# Supplementary Material

In the supplementary material, we show more quantitative and qualitative results in the following aspects:

- In the paper, we train the proposed work on the DUTS training set [8]. However, some works (DSS [5], Amulet [9], $\mathrm{R}^3$Net [3], RANet [1]) train their model on MSRA-B [7] or MSRA10K [2] dataset (there is a large overlap between these two datasets [5]). Therefore, we re-train the proposed model on MSRA-B dataset and compare it with these four methods on six metrics. And the results are shown in Section 1.
- In the paper, we show weighted F-measure and structure similarity scores, PR and F-measure curves on five traditional benchmark datasets. In section 2, we exhibit the quantitative comparison on the last dataste (HKU-IS [6]). Meanwhile, we present more visual comparisons in the supplementary material.
- In the paper, we compare the proposed model and existing algorithms on the SOC dataset using structure similarity. Furthermore, the comparisons in other three scores are added in Section 3.

## 1. Compared to existing models trained on MSRA-B or MSRA10K

In this section, we re-train the proposed model on MSRA-B dataset, and compare it with four existing models which are also trained on MSRA-B or MSRA10K dataset.

| Method | Dataset | ECSSD | | HKU-IS | | PASCAL-S | | DUT-OMRON | | DUTS-TEST | | THUR15K | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | maxF↑ | MAE↓ | maxF↑ | MAE↓ | maxF↑ | MAE↓ | maxF↑ | MAE↓ | maxF↑ | MAE↓ | maxF↑ | MAE↓ |
| DSS [5] | MB | 0.908 | 0.063 | 0.898 | 0.051 | 0.826 | 0.102 | 0.764 | 0.072 | 0.813 | 0.065 | 0.761 | 0.083 |
| Amulet [9] | MK | 0.913 | 0.059 | 0.887 | 0.053 | 0.828 | 0.095 | 0.737 | 0.083 | 0.779 | 0.085 | 0.756 | 0.093 |
| RANet [1] | MB | 0.918 | 0.059 | 0.913 | 0.045 | 0.834 | 0.104 | 0.786 | 0.062 | 0.831 | 0.060 | 0.772 | 0.075 |
| $\mathrm{R}^3$Net [3] | MK | 0.929 | 0.051 | 0.910 | 0.047 | 0.837 | 0.101 | 0.793 | 0.073 | 0.828 | 0.067 | 0.781 | 0.078 |
| Ours | MB | 0.937 | 0.046 | 0.921 | 0.041 | 0.856 | 0.082 | 0.801 | 0.061 | 0.846 | 0.055 | 0.793 | 0.069 |

Table 1: *Comparisons of scores of maximum F-measure (maxF) and mean absolute error (MAE). MB: MSRA-B dataset. MK: MSRA10K datset*

| Method | Dataset | ECSSD | | HKU-IS | | PASCAL-S | | DUT-OMRON | | DUTS-TEST | | THUR15K | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $F_\beta^\omega$↑ | $S_\alpha$↑ | $F_\beta^\omega$↑ | $S_\alpha$↑ | $F_\beta^\omega$↑ | $S_\alpha$↑ | $F_\beta^\omega$↑ | $S_\alpha$↑ | $F_\beta^\omega$↑ | $S_\alpha$↑ | $F_\beta^\omega$↑ | $S_\alpha$↑ |
| DSS [5] | MB | 0.842 | 0.883 | 0.826 | 0.879 | 0.730 | 0.797 | 0.640 | 0.789 | 0.691 | 0.826 | 0.633 | 0.802 |
| Amulet [9] | MK | 0.843 | 0.894 | 0.812 | 0.882 | 0.735 | 0.815 | 0.627 | 0.781 | 0.656 | 0.803 | 0.652 | 0.797 |
| RANet [1] | MB | 0.860 | 0.894 | 0.848 | 0.888 | 0.737 | 0.792 | 0.695 | 0.812 | 0.720 | 0.839 | 0.691 | 0.813 |
| $\mathrm{R}^3$Net [3] | MK | 0.855 | 0.910 | 0.815 | 0.894 | 0.732 | 0.809 | 0.652 | 0.819 | 0.692 | 0.837 | 0.642 | 0.820 |
| Ours | MB | 0.885 | 0.914 | 0.859 | 0.902 | 0.771 | 0.833 | 0.704 | 0.827 | 0.752 | 0.852 | 0.709 | 0.830 |

Table 2: *Comparisons of scores of weighted F-measure ($F_\beta^\omega$) and structure similarity ($S_\alpha$). MB: MSRA-B dataset. MK: MSRA10K datset*

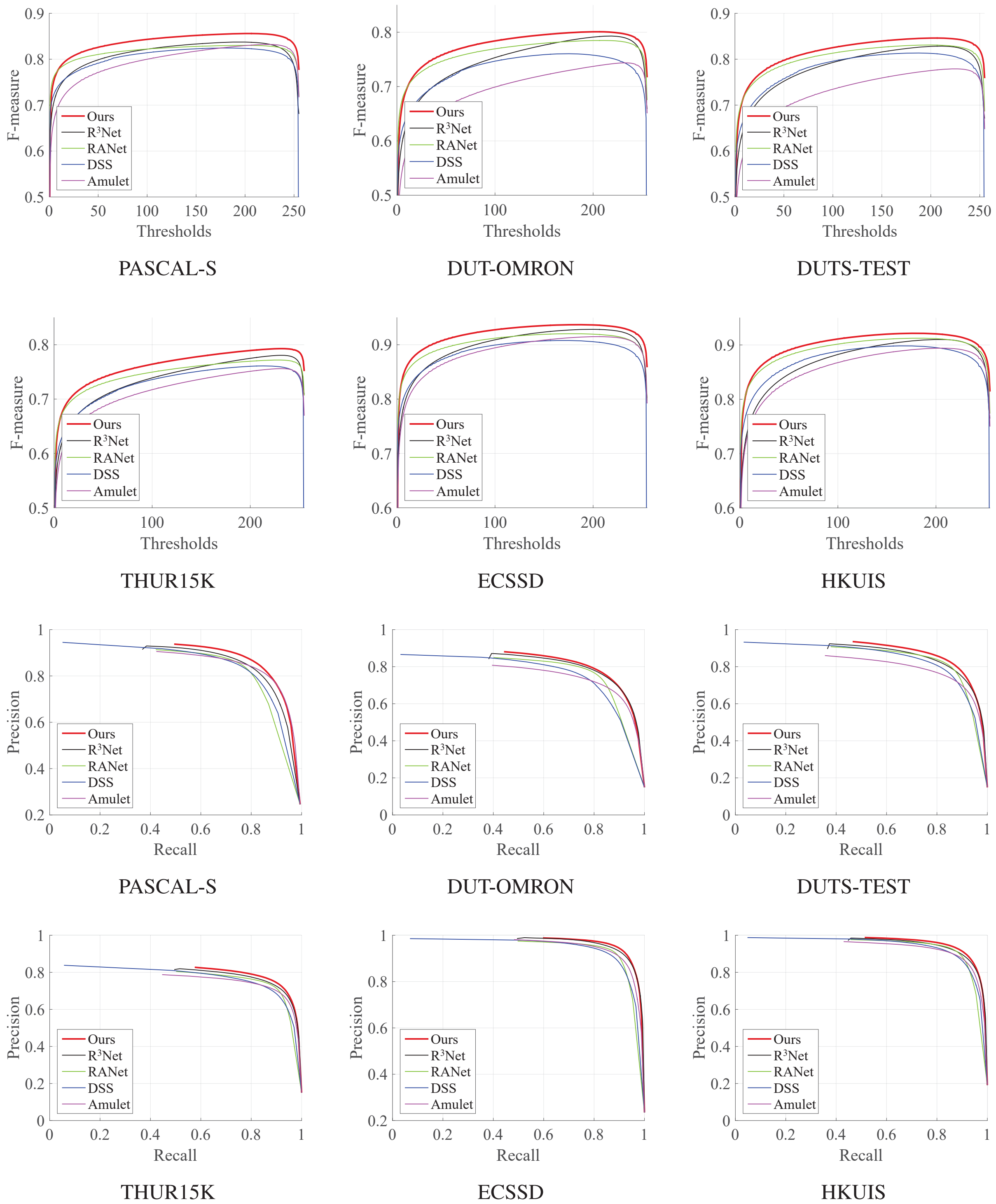


Figure 1: *Comparisons of F-measure curves and Precision-Recall (PR) curves on six traditional benchmark datasets.*

## 2. More comparisons with existing 10 algorithms

In the paper, we show weighted F-measure score, structure similarity score, F-measure curve, Precision-Recall curve on five benchmark datasets. Here we show these results of HUKIS dataset in Fig. 2. It is obviously that our model outperforms 10 existing state-of-the-art algorithms on these metrics. Then we show more visual comparisons.

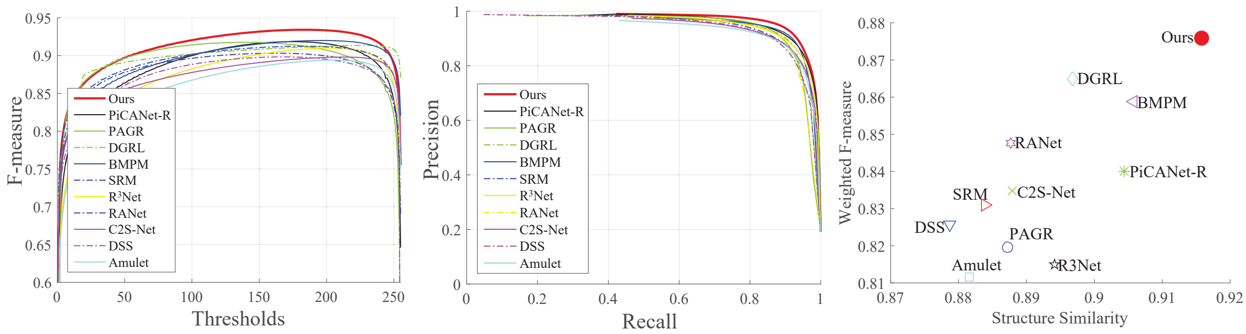


Figure 2: *Comparisons of weighted F-measure score, structure similarity score, F-measure curve, Precision-Recall curve on HKUIS dataset.*

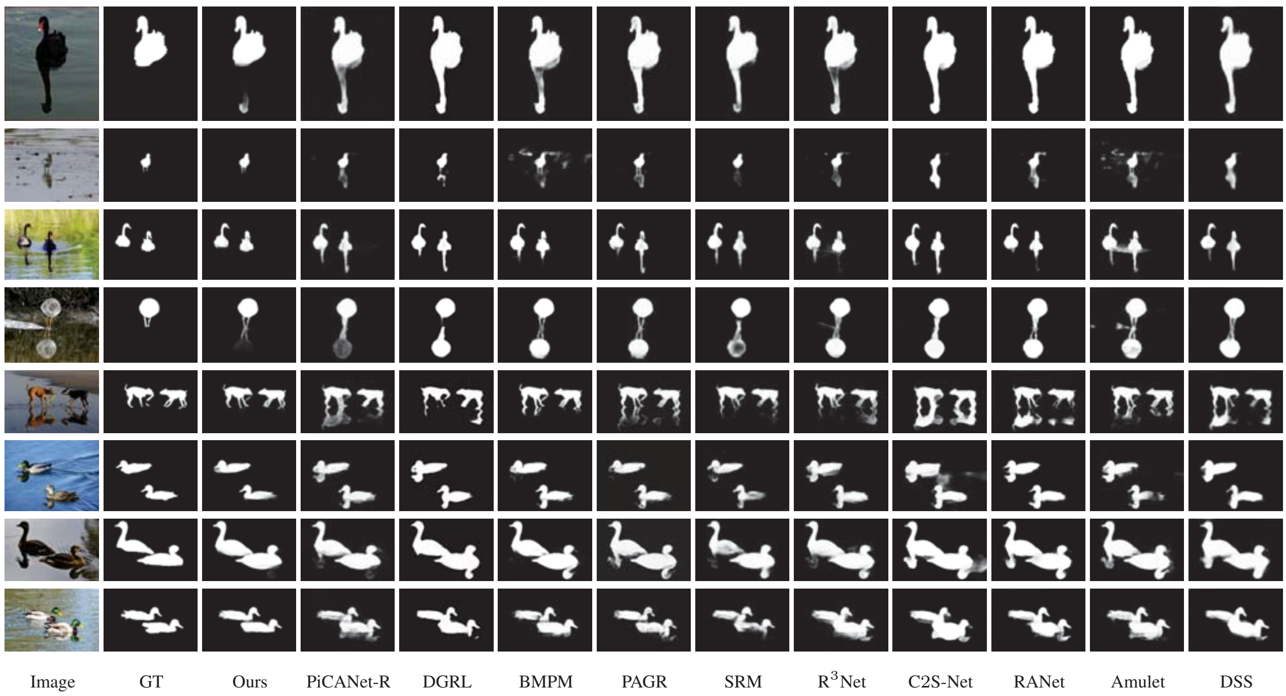


Figure 3: *Visual comparisons with the existing methods in one challenging case: objects with reflection.*

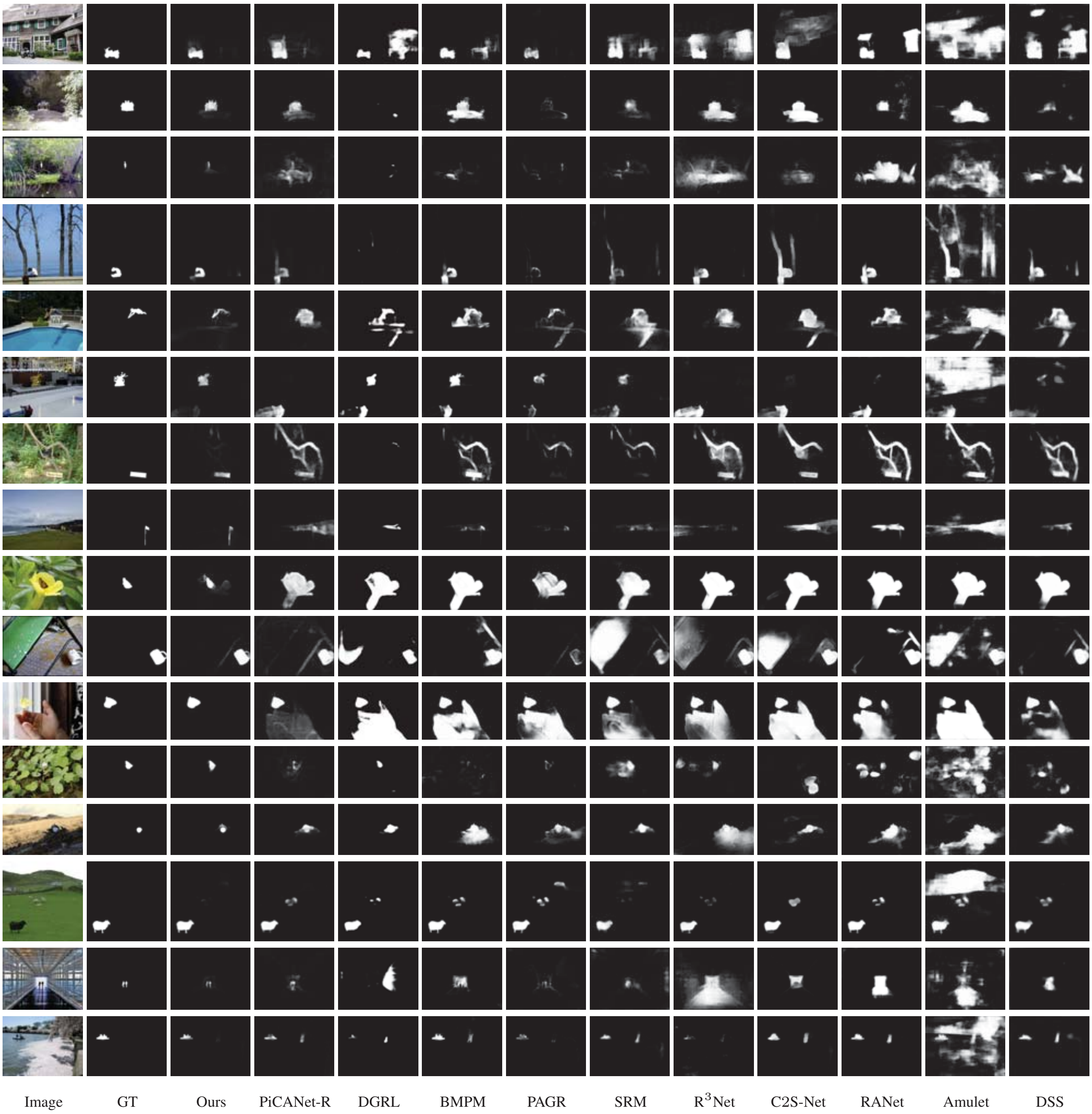


Figure 4: *Visual comparisons with the existing methods in one challenging case: small object.*

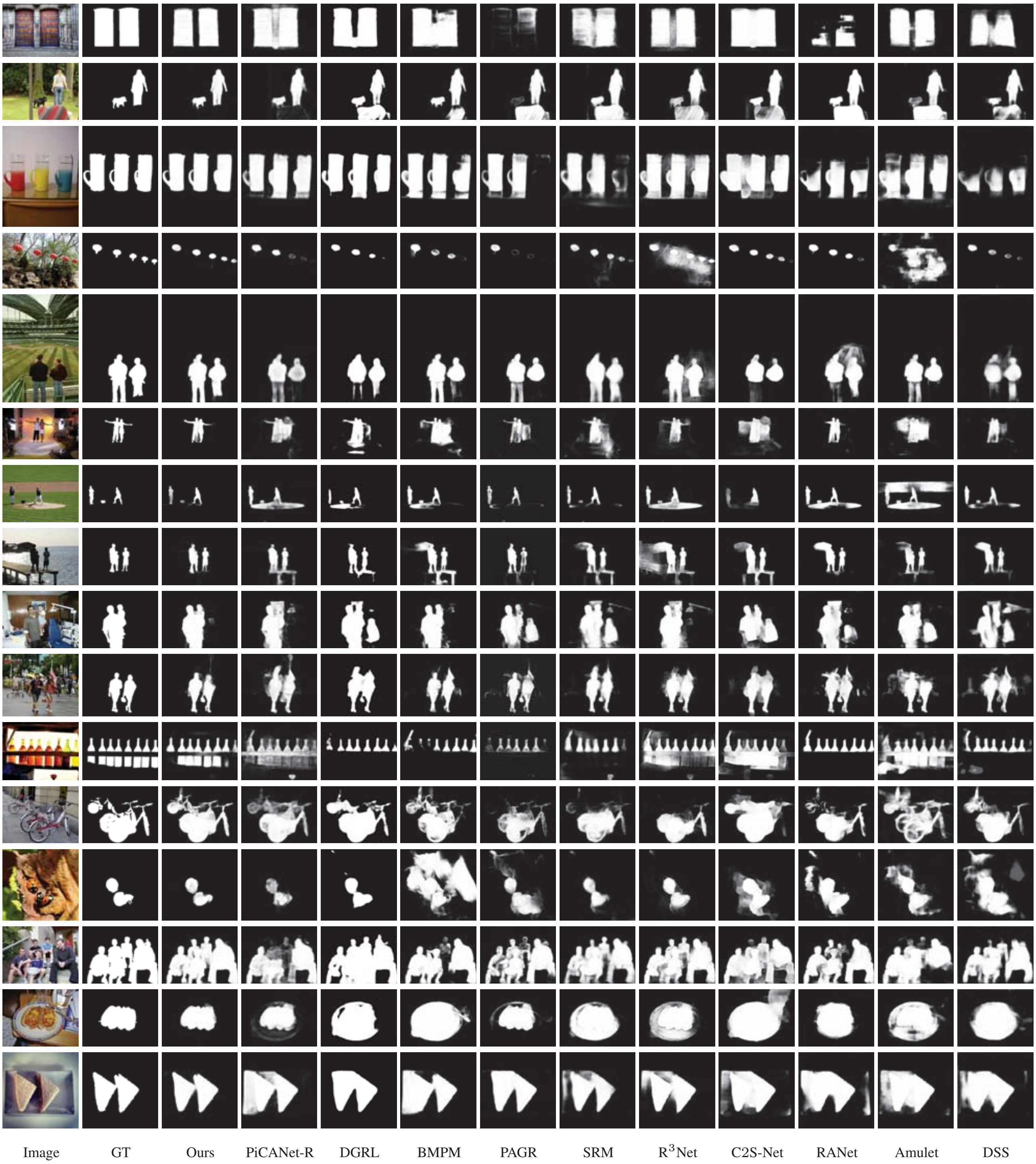


Figure 5: *Visual comparisons with the existing methods in one challenging case: multiple objects.*

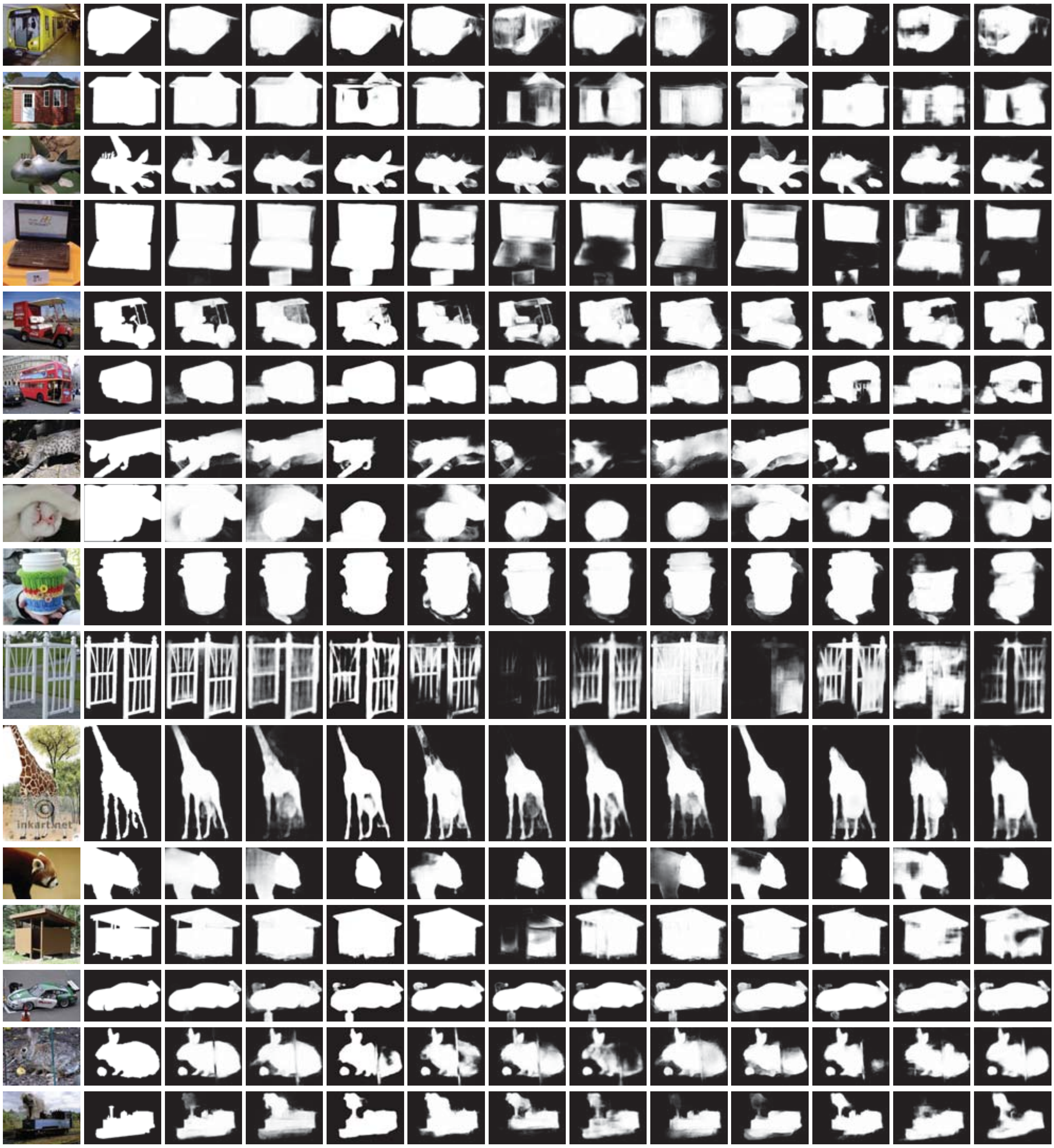


Figure 6: *Visual comparisons with the existing methods in one challenging case: large object.*

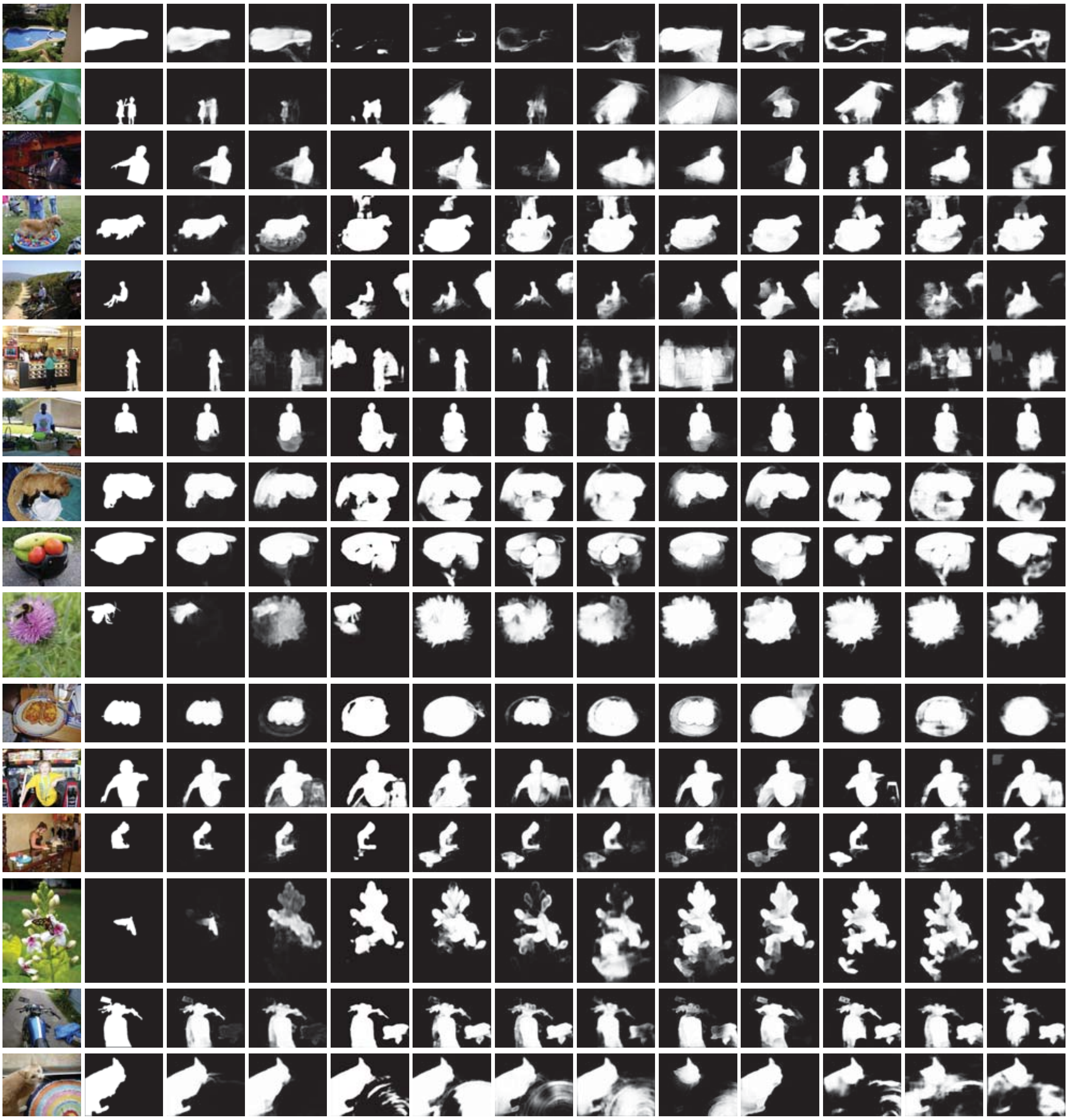


Figure 7: *Visual comparisons with the existing methods in one challenging case: complex scene.*

## 3. More results on SOC dataset

In the paper, we present the attribute-based structure similarity scores of the proposed model and compared algorithms. Here we show the attribute-based MAE, maxF and weighted F-measure scores in Table 3, Table 4 and Table 5 respectively.

| Attr | DSS | Amulet | RANet | C2S-Net | R3Net | SRM | DGRL | BMPM | PiCANet-R | Ours |
|---|---|---|---|---|---|---|---|---|---|---|
| AC | 0.119 | 0.133 | 0.139 | 0.105 | 0.140 | 0.089 | 0.084 | 0.097 | 0.097 | 0.078 |
| BO | 0.327 | 0.276 | 0.409 | 0.227 | 0.433 | 0.239 | 0.184 | 0.239 | 0.208 | 0.224 |
| CL | 0.168 | 0.165 | 0.192 | 0.141 | 0.174 | 0.139 | 0.119 | 0.132 | 0.124 | 0.110 |
| HO | 0.123 | 0.130 | 0.150 | 0.115 | 0.146 | 0.104 | 0.089 | 0.101 | 0.097 | 0.084 |
| MB | 0.131 | 0.135 | 0.150 | 0.097 | 0.157 | 0.092 | 0.073 | 0.076 | 0.069 | 0.059 |
| OC | 0.157 | 0.167 | 0.193 | 0.133 | 0.191 | 0.140 | 0.118 | 0.124 | 0.126 | 0.113 |
| OV | 0.181 | 0.167 | 0.219 | 0.148 | 0.220 | 0.135 | 0.114 | 0.128 | 0.114 | 0.110 |
| SC | 0.112 | 0.131 | 0.131 | 0.102 | 0.138 | 0.101 | 0.086 | 0.091 | 0.097 | 0.076 |
| SO | 0.112 | 0.156 | 0.114 | 0.118 | 0.117 | 0.106 | 0.096 | 0.096 | 0.102 | 0.085 |
| Avg | 0.130 | 0.153 | 0.148 | 0.124 | 0.147 | 0.111 | 0.099 | 0.104 | 0.104 | 0.091 |

Table 3: *Attribute-based MAE scores in SOC dataset [4]*

| Attr | DSS | Amulet | RANet | C2S-Net | R3Net | SRM | DGRL | BMPM | PiCANet-R | Ours |
|---|---|---|---|---|---|---|---|---|---|---|
| AC | 0.740 | 0.754 | 0.722 | 0.767 | 0.718 | 0.789 | 0.784 | 0.770 | 0.789 | 0.817 |
| BO | 0.819 | 0.850 | 0.767 | 0.875 | 0.793 | 0.875 | 0.895 | 0.868 | 0.883 | 0.885 |
| CL | 0.713 | 0.728 | 0.677 | 0.761 | 0.727 | 0.758 | 0.769 | 0.750 | 0.782 | 0.800 |
| HO | 0.764 | 0.770 | 0.727 | 0.767 | 0.738 | 0.793 | 0.805 | 0.788 | 0.812 | 0.838 |
| MB | 0.769 | 0.752 | 0.757 | 0.850 | 0.752 | 0.841 | 0.838 | 0.830 | 0.866 | 0.891 |
| OC | 0.715 | 0.734 | 0.659 | 0.750 | 0.686 | 0.726 | 0.750 | 0.758 | 0.759 | 0.784 |
| OV | 0.756 | 0.798 | 0.709 | 0.800 | 0.726 | 0.822 | 0.824 | 0.829 | 0.848 | 0.844 |
| SC | 0.728 | 0.727 | 0.708 | 0.738 | 0.704 | 0.745 | 0.759 | 0.766 | 0.759 | 0.806 |
| SO | 0.648 | 0.614 | 0.639 | 0.648 | 0.643 | 0.673 | 0.662 | 0.675 | 0.679 | 0.727 |
| Avg | 0.701 | 0.691 | 0.673 | 0.714 | 0.684 | 0.735 | 0.731 | 0.737 | 0.745 | 0.778 |

Table 4: *Attribute-based maxF scores in SOC dataset [4]*

| Attr | DSS | Amulet | RANet | C2S-Net | R3Net | SRM | DGRL | BMPM | PiCANet-R | Ours |
|---|---|---|---|---|---|---|---|---|---|---|
| AC | 0.622 | 0.621 | 0.586 | 0.655 | 0.570 | 0.681 | 0.713 | 0.671 | 0.671 | 0.724 |
| BO | 0.635 | 0.718 | 0.516 | 0.757 | 0.466 | 0.752 | 0.815 | 0.744 | 0.774 | 0.761 |
| CL | 0.573 | 0.608 | 0.513 | 0.647 | 0.569 | 0.647 | 0.691 | 0.643 | 0.667 | 0.707 |
| HO | 0.651 | 0.645 | 0.599 | 0.667 | 0.606 | 0.694 | 0.738 | 0.696 | 0.701 | 0.748 |
| MB | 0.648 | 0.641 | 0.597 | 0.724 | 0.576 | 0.732 | 0.778 | 0.718 | 0.773 | 0.817 |
| OC | 0.591 | 0.603 | 0.507 | 0.650 | 0.521 | 0.628 | 0.681 | 0.656 | 0.655 | 0.692 |
| OV | 0.628 | 0.684 | 0.552 | 0.703 | 0.554 | 0.724 | 0.759 | 0.728 | 0.759 | 0.763 |
| SC | 0.615 | 0.600 | 0.577 | 0.635 | 0.556 | 0.645 | 0.692 | 0.668 | 0.640 | 0.713 |
| SO | 0.515 | 0.471 | 0.508 | 0.525 | 0.492 | 0.547 | 0.582 | 0.562 | 0.543 | 0.610 |
| Avg | 0.572 | 0.561 | 0.535 | 0.602 | 0.532 | 0.623 | 0.658 | 0.632 | 0.630 | 0.677 |

Table 5: *Attribute-based weighted F-measure scores in SOC dataset [4].*

## References


[1] S. Chen, X. Tan, B. Wang, and X. Hu. Reverse attention for salient object detection. In *ECCV*, pages 236–252, 2018.

[2] M. Cheng, N. J. Mitra, X. Huang, P. H. S. Torr, and S. Hu. Global contrast based salient region detection. *IEEE TPAMI*, 37(3):569–582, 2015.

[3] Z. Deng, X. Hu, L. Zhu, X. Xu, J. Qin, G. Han, and P. Heng. $R^3$net: Recurrent residual refinement network for saliency detection. In *IJCAI*, pages 684–690, 2018.

[4] D. Fan, M. Cheng, J. Liu, S. Gao, Q. Hou, and A. Borji. Salient objects in clutter: Bringing salient object detection to the foreground. In *ECCV*, pages 196–212, 2018.

[5] Q. Hou, M.-M. Cheng, X. Hu, A. Borji, Z. Tu, and P. Torr. Deeply supervised salient object detection with short connections. *IEEE TPAMI*, 41(4):815–828, 2019.

[6] G. Li and Y. Yu. Visual saliency based on multiscale deep features. In *CVPR*, pages 5455–5463, 2015.

[7] T. Liu, J. Sun, N.-N. Zheng, X. Tang, and H.-Y. Shum. Learning to detect a salient object. In *CVPR*, pages 1–8, 2007.

[8] L. Wang, H. Lu, Y. Wang, M. Feng, D. Wang, B. Yin, and X. Ruan. Learning to detect salient objects with image-level supervision. In *CVPR*, pages 136–145, 2017.

[9] P. Zhang, D. Wang, H. Lu, H. Wang, and X. Ruan. Amulet: Aggregating multi-level convolutional features for salient object detection. In *ICCV*, pages 202–211, 2017.