Supplementary Material: Collaborative and Adversarial Learning of Focused and Dispersive Representations for Semi-supervised Polyp Segmentation

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1. The Setting of Hyper Parameters

In this work, we introduce four kinds of loss functions to compute the losses when our proposed method is trained under the supervised stage and semi-supervised stage, including $\mathcal{L}_{dice}$ for calculating the segmentation loss, $\mathcal{L}_{semi}$ for calculating the divergence between the confidence maps from two kinds of segmentation networks, $\mathcal{L}_{adv}$ for training the first discriminator to produce confidence maps with high quality and $\mathcal{L}'_{adv}$ for training the second discriminator to distinguish the segmentation results. Among these loss functions, T_{semi} is a hyper parameter set as the threshold to control the sensitivity of the self-taught process (signal maps). In the training process of our proposed method, we found that the adjustment results of T_{semi} was similar to the analysis of Hung's. Besides, λ_{adv}, λ'_{adv} and λ_{semi} are set to balance the primary adversarial training with labeled and unlabeled data. Furthermore, λ_{D_2} and λ'_{D_2} are two hyper parameters set to balance the auxiliary discriminator training according to the amount of labeled and unlabeled data. The complete hyper parameters analysis can be seen in Table 1 and Table 2.

As shown in Table 3, our proposed method trained with fully labeled polyp images can achieve comparable segmentation results to PraNet [2] and HarDNet-MSEG [3].

2. More Experiments Results of Different Labeled Amount

To further explore the effectiveness of our proposed semi-supervised method for polyp segmentation, we evaluate the proposed method on the Kvasir-SEG [4] dataset and CVC-Clinic DB [1] with more different labeled amount settings. Statistical comparisons are as shown in Table 3.

3. More Comparison with Other Semi-supervised Methods

We also compare our proposed method with other semi-supervised methods, including TCSM_v1 [5], TCSM_v2 [6] and UA-MT [7]. Specially, the latter two semi-supervised methods apply the method of mean teacher, which has brought improvement to TCSM_v1. For UA-MT, the proposed mechanism of uncertainty estimation can improve the credibility of predicted target generated by the teacher model to a certain extent. However, these methods are devoted to improve the reliability of teacher model, ignoring the effective extraction of edge information. The relative experimental results are shown in Table 4.

Labeled Amount	λ_{adv}	λ'_{adv}	λ_{semi}	Dice	IoU	MAE
100%	0.005	\	\	0.8610	0.7826	0.0593
100%	**0.01**	\	\	**0.8682**	**0.7882**	**0.0540**
100%	0.02	\	\	0.8669	0.7846	0.0568
100%	0.05	\	\	0.8601	0.7819	0.0574
30%	**0.01**	**0.001**	**0.1**	**0.8095**	**0.7163**	**0.0658**
30%	0.01	0.001	0.2	0.8003	0.6800	0.0690
30%	0.01	0.001	0.5	0.7991	0.6987	0.0723
30%	0.01	0.002	0.1	0.8041	0.7128	0.0678
30%	0.01	0.002	0.2	0.7913	0.6956	0.0790
30%	0.01	0.002	0.5	0.7993	0.6999	0.0761
30%	0.01	0.005	0.1	0.8056	0.7172	0.0677
30%	0.01	0.005	0.2	0.8042	0.7058	0.0681
30%	0.01	0.005	0.5	0.7966	0.7111	0.0752

Table 1. Hyper parameter analysis for the primary adversarial learning on Kvasir-SEG dataset. Note that λ_{D_2} and λ'_{D_2}, which are the hyper parameters in auxiliary adversarial training, are set to the same as 0.01 and 0.05 respectively.

Labeled Amount	λ_{D_2}	λ'_{D_2}	Dice	IoU	MAE
30%	0.01	0.01	0.7945	0.6968	0.0865
30%	0.01	0.02	0.7975	0.7081	0.0741
30%	0.01	0.03	0.7982	0.7092	0.0716
30%	0.01	0.04	0.8030	0.7137	0.0698
30%	**0.01**	**0.05**	**0.8095**	**0.7163**	**0.0658**
30%	0.01	0.06	0.7938	0.7082	0.0751

Table 2. Hyper parameter analysis for the auxiliary adversarial learning on Kvasir-SEG dataset. The setting of hyper parameters for primary adversarial training are the same.

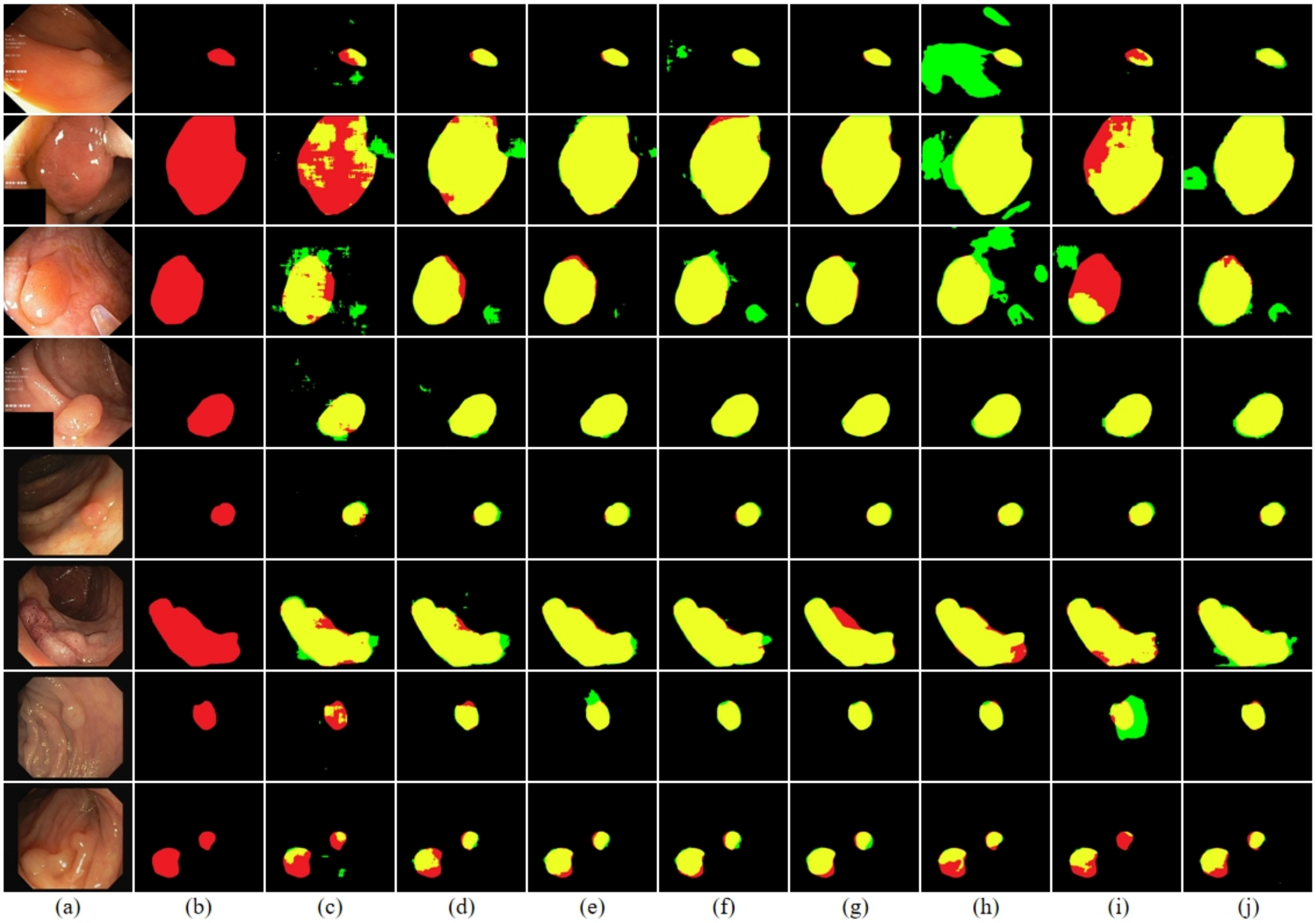

Figure 1. More comparisons with different State-of-the-art methods on the Kvasir-SEG dataset and CVC-Clinic DB. (a) Input image. (b) Ground Truth. (c) ResU-Net. (d) U-Net++. (e) CE-Net. (f) CPF-Net. (g) PraNet. (h) HarDNet-MSEG. (i) Hung's. (j)Ours. Note that, Hung's method and our semi-supervised polyp segmentation method are trained with only 30% of labeled data. Red, green and yellow regions represent the ground truth, prediction and their overlapping regions respectively.

Dataset	Labeled Amount	Dice	IoU	MAE
Kvasir-SEG	10%	0.7112	0.6066	0.1043
	50%	0.8324	0.7303	0.0603
	100%	0.8682	0.7882	0.0540
CVC-Clinic DB	10%	0.7506	0.6546	0.0478
	50%	0.9218	0.8595	0.0153
	100%	0.9472	0.8914	0.0094

Table 3. Statistical comparison of different labeled amount on the Kvasir-SEG dataset and the CVC-Clinic DB.

4. More Visual Comparison Results

More visual polyp segmentation results on the Kvasir-SEG [4] dataset and CVC-Clinic DB [1] are presented in Figure 1.

Model	Labeled Amount	Dice	IoU	MAE
TCSM_v1	15%	0.6919	0.5826	0.1063
TCSM_v1	30%	0.7591	0.6783	0.0844
TCSM_v2	15%	0.7173	0.6137	0.1002
TCSM_v2	30%	0.7731	0.6866	0.0808
UA-MT	15%	0.7409	0.6437	0.0875
UA-MT	30%	0.7893	0.6995	0.0751
Ours	**15%**	**0.7676**	**0.6723**	**0.0816**
Ours	**30%**	**0.8095**	**0.7163**	**0.0658**

Table 4. Statistical comparison with TCSM_v1 [5], TCSM_v2 [6] and UA-MT [7] on the Kvasir-SEG dataset

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