Learning to Promote Saliency Detectors
Supplementary Material

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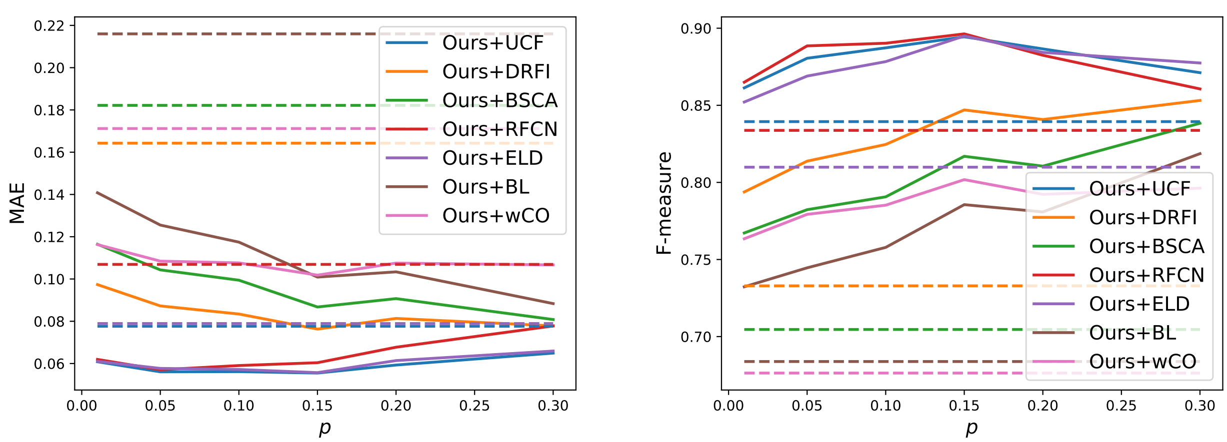
1. Sensitivity Analysis

During training, the anchors are produced according to the ground truth maps with noise, which is obtained by randomly flipping the elements of each ground truth map with probability p. We train our model using $p = 0.01, 0.05, 0.1, 0.15, 0.2, 0.3$ to analyze sensitivity of the proposed method to p. We find that our method is robust to variations in p. As shown in Figure 1, although the degree of the improvement depends on p, our proposed method greatly elevates the performance of the baseline methods over a wide range of p.

2. Visual effect

We show saliency maps produced by applying the proposed method to 6 state-of-the-art methods (SRM [4], Amulet [5], NLDF [3], MCDL [2], DRFI [1], wCO [6]) in Figures 2, 3, 4, 5, 6, 7, respectively. The areas mislabeled by the baseline methods are corrected as the iterations progress. In addition, it can be seen from these figures that the proposed method can better keep detailed information and produces sharper saliency maps.



(a) (b)

Figure 1. Sensitivity analysis of our method with respect to p, measured in terms of MAE (a) and F-measure (b). Our method is applied to the state-of-the-art methods in order to promote them. The solid lines in different colors show the effect of applying our method to different baseline methods (i.e., promoted ones), and the dashed lines indicate the performance of the corresponding baseline methods (i.e., original models).

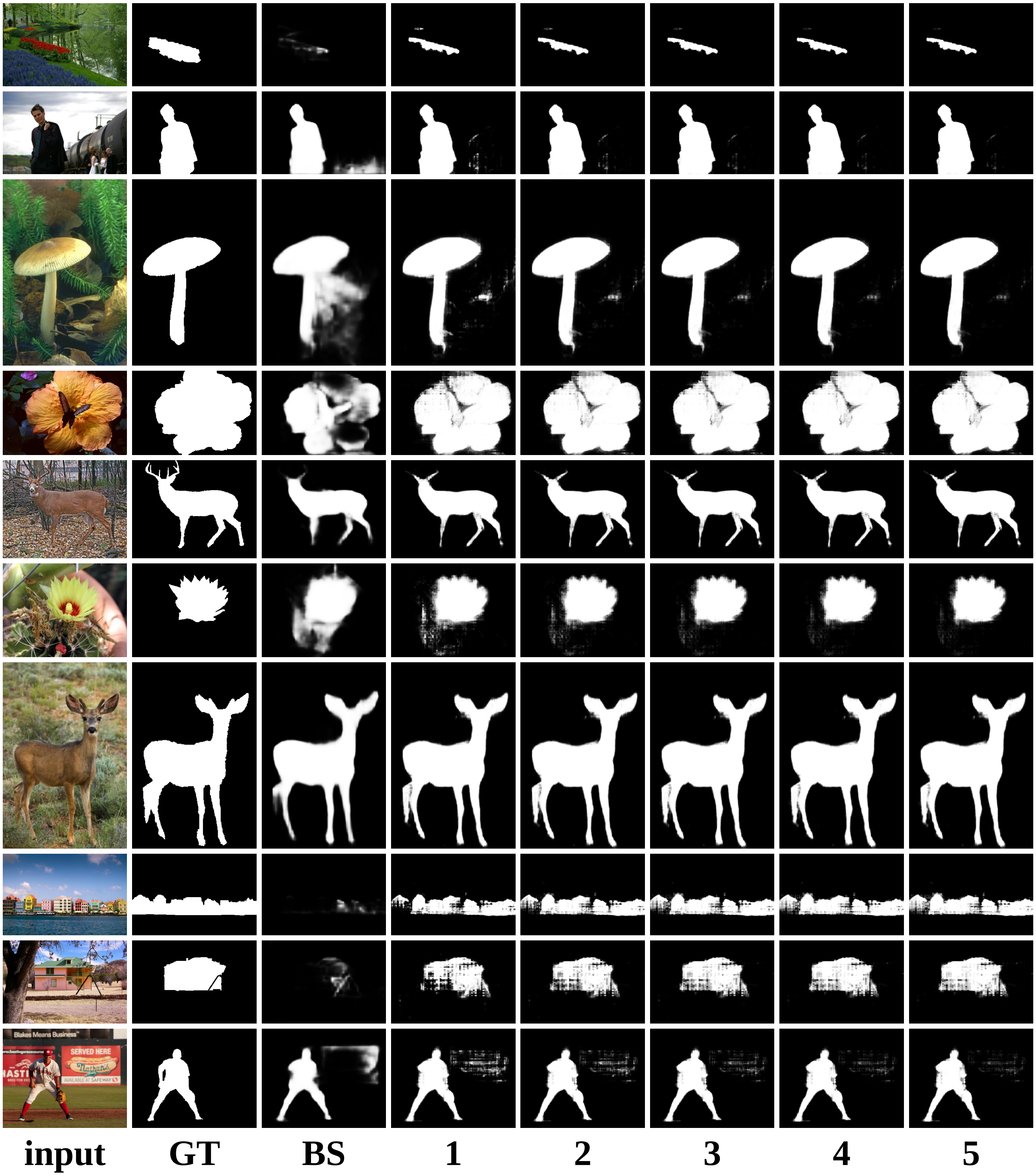


Figure 2. Visual effect of applying the proposed method to SRM [4]. GT: ground truth maps, BS: the baseline method, 1-5: effect of iterating Alg. 2 for 1-5 times.

References

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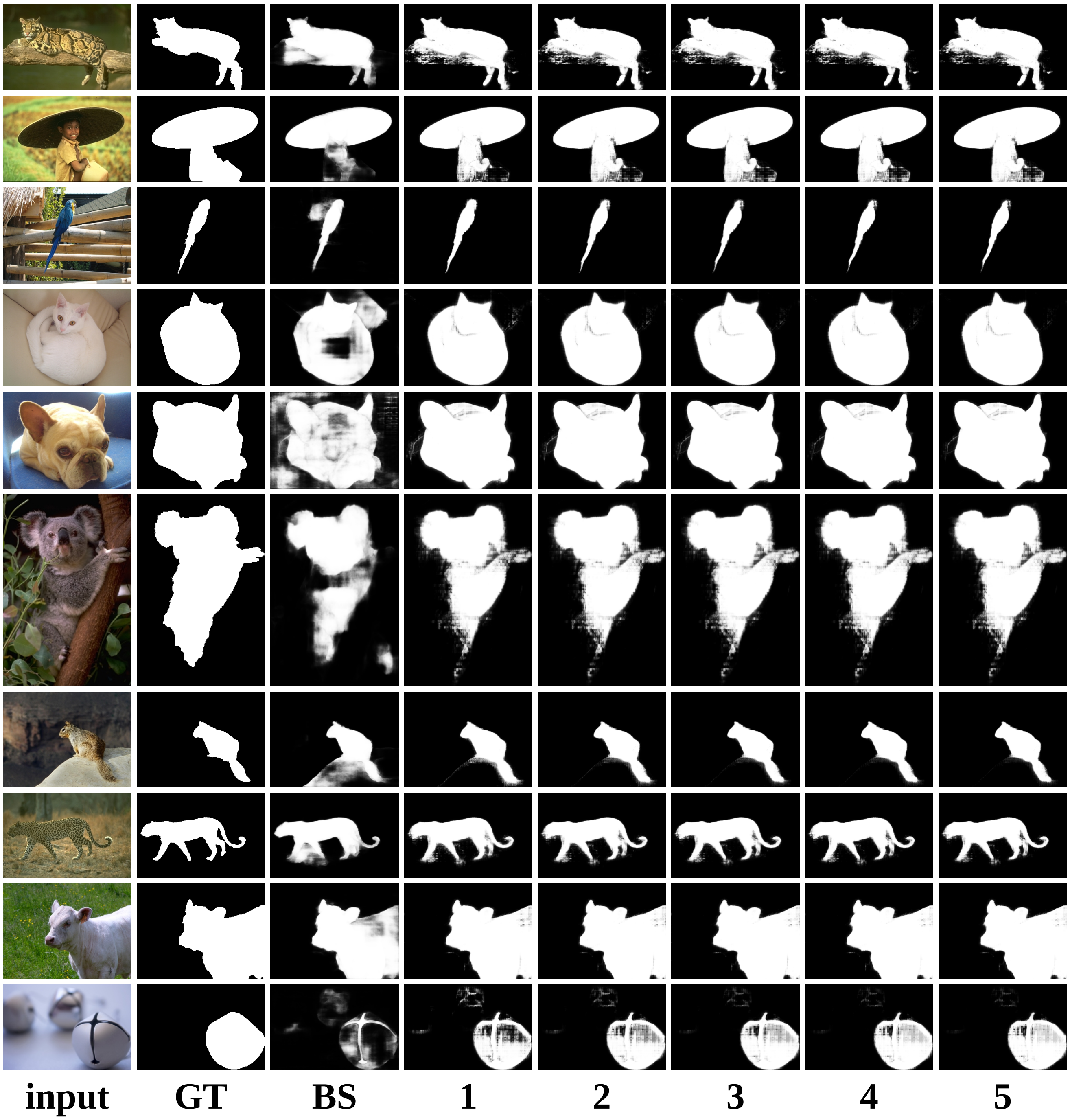

Figure 3. Visual effect of applying the proposed method to Amulet [5]. GT: ground truth maps, BS: the baseline method, 1-5: effect of iterating Alg. 2 for 1-5 times.

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Figure 4. Visual effect of applying the proposed method to NLDF [3]. GT: ground truth maps, BS: the baseline method, 1-5: effect of iterating Alg. 2 for 1-5 times.

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Figure 5. Visual effect of applying the proposed method to MCDL [2]. GT: ground truth maps, BS: the baseline method, 1-5: effect of iterating Alg. 2 for 1-5 times.

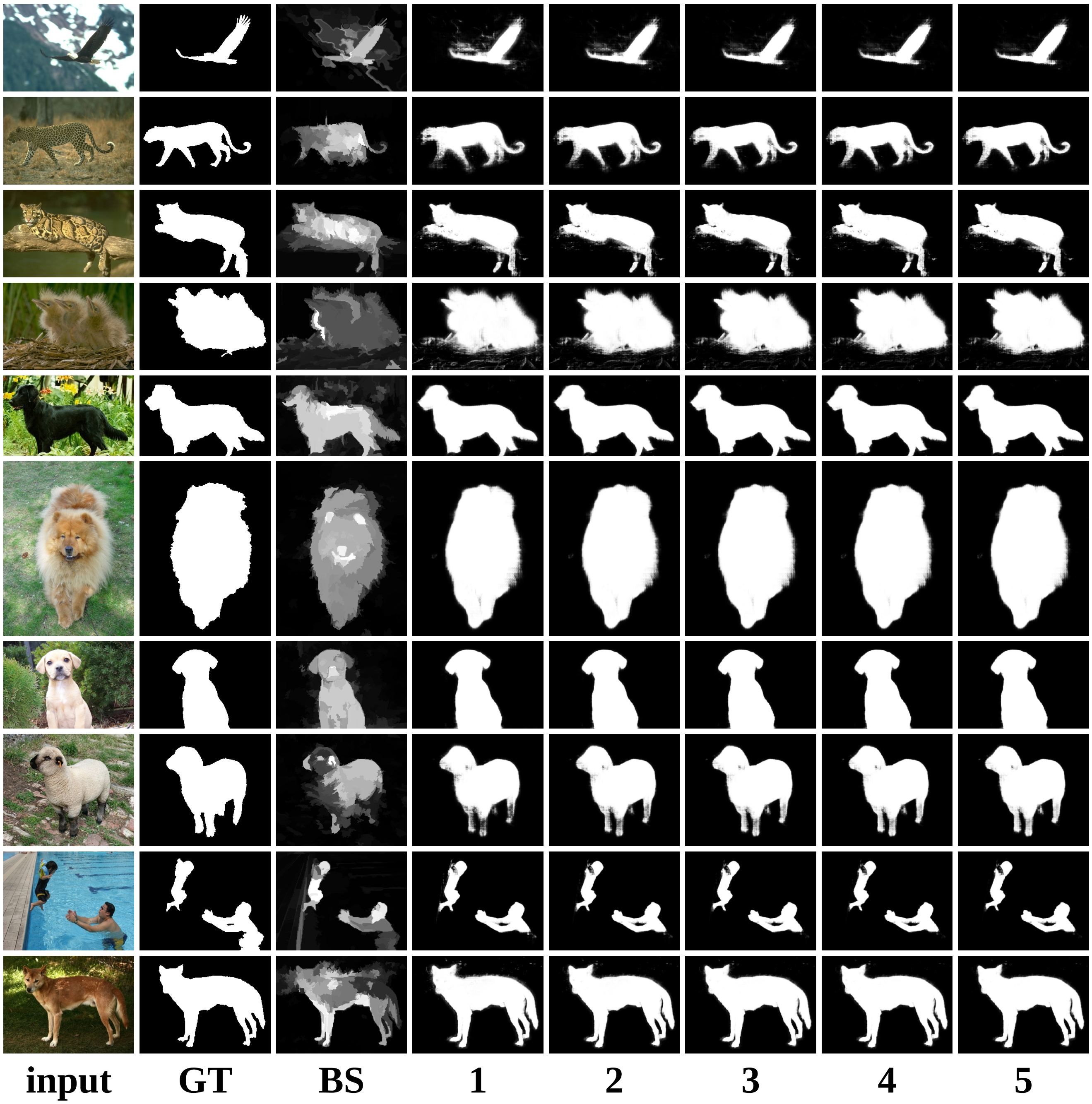

Figure 6. Visual effect of applying the proposed method to DRFI [1]. GT: ground truth maps, BS: the baseline method, 1-5: effect of iterating Alg. 2 for 1-5 times.

Figure 7. Visual effect of applying the proposed method to DRFI [6]. GT: ground truth maps, BS: the baseline method, 1-5: effect of iterating Alg. 2 for 1-5 times.