Bi-directional Object-Context Prioritization Learning for Saliency Ranking — Supplementary Material

Anonymous CVPR submission

Paper ID 7870

In this supplemental, we first provide more quantitative experiments to analyze our model design. Specifically, we investigate how the parameter settings of R in the SOS module and P in the OCOR module affect the performance in Table 1 and Table 2, respectively. According to Table 1 and Table 2, we set R to 4 and P to 8 in our implementation. We also evaluate the backbone choices for our model in Table 3. Note that even if we use the ResNet-50 backbone to initialize our model, it can still achieve the best performance against other state-of-the-art methods on the SA-SOR and SOR metrics (refer to Table 1 in the main submission for comparison). We choose the Swin-L backbone as it provides the best performance.

We then provide more qualitative comparisons of our method *vs*. existing saliency ranking methods (RSDNet [4], ASSR [8], and IRSR [7]) and the adapted baseline methods (BlendMask [2], CenterMask [5], SOLOv2 [9], Cascade R-CNN [1], CBNetv2 [6], and QueryInst [3]) in Figure 1, 2, 3, 4, 5, and 6, respectively. These images cover diverse daily scenarios and the comparisons generally verify the superiority of our method.

Table 1. Evaluation on different parameter settings for R in SOS module.

Settings of S	SA-SOR ↑	SOR↑	MAE↓
$R = 16$	0.724	0.895	0.084
$R = 8$	0.729	0.890	0.082
$R = 2$	0.735	0.899	0.081
$R = 4$ (Ours)	**0.738**	**0.904**	**0.078**

Table 2. Evaluation on different parameter settings for P in OCOR module.

Settings of P	SA-SOR ↑	SOR↑	MAE↓
$P = 1$	0.727	0.888	0.081
$P = 2$	0.731	0.892	0.081
$P = 4$	0.736	0.900	0.080
$P = 16$	0.737	**0.905**	0.080
$P = 8$ (Ours)	**0.738**	0.904	**0.078**

Table 3. Evaluation on different backbone choices for our model.

Backbone	SA-SOR ↑	SOR↑	MAE↓
ResNet-50	0.723	0.877	0.085
ResNet-101	0.727	0.885	0.084
Swin-T	0.726	0.890	0.084
Swin-B	0.730	0.896	0.080
Swin-L (Ours)	**0.738**	**0.904**	**0.078**

References

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Figure 1. More visual comparison of our method to existing saliency ranking methods and adapted baseline methods.

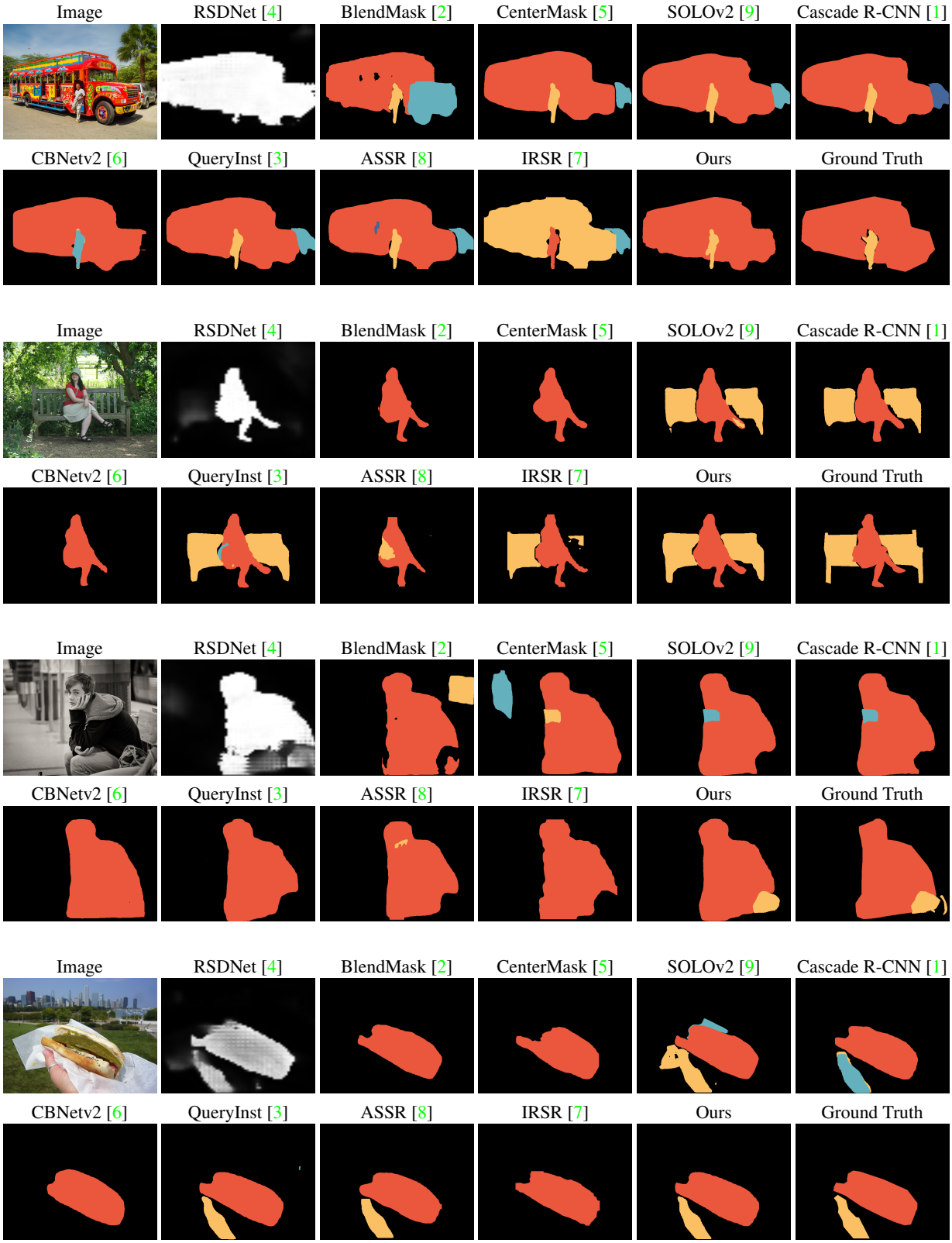

Figure 2. More visual comparison of our method to existing saliency ranking methods and adapted baseline methods.

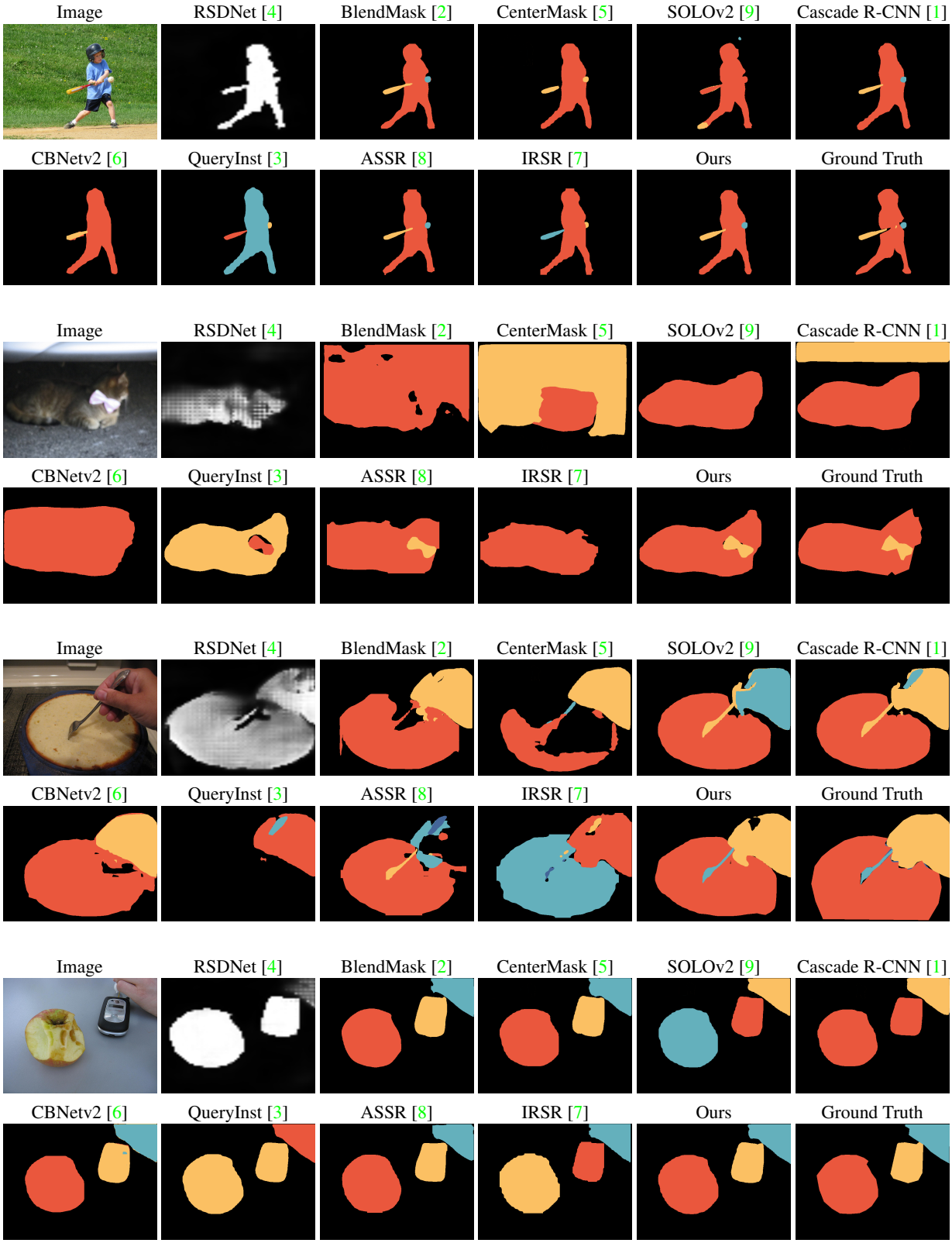

Figure 3. More visual comparison of our method to existing saliency ranking methods and adapted baseline methods.

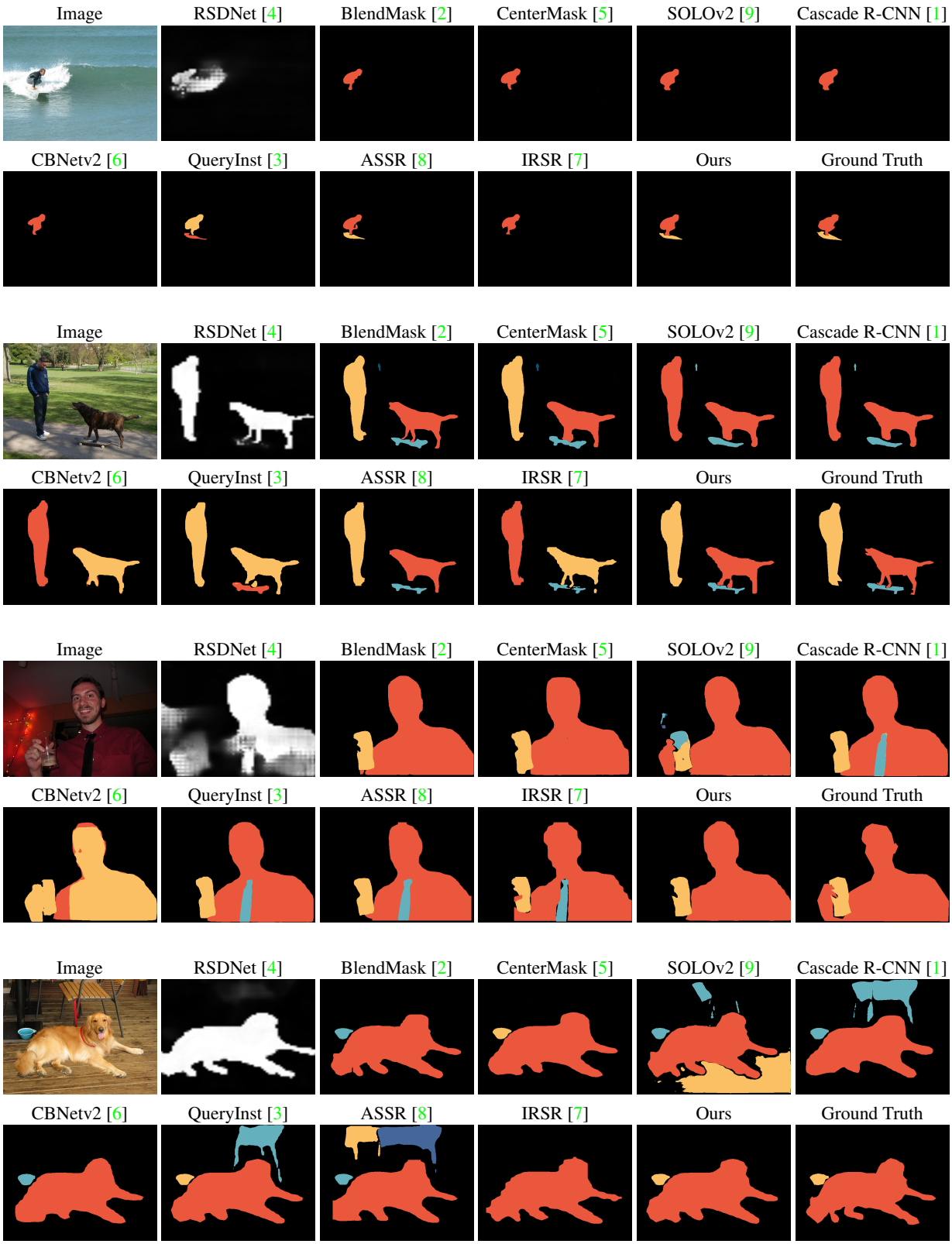

Figure 4. More visual comparison of our method to existing saliency ranking methods and adapted baseline methods.

Figure 5. More visual comparison of our method to existing saliency ranking methods and adapted baseline methods.

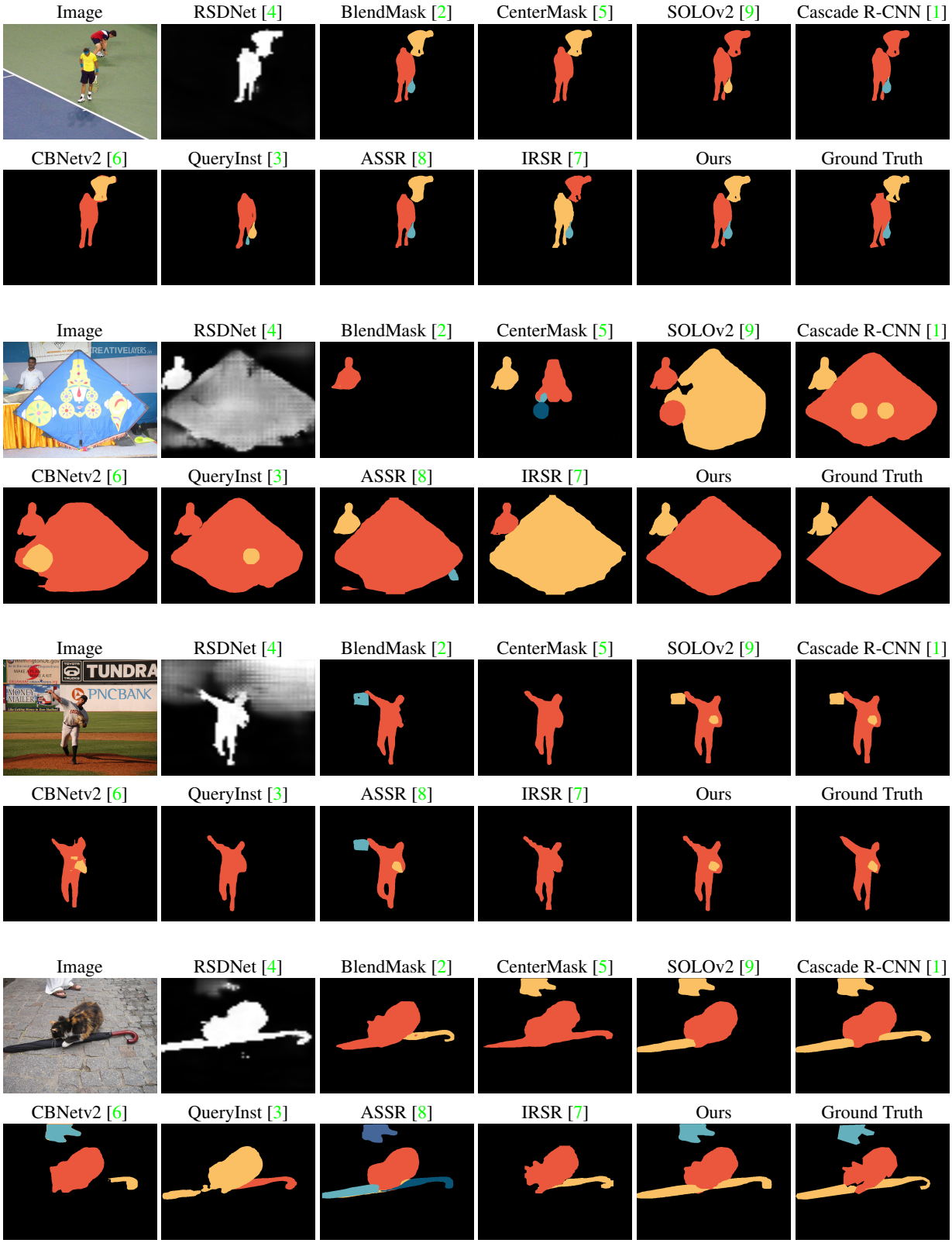

Figure 6. More visual comparison of our method to existing saliency ranking methods and adapted baseline methods.

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