Supplementary Material to: Unsupervised Domain Adaptive Fundus Image Segmentation with Few Labeled Source Data

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Fourier Transform	β parameter		
REFUGE to RIM ONE-r3	0.7963	0.8884	0.6185
RIM ONE-r3 to REFUGE	0.1112	0.3517	0.9209
REFUGE to Drishti-GS	0.4235	0.0720	0.2372
Drishti-GS to REFUGE	0.6194	0.5651	0.0056

Table 1: The selection of the optimal β parameters for Fourier transform. Referring to the searching-based multi-style invariant mechanism (SMSI), the transformation of REFUGE to the other two target domains is required in the first stage as $X_{s\to t}$, transformation of two target domains to REFUGE is required in the second stage as $X_{t\to s}$.

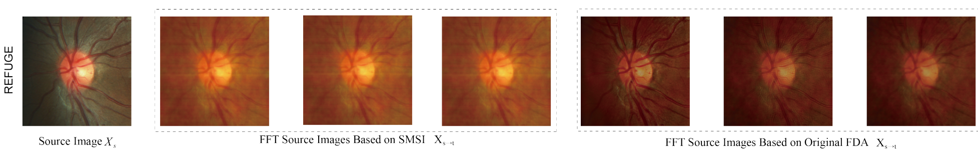

Figure 1: Exhibition of synthesis images based on original FDA and SMSI. For original FDA, $\beta = 0.01/0.05/0.09$ values are selected.

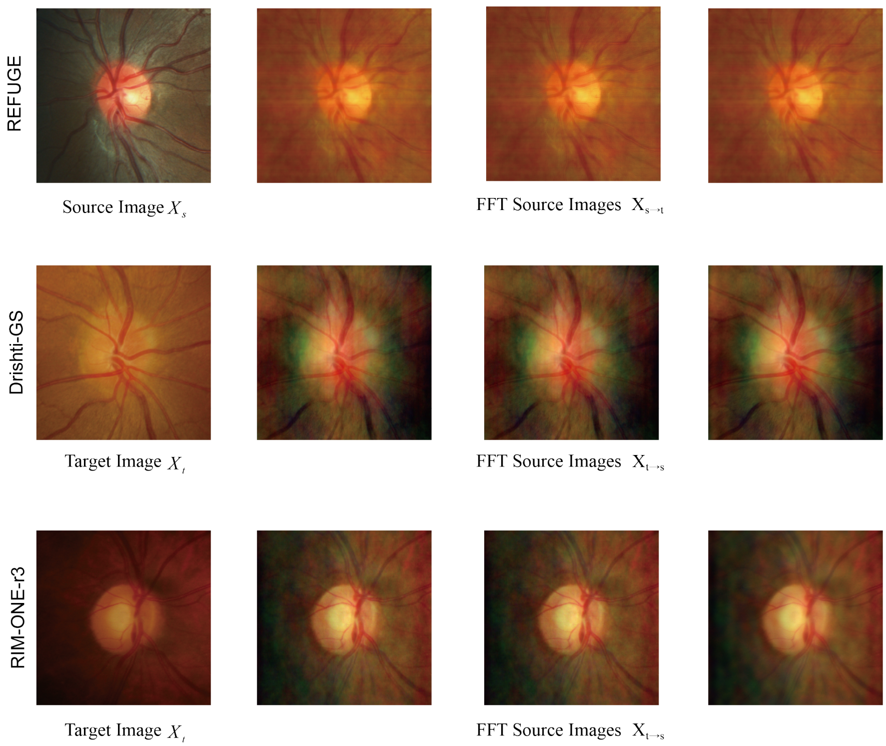

Figure 2: Exhibition of synthesis images based on SMSI. Referring to Table 1 for each dataset, three optimal β values are selected.

Methods	Dice Metric [%]			ASD Metric [pixel]		
	Cup	Disc	Average	Cup	Disc	Average
RIM-ONE-r3						
10 shots	78.16	88.45	83.30	9.82	11.78	10.80
20 shots	79.45	88.41	83.93	9.27	10.97	10.12
30 shots	79.68	88.25	83.97	8.99	10.65	9.82
Drishti-GS						
10 shots	83.64	95.47	89.56	11.04	5.25	8.14
20 shots	82.68	96.49	89.59	11.33	4.02	7.68
30 shots	84.93	96.27	90.60	10.06	4.25	7.15

Table 2: Experimental results of our proposed method in terms of Dice and ASD metrics on RIM-ONE-r3 and Drishti-GS target datasets with randomly selected 10, 20, and 30 shots source data.

Methods	Cup Dice	Disc Dice	Average Dice
RIM-ONE-r3			
CADA [4]	64.04	76.64	70.34
TAU [7]	54.20	78.60	66.40
ECSD-Net [3]	80.20	86.50	83.35
BEAL [5]	81.00	89.80	85.40
DPL [1]	79.78	90.13	84.96
pOSAL [6]	78.70	86.50	82.60
Feng et al. [2]	84.10	90.50	87.30
Ours*	83.47	87.85	85.66
Drishti-GS			
CADA [4]	84.00	89.00	86.50
TAU [7]	61.00	88.50	74.75
ECSD-Net [3]	87.60	96.50	92.05
BEAL [5]	86.20	96.10	91.15
DPL [1]	83.53	96.39	89.96
pOSAL [6]	85.80	96.50	91.15
Feng et al. [2]	89.20	96.60	92.90
Ours*	86.68	96.17	91.43

Table 3: Comparing our method to other fundus segmentation methods. the results of other methods are obtained by using 400 fully labeled source domain images, whereas our method only uses 40 source images. The training and testing images in the target domain used by all comparison methods are the same. The results for other methods are directly referenced from the articles. *Our method can achieve comparable and even better UDA segmentation performance only using 10% labeled source data, which indicates the effectiveness of our method, as well as maintaining the data efficiency.

Methods	Dice Metric [%]			ASD Metric [pixel]			Training Time [s/iter]	Model Size [M]
	Cup	Disc	Average	Cup	Disc	Average		
RIM-ONE-r3								
CyCADA	66.61	76.99	71.80	47.35	41.62	44.48	12.14	31.04
ADVENT	67.99	80.67	74.33	42.04	33.43	37.74	12.19	42.61
PixMatch	70.50	75.20	72.85	16.33	35.90	26.12	13.26	42.61
LTIR	69.28	79.82	74.55	15.52	27.10	21.31	11.04	28.91
MT	70.04	82.66	76.35	13.23	20.54	16.88	8.23	31.04
PCS	65.71	78.00	71.86	18.04	26.09	22.06	14.13	59.34
Ours	**83.47**	**87.85**	**85.66**	**7.33**	**11.33**	**8.64**	79.91	7.62
Drishti-GS								
CyCADA	81.83	91.54	86.68	12.55	12.32	12.43	7.71	31.04
ADVENT	81.82	92.32	87.07	12.43	10.59	15.25	7.33	42.61
PixMatch	75.31	93.13	84.22	16.91	8.34	12.63	8.71	42.61
LTIR	76.72	94.17	85.44	15.82	7.20	11.51	5.94	42.61
MT	75.33	91.62	83.48	16.53	9.79	13.16	8.29	31.04
PCS	78.67	89.63	84.15	17.09	13.64	15.36	8.26	59.34
Ours	**86.68**	**96.17**	**91.43**	**8.85**	**4.35**	**6.60**	86.43	7.62

Table 4: Experimental results of different domain adaptation approaches in terms of Dice and ASD metrics on RIM-ONE-r3 and Drishti-GS target datasets with 40 (10%) labeled source data. Models' training time and models' sizes are also shown.

References

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