



MCF: Mutual Correction Framework for Semi-Supervised Medical Image Segmentation

Yongchao Wang, Bin Xiao, Xiuli Bi, Weisheng Li, Xinbo Gao

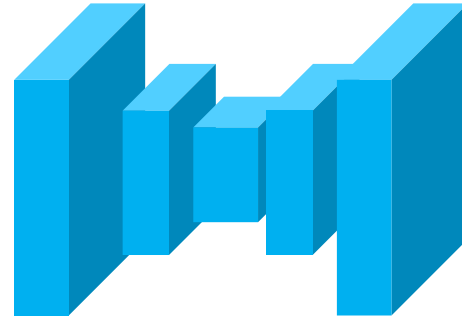
Chongqing University of Posts and Telecommunications
Chongqing, China

Poster : WED-PM-314



strong

learning ability



Convolutional Neural Network

corrective ability

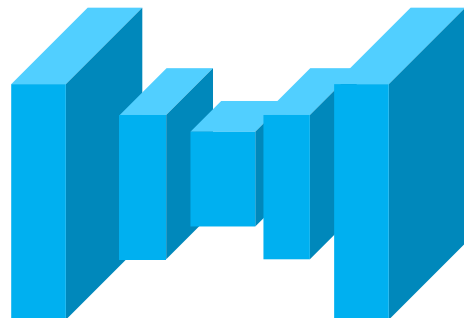
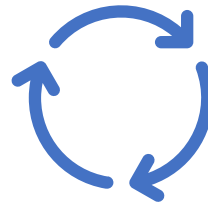


cognitive biases

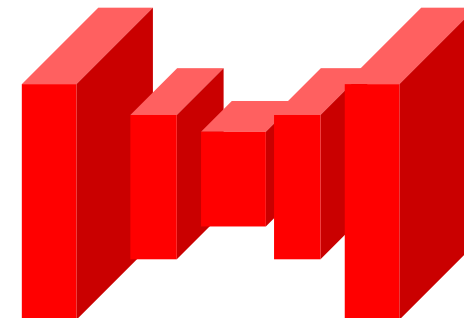


weak

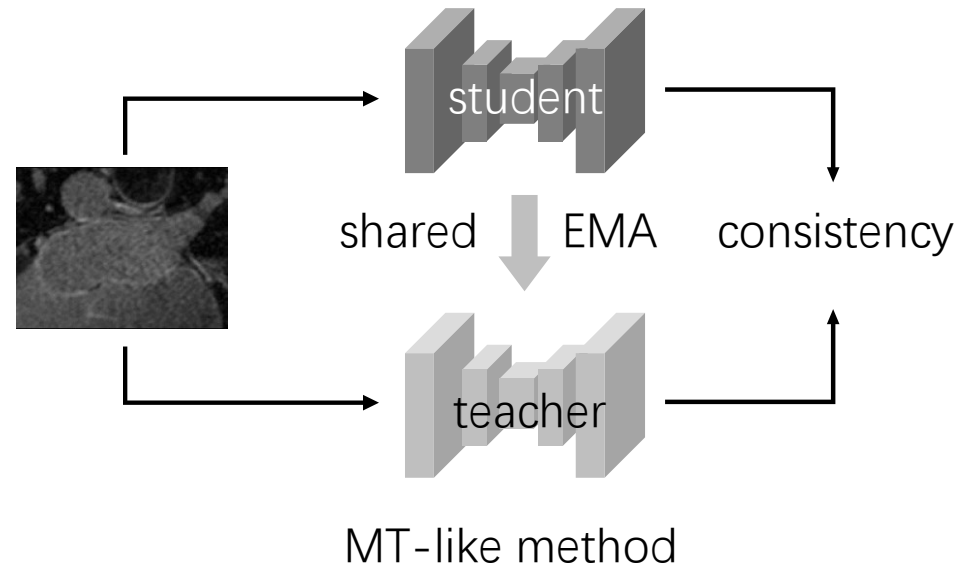
mutual correction



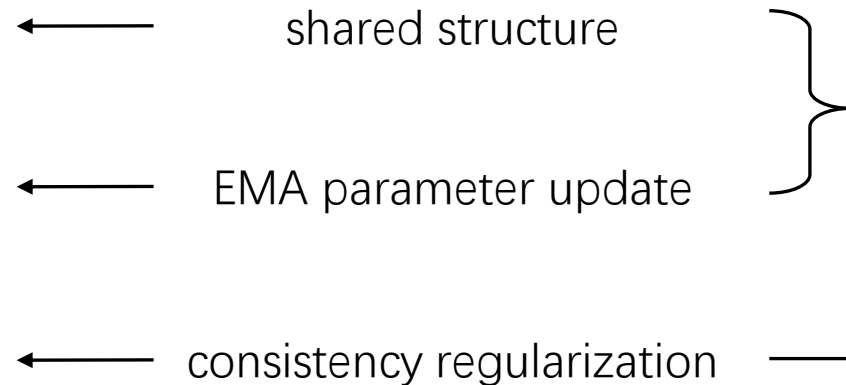
interaction



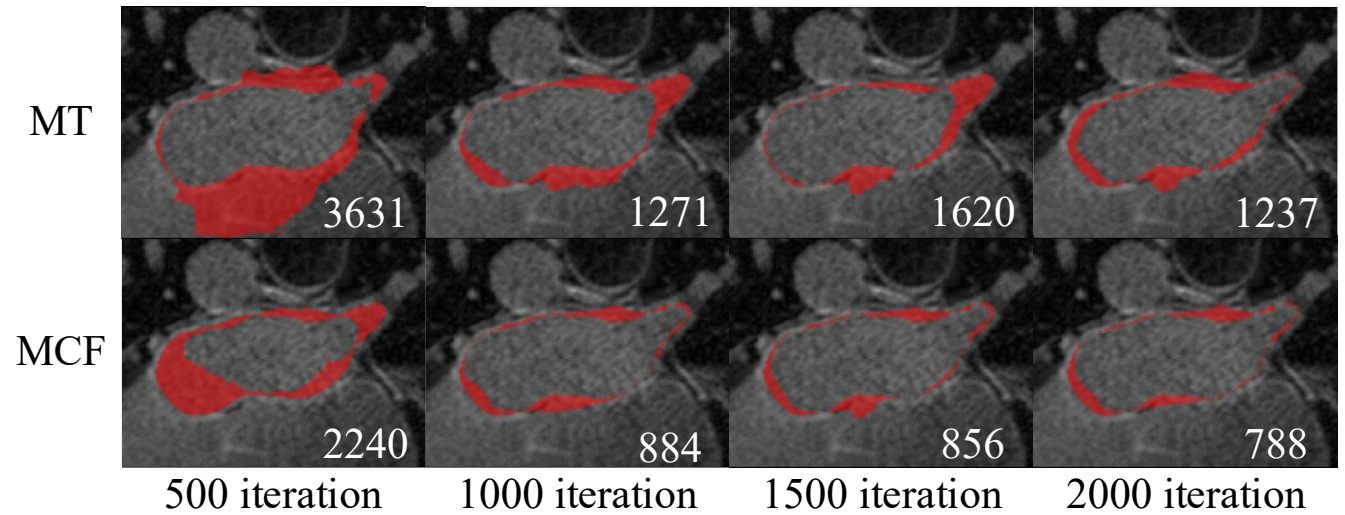
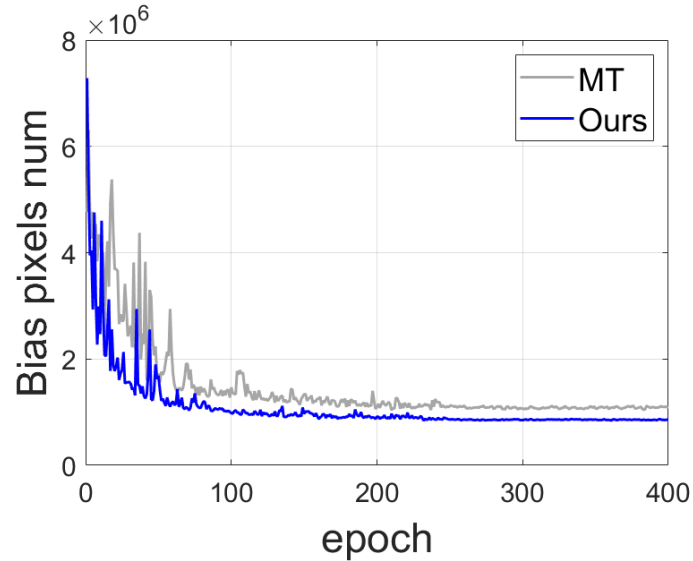
Cognitive biases in MT based methods



shortcoming
reduces model diversity
performance limitations
biased Pseudo-Labeling

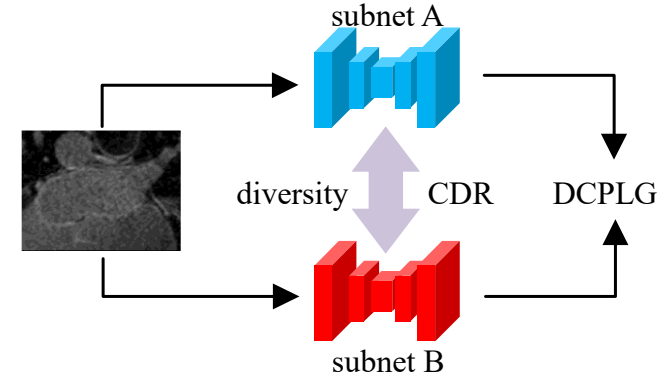
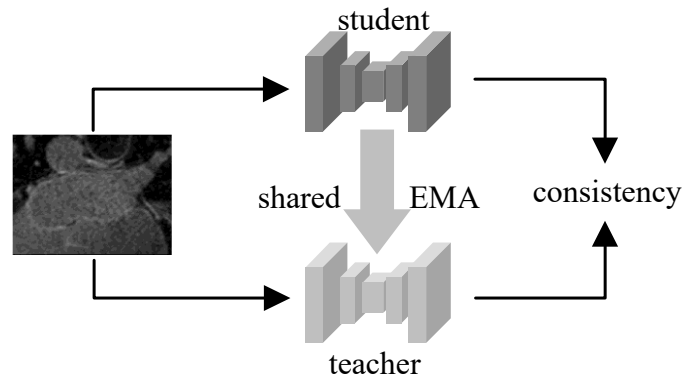


benefit
consistent predictions
supervised on unlabeled data



Cognitive bias is the phenomenon in which the model persists in mispredictions, caused by overfitting to wrong supervision signals [1].

Mutual Correction Framework



shared structure



different structure

EMA parameter update



independent parameter update

consistency regularization



dynamic pseudo-label generation

Mutual Correction Framework

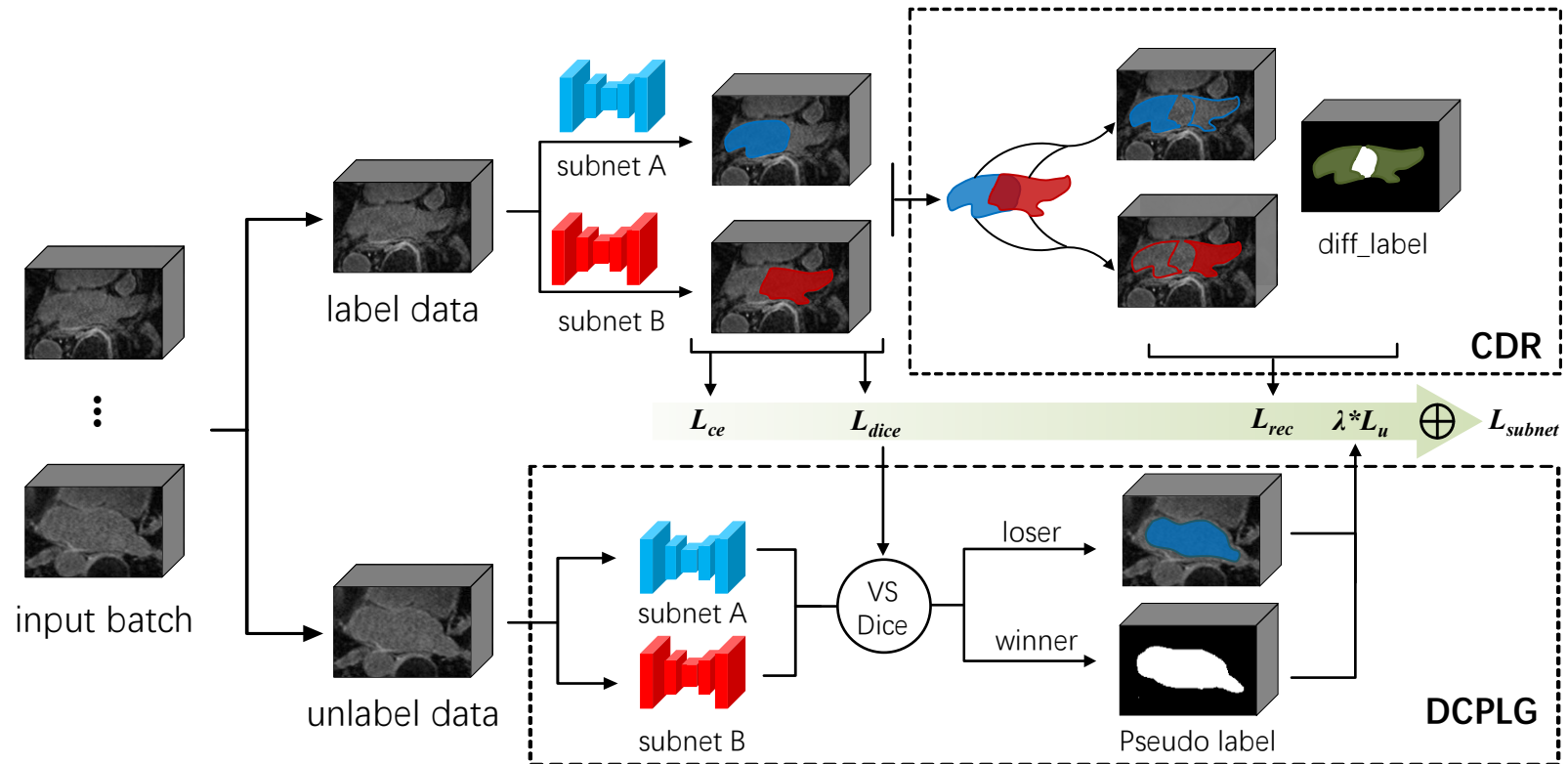


Table 1. 5-fold cross-validation comparison results on the LA MRI dataset (average \pm standard deviation)

Method	Volumes used		Metrics			
	Labeled	Unlabeled	Dice(%) \uparrow	Jaccard(%) \uparrow	95HD(voxel) \downarrow	ASD(voxel) \downarrow
VNet	80(100%)	0	91.28 \pm 0.008	84.07 \pm 0.012	5.00 \pm 0.757	1.61 \pm 0.291
3D-ResVNet	80(100%)	0	91.09 \pm 0.013	83.90 \pm 0.017	4.77 \pm 1.641	1.75 \pm 0.195
VNet	16(20%)	0	83.34 \pm 0.023	72.49 \pm 0.029	14.77 \pm 1.169	3.87 \pm 0.337
3D-ResVNet	16(20%)	0	84.09 \pm 0.022	73.56 \pm 0.025	17.36 \pm 2.748	4.96 \pm 1.008
MT	16(20%)	64	85.89 \pm 0.024	76.58 \pm 0.027	12.63 \pm 5.741	3.44 \pm 1.382
UA-MT	16(20%)	64	85.98 \pm 0.014	76.65 \pm 0.017	9.86 \pm 2.707	2.68 \pm 0.776
SASSNet	16(20%)	64	86.21 \pm 0.023	77.15 \pm 0.024	9.80 \pm 1.842	2.68 \pm 0.416
DTC	16(20%)	64	86.36 \pm 0.023	77.25 \pm 0.020	9.02 \pm 1.015	2.40 \pm 0.223
*MC-Net	16(20%)	64	87.65 \pm 0.011	78.63 \pm 0.013	9.70 \pm 2.361	3.01 \pm 0.700
MCF(Ours)	16(20%)	64	88.71\pm0.018	80.41\pm0.022	6.32\pm0.800	1.90\pm0.187

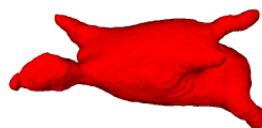
* means we report our reproduced results here because MC-Net does not release source code.



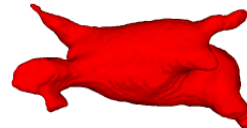
(a) MT



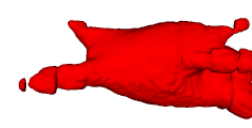
(b) UA-MT



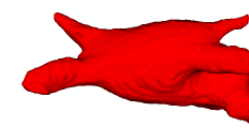
(c) SASSNet



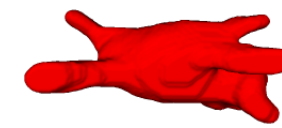
(d) DTC



(e) MCNet



(f) Ours

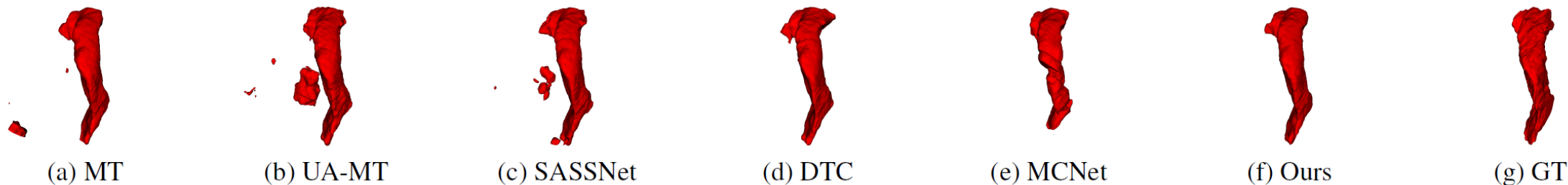


(g) GT

Table 2. 4-fold cross-validation comparison results on the Pancreas CT dataset (average \pm standard deviation)

Method	Volumes used		Metrics			
	Labeled	Unlabeled	Dice(%) \uparrow	Jaccard(%) \uparrow	95HD(voxel) \downarrow	ASD(voxel) \downarrow
VNet	62(100%)	0	80.75 \pm 0.010	68.49 \pm 0.014	7.23 \pm 0.564	1.69 \pm 0.363
3D-ResVNet	62(100%)	0	79.78 \pm 0.021	67.29 \pm 0.025	7.30 \pm 1.632	1.60 \pm 0.074
VNet	12(20%)	0	64.18 \pm 0.073	49.26 \pm 0.077	17.74 \pm 3.572	4.69 \pm 0.935
3D-ResVNet	12(20%)	0	66.53 \pm 0.043	51.25 \pm 0.047	19.01 \pm 4.129	5.64 \pm 1.467
MT	12(20%)	50	74.43 \pm 0.024	60.53 \pm 0.030	14.93 \pm 2.000	4.61 \pm 0.929
UA-MT	12(20%)	50	74.01 \pm 0.029	60.00 \pm 3.031	17.00 \pm 3.031	5.19 \pm 1.267
SASSNet	12(20%)	50	73.57 \pm 0.017	59.71 \pm 0.020	13.87 \pm 1.079	3.53 \pm 1.416
DTC	12(20%)	50	73.23 \pm 0.024	59.18 \pm 0.027	13.20 \pm 2.241	3.81 \pm 0.953
*MC-Net	12(20%)	50	73.73 \pm 0.019	59.19 \pm 0.021	13.65 \pm 3.902	3.92 \pm 1.055
MCF(Ours)	12(20%)	50	75.00\pm0.026	61.27\pm0.030	11.59\pm1.611	3.27\pm0.919

* means we report our reproduced results here because MC-Net does not release source code.



Effects of different components.

Method	Metrics			
	Dice(%) \uparrow	Jaccard(%) \uparrow	95HD(voxel) \downarrow	ASD(voxel) \downarrow
V	85.63	75.67	14.40	3.69
V+CDR	87.69	78.34	8.57	2.31
V+DCPLG	89.81	81.62	7.32	2.36
R	85.67	75.49	13.16	3.25
R+CDR	87.57	78.14	9.03	2.34
R+DCPLG	89.27	80.69	6.86	2.10
V-m-R	86.53	76.89	11.30	2.70
V+R+CDR	88.21	79.16	7.89	1.98
V+R+DCPLG	90.13	81.92	6.73	1.86
MCF	90.49	82.70	5.62	1.61

“V” refers to VNet

“R” refers to 3D-ResVNet

V-m-R refers integrating VNet and 3D-ResNet with the averaging operation

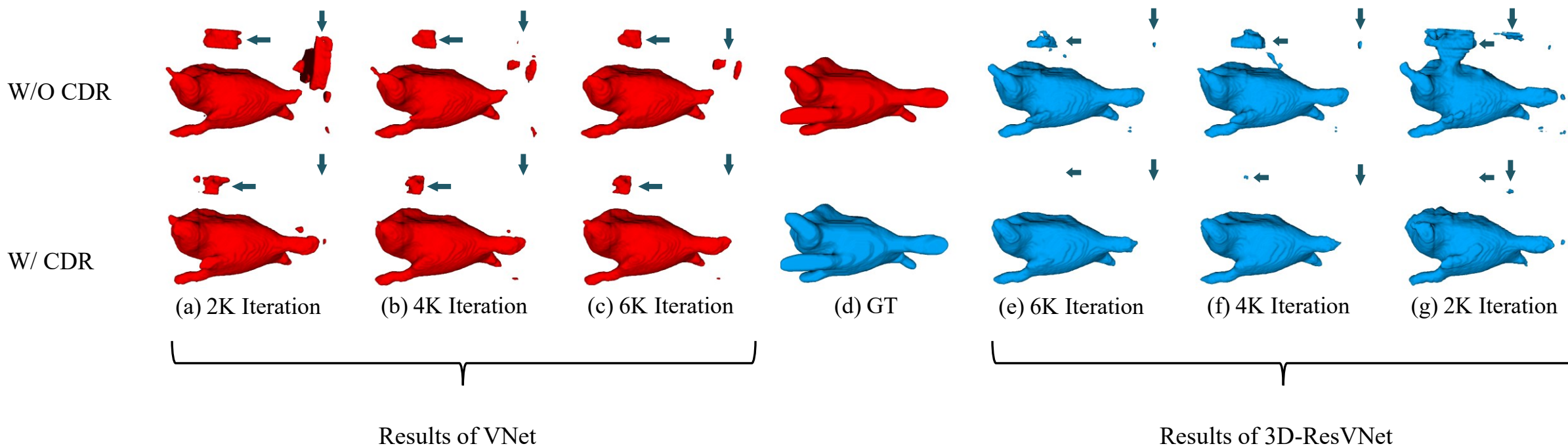
Ablation for rectification loss

Loss function	Metrics			
	Dice(%) \uparrow	Jaccard(%) \uparrow	95HD(voxel) \downarrow	ASD(voxel) \downarrow
CE loss	90.28	82.34	5.60	1.68
MSE loss	90.49	82.70	5.62	1.61

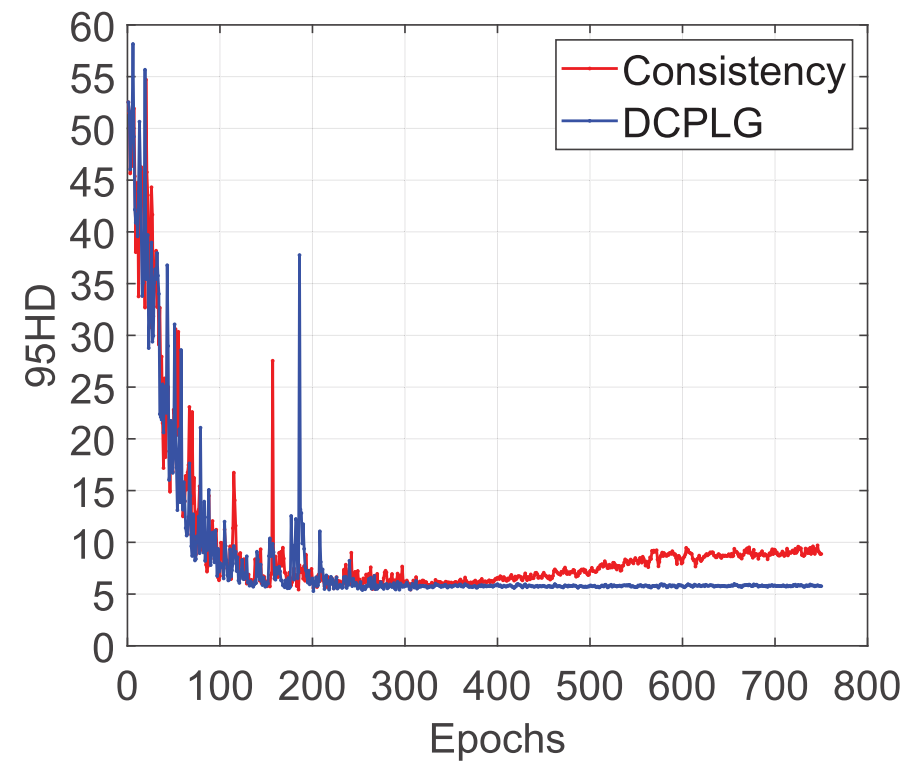
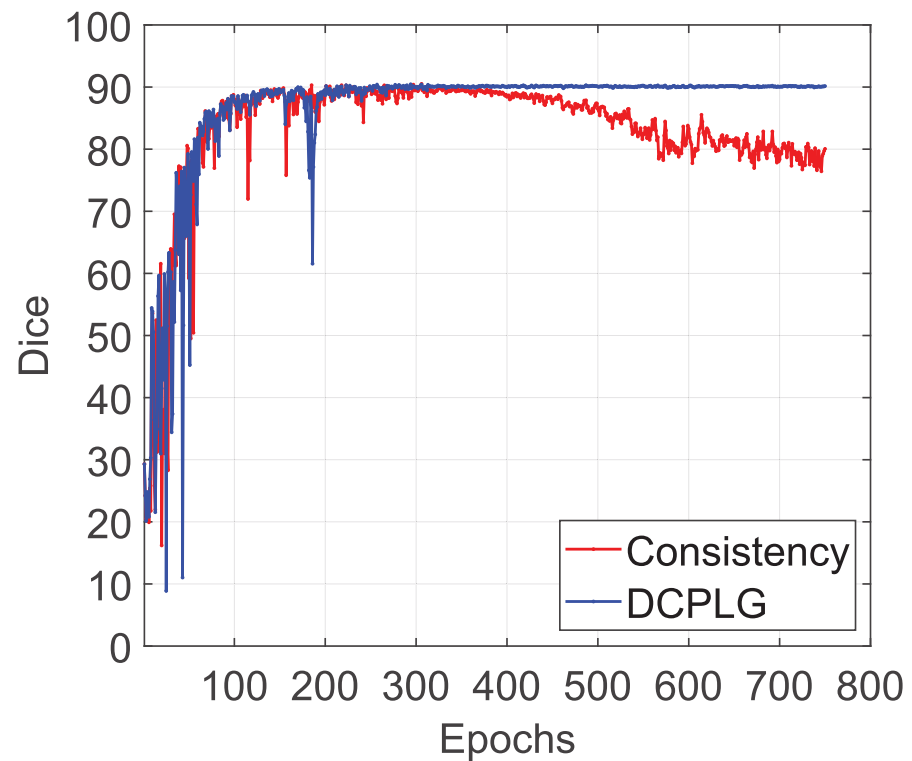
Ablation for different values of β

β	Metrics			
	Dice(%) \uparrow	Jaccard(%) \uparrow	95HD(voxel) \downarrow	ASD(voxel) \downarrow
0.3	90.23	82.32	5.89	1.69
0.4	90.27	82.41	5.85	1.64
0.5	90.49	82.70	5.62	1.61
0.6	90.26	82.43	5.86	1.65
0.7	90.24	82.38	5.88	1.67

Effects of CDR



consistency regularization VS training and DCPLG pseudo label training



- We propose a new framework called MCF for semi-supervised medical image segmentation, which enables the network to be aware of its own mistakes and perform bias correction through inter-subnet interactions.
- The CDR takes the difference predictions of the subnets as potential bias areas and guides the network to review and correct them.
- The DCPLG is used to dynamically select pseudo-label generators to improve the quality of pseudo-labels.