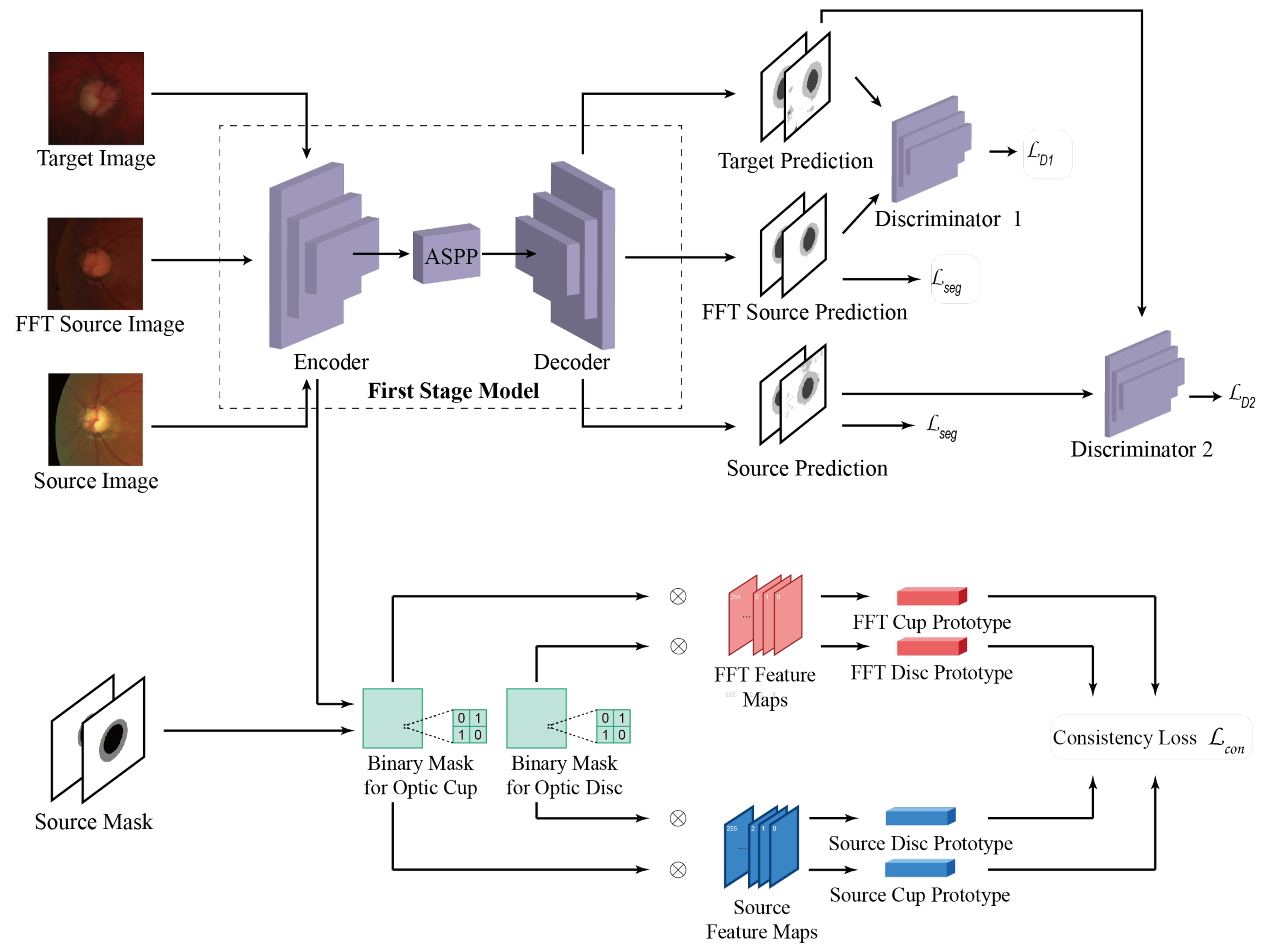
Main contributions: A novel framework is proposed for domain adaptive optic disc and cup segmentation given only a few labeled source data. The framework alleviates the domain bias issue under the data-scarce setting and includes uniquely designed modules of Searching-based Multi-style Mechanism, Class-prototype Consistency Mechanism, and Cross-style Self-supervised Learning. In comparison to alternative unsupervised domain adaptation methods and even fully supervised networks, the model has been trained to reach competitive outcomes.

Optic Cup and Disc Segmentation Tasks



In clinical practice, accurate examination of the head of the optic nerve i.e., cup-to-disc ratio is crucial for early detection and treatment of glaucoma diagnosis

Class-Prototype Consistency Mechanism



Masked pooling technique is used to force the model to focus on the target content of image

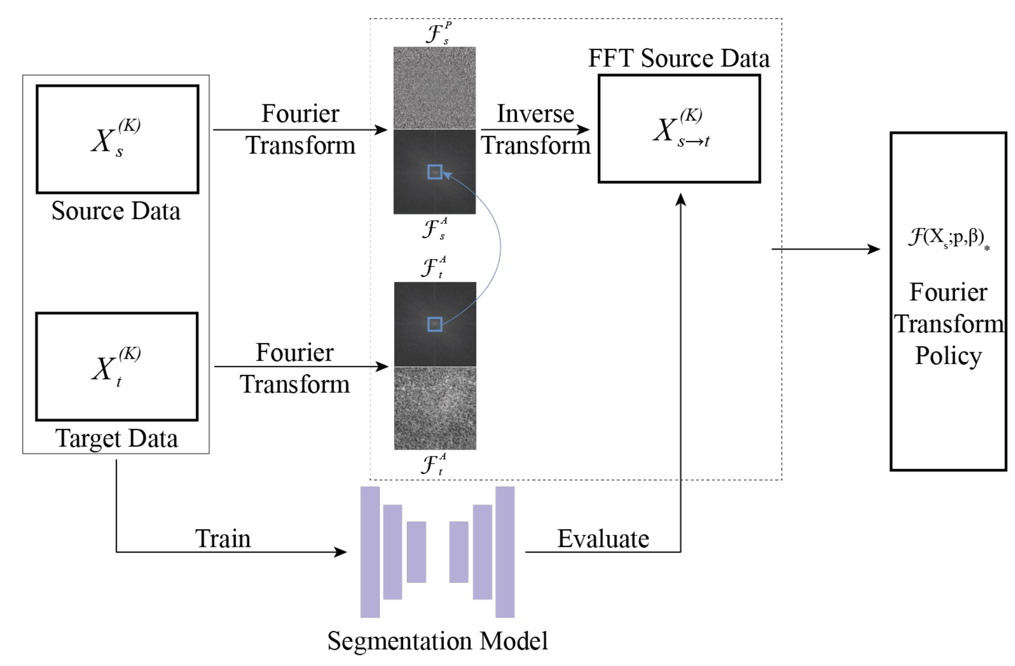
Target Dataset 1: RIM-ONE-R3

Methods	Cup Dice	Disc Dice	Average Dice	Cup ASD	Disc ASD	Avergae ASD
CyCADA	69.94 (0.58)	72.50 (0.37)	71.32 (0.48)	19.55 (0.22)	37.00 (0.35)	28.28 (0.29)
AdvEnt	67.73 (0.63)	78.54 (1.19)	73.34 (0.91)	30.96 (1.79)	32.48 (1.55)	31.72 (1.67)
FDA	69.38 (0.20)	78.07 (1.10)	73.72 (0.65)	21.15 (1.47)	28.86 (1.41)	25.01 (1.44)
PixMatch	64.91 (1.14)	75.88 (1.93)	70.39 (1.53)	18.60 (0.39)	30.50 (1.42)	24.55 (0.91)
LTIR	65.84 (0.09)	78.01 (1.97)	71.92 (1.03)	24.72 (0.98)	29.51 (1.46)	27.11 (1.22)
MT	63.50 (1.51)	67.92 (1.05)	65.71 (1.28)	20.72 (1.88)	39.26 (1.86)	29.99 (1.87)
PCS	60.77 (1.19)	73.90 (1.50)	67.33 (1.35)	24.20 (1.86)	32.13 (1.51)	28.16 (1.69)
BEAL	67.69 (1.49)	78.88 (1.23)	73.29 (1.36)	21.36 (1.93)	34.95 (1.79)	28.16 (1.86)
DPL	68.58 (0.33)	87.61 (0.61)	78.02 (0.47)	12.46 (0.59)	19.01 (0.45)	15.74 (0.52)
Ours	**78.16 (0.96)**	**88.45 (0.36)**	**83.30 (0.66)**	**9.82 (0.65)**	**11.78 (0.75)**	**10.80 (0.70)**

Target Dataset 2: Drishti-GS

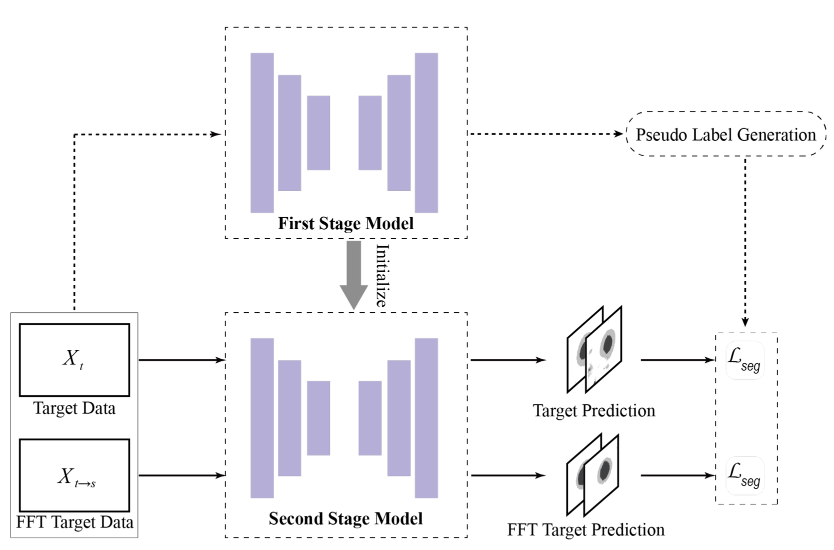
Methods	Cup Dice	Disc Dice	Average Dice	Cup ASD	Disc ASD	Avergae ASD
CyCADA	78.85 (0.80)	92.15 (0.52)	85.50 (0.66)	15.33 (0.30)	12.84 (1.85)	14.09 (1.08)
AdvEnt	79.17 (0.79)	91.47 (0.47)	85.32 (0.63)	15.42 (0.85)	15.08 (1.29)	15.25 (1.07)
FDA	83.57 (0.40)	94.13 (0.67)	88.85 (0.54)	12.40 (0.25)	7.68 (0.50)	10.04 (0.38)
PixMatch	76.45 (1.60)	91.97 (0.47)	84.21 (1.04)	17.06 (1.13)	10.92 (1.04)	13.99 (1.09)
LTIR	80.82 (1.00)	92.86 (0.73)	86.84 (0.87)	13.29 (0.74)	8.83 (0.94)	11.06 (0.84)
MT	72.82 (1.54)	90.37 (0.99)	81.59 (1.27)	19.43 (0.30)	13.11 (1.73)	16.39 (1.02)
PCS	74.88 (1.19)	88.33 (0.03)	81.21 (0.61)	19.81 (1.45)	18.90 (0.78)	19.56 (1.12)
BEAL	75.91(1.29)	93.44 (0.36)	84.68 (0.83)	17.48 (1.47)	10.42 (0.36)	13.95 (0.92)
DPL	78.60 (0.17)	95.28 (0.82)	86.94 (0.50)	19.99 (0.82)	6.07 (0.16)	13.03 (0.49)
Ours	**83.64(0.20)**	**95.47(0.23)**	**89.56(0.22)**	**11.04(0.51)**	**5.25(0.25)**	**8.14(0.38)**

Searching-based Multi-style Mechanism



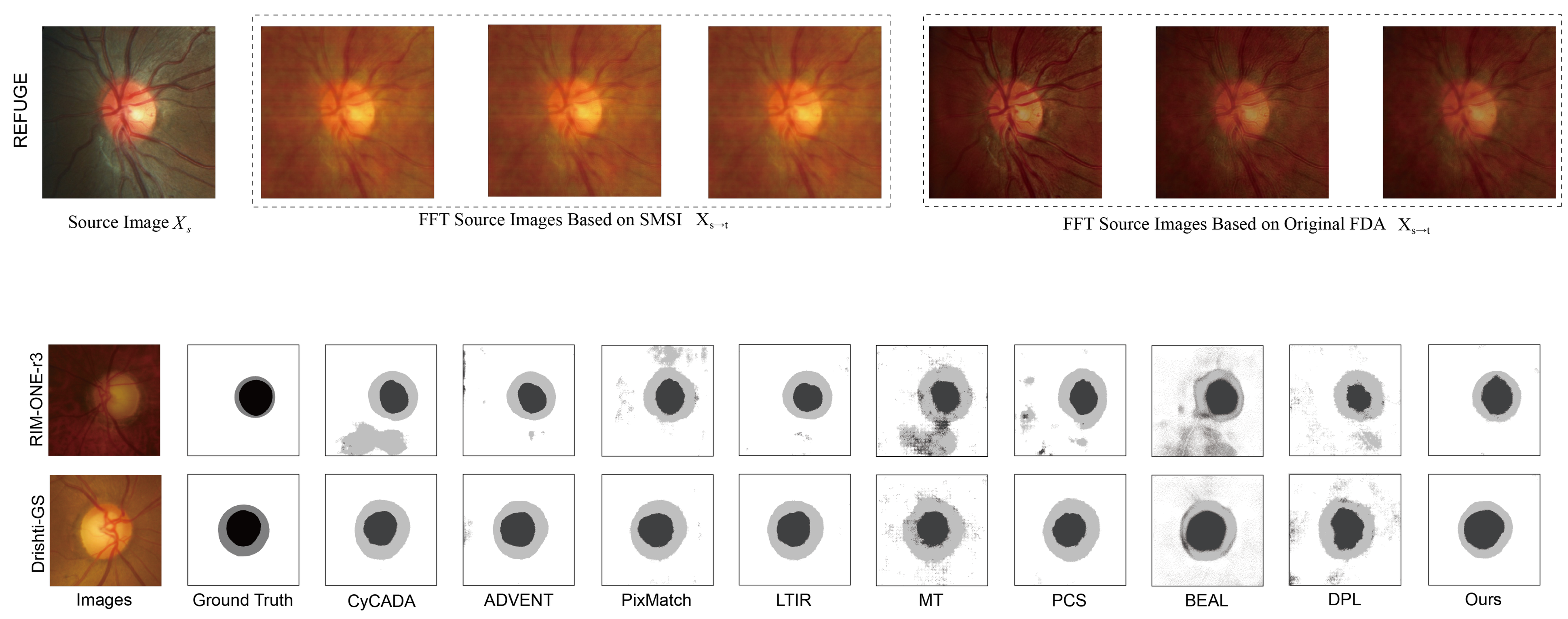
By introducing little extra computations to the framework, the frequency learning-based methods can achieve style transformation in an efficient manner. However, current frequency space methods heavily rely on non-learnable parameter selection, to avoid massive experiments for selecting the appropriate parameters, the SMSI is developed based on AutoML techniques. The mechanism alleviates the domain gap at the appearance level and enlarges the data-scarce source domain.

Cross-style Self-supervised Learning



When dealing with model adaptation towards the target domain, a consummate resource is the target ground truth masks, which are not available in UDA settings. As compensation, highly-confident pseudo labels can be created for unlabeled target images. However, solely training the model with the target pseudo labels brings noise to the optimization process due to the gap between the pseudo and real labels. To stabilize the training process, we propose a cross-style self-supervised learning strategy, to jointly re-train the model using the target images and the Fourier transformed target images with source-like styles and their pseudo labels.

Comparison of Different Experiment Results



Segmentation results from some of the comparison experiments and proposed method

As presented in figure, the segmentation results of some experiments show that focusing on content rather than appearance enables the network to better distinguish target objects from irrelevant backgrounds. The segmentation predictions from several comparison methods are significantly distracted by the background noise. Additionally, regardless of domain differences, the network faces difficulties when attempting to determine the spatial prior knowledge of the optic disc and optic cup. Our predictions alleviate these issues, have a much clear boundary between the cup and disc, and exhibit much fewer background segmentation error.

Related References

[1] Cheng Chen, Quande Liu, Yueming Jin, Qi Dou, and Pheng-Ann Heng. Source-free domain adaptive fundus image segmentation with denoised pseudo-labeling. In International Conference on Medical Image Computing and Computer-Assisted Intervention, 2021.

[2] Tuan-Hung Vu, Himalaya Jain, Maxime Bucher, Matthieu Cord, and Patrick Pérez. Advent: Adversarial entropy minimization for domain adaptation in semantic segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 2517–2526, 2019.

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