Weakly Supervised Video Salient Object Detection
(Supplementary Materials)

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Abstract

In this supplementary material, we further show our weak label (the fixation guided scribble annotation) and configuration comparison of our method and existing methods. We also show other prediction boosting techniques and more qualitative comparison.

1. Fixation Guided Scribble Annotation

In Figure 1, we visualize more samples to show the scribble annotation in the proposed dataset. During annotating, an annotator is required to look the at RGB image(Figure 1 (a)) and the fixation map (Figure 1 (b)) at the same time. Based on this, the annotator annotates the foreground in objects with peak response regions and background in other regions, and we then obtain our scribble annotation (Figure 1 (d)). Note that, in the whole process of annotating, the clean GT (Figure 1 (c)) is not available to the annotator. Our dataset will be released to the public.

2. Configuration Comparison

We show more detailed configurations of our method and competing methods in Table 1, which clearly shows that our model has the cheapest condfiguration, leading to the least effort of annotation. Meanwhile, the efficiency of our model during inference further illustrates the effectiveness of our solution.

3. Effectiveness of boosting

Apart from the proposed saliency boosting strategy, we also try a traditional boosting strategy, named Ours-b. In this setting, we first use our scribble label to train the model. After several epochs of training, we adopt the prediction from the model as the pseudo label to finetune the whole model. From Table 2, we can find that Ours-b can bring improvements to on VOS [8], DAVIS [12] and FBMS [11]. While our boosting strategy can bring improvements and show effectiveness on more datasets. In Figure 2, we illustrate the comparison of pseudo labels from our strategy (Figure 2 (c)) and from the traditional strategy (Figure 2 (d)). It is clear that, our pseudo labels are closer to the clean GT (Figure 2 (b)).

4. Qualitative Comparison

In Figure 3, we visualize more samples from the testing sets of DAVSOD and DAVIS to compare our performance with competing techniques to further show the superior performance of our solution.

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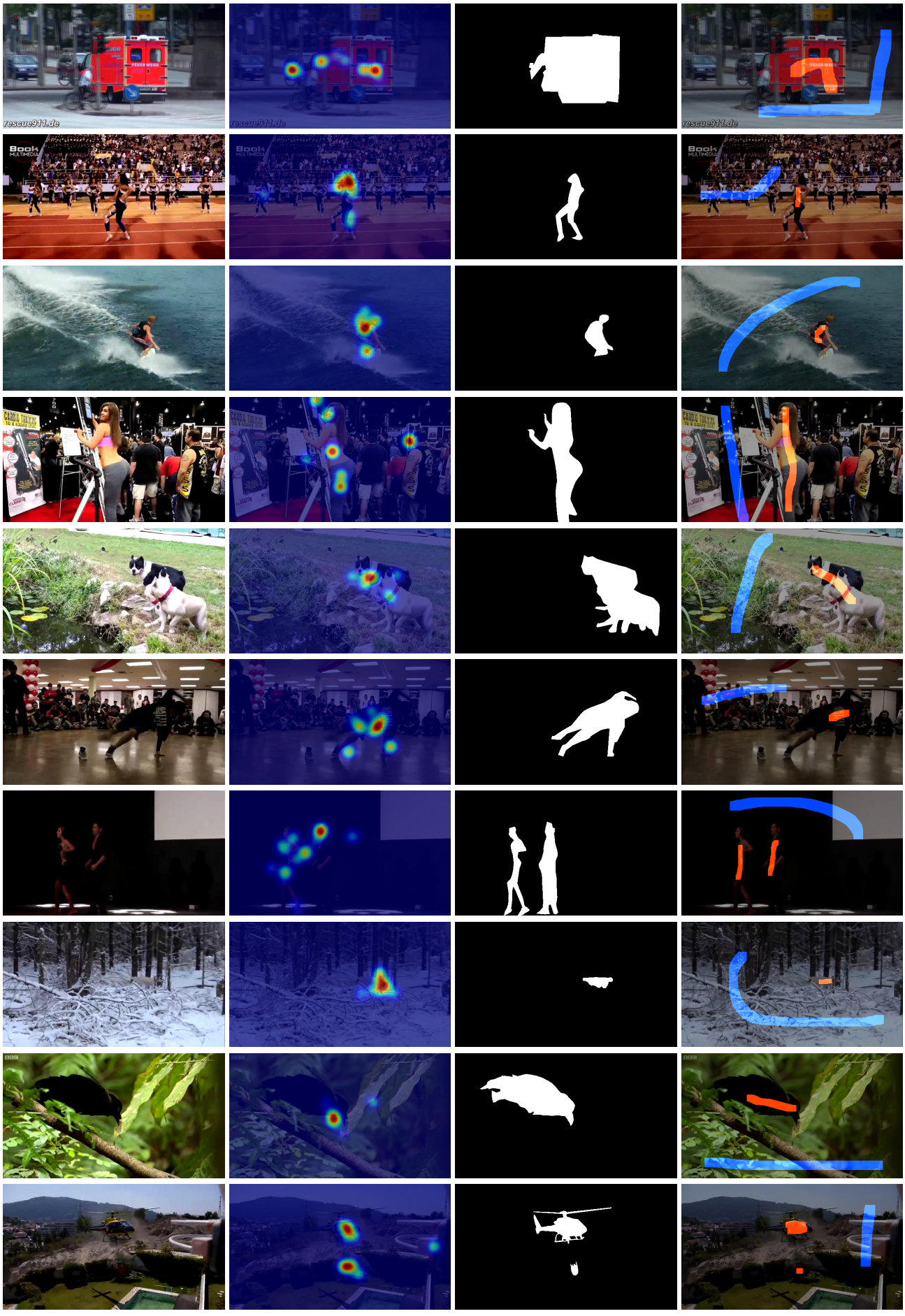

(a) Image (b) Fixation (c) Clean GT (d) Our GT

Table 1. Network setting of competing methods and ours. T.D. = Training data. DUTS [15]; MSRA10K [1]; S-DUTS [21]; HKU-IS [6]; DUTO [20]; DAVIS [12]; DAVSOD [2]; VOS [8]; FBMS [11]; ViSal [16]; SegV2 [4]

Method	**Ours**	**SSOD[21]**	**EGNet[22]**	**SCRN[18]**	**PoolNet[9]**	**FCNS[17]**
Time (s)	0.035	0.166	0.020	0.029	0.033	0.470
Backbone	ResNet-50	VGG-16	ResNet-50	ResNet-50	ResNet-50	VGG-16
T.D.	S-DUTS DAVSOD-S DAVIS-S	S-DUTS DAVSOD-S DAVIS-S	DUTS	DUTS	DUTS	MSRA10K DUTO FBMS SegV2
Method	**PDB[14]**	**FGRN[5]**	**MGA[7]**	**RCRNet[19]**	**SSAV[2]**	**PSCA[3]**
Time (s)	0.050	0.090	0.070	0.037	0.050	0.010
Backbone	ResNet-50	ResNet-101	ResNet-101	ResNet-50	ResNet-50	MobileNetV3
T.D.	pretrain:DUTO MSRA10K train:DAVIS	SegV2 FBMS DAVIS	DUTS DAVIS FBMS	MSRA10K HKU-IS train:VOS DAVIS FBMS	DUTO DAVSOD DAVIS	DUTS DAVSOD DAVSOD
Method	**TENet[13]**	**MuG[10]**				
Time (s)	0.060	0.600				
Backbone	ResNet-50	ResNet-50				
T.D.	DUTS DAVIS DAVSOD	OxUvA				

Table 2. Performance of our ablation study related experiments.

Method	VOS			DAVIS			DAVSOD			FBMS			SegV2			ViSal		
	$S_\alpha \uparrow$	$F_\beta \uparrow$	$\mathcal{M} \downarrow$	$S_\alpha \uparrow$	$F_\beta \uparrow$	$\mathcal{M} \downarrow$	$S_\alpha \uparrow$	$F_\beta \uparrow$	$\mathcal{M} \downarrow$	$S_\alpha \uparrow$	$F_\beta \uparrow$	$\mathcal{M} \downarrow$	$S_\alpha \uparrow$	$F_\beta \uparrow$	$\mathcal{M} \downarrow$	$S_\alpha \uparrow$	$F_\beta \uparrow$	$\mathcal{M} \downarrow$
Ours	0.750	0.666	0.091	0.828	0.779	0.037	**0.705**	**0.605**	**0.103**	0.778	0.786	**0.072**	0.804	0.738	0.033	0.857	0.831	0.041
Ours-b	0.753	0.678	0.089	0.836	**0.800**	**0.036**	0.690	0.575	0.110	0.786	0.778	0.075	0.804	0.728	0.033	0.836	0.808	0.054
Ours*	**0.765**	**0.702**	**0.089**	**0.846**	0.793	0.038	0.694	0.593	0.115	**0.803**	**0.792**	0.073	**0.819**	**0.762**	**0.033**	**0.883**	**0.875**	**0.035**

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v (a) Image (b) GT (c) boosted (d) traditional

Figure 2. Boosting strategy comparison.

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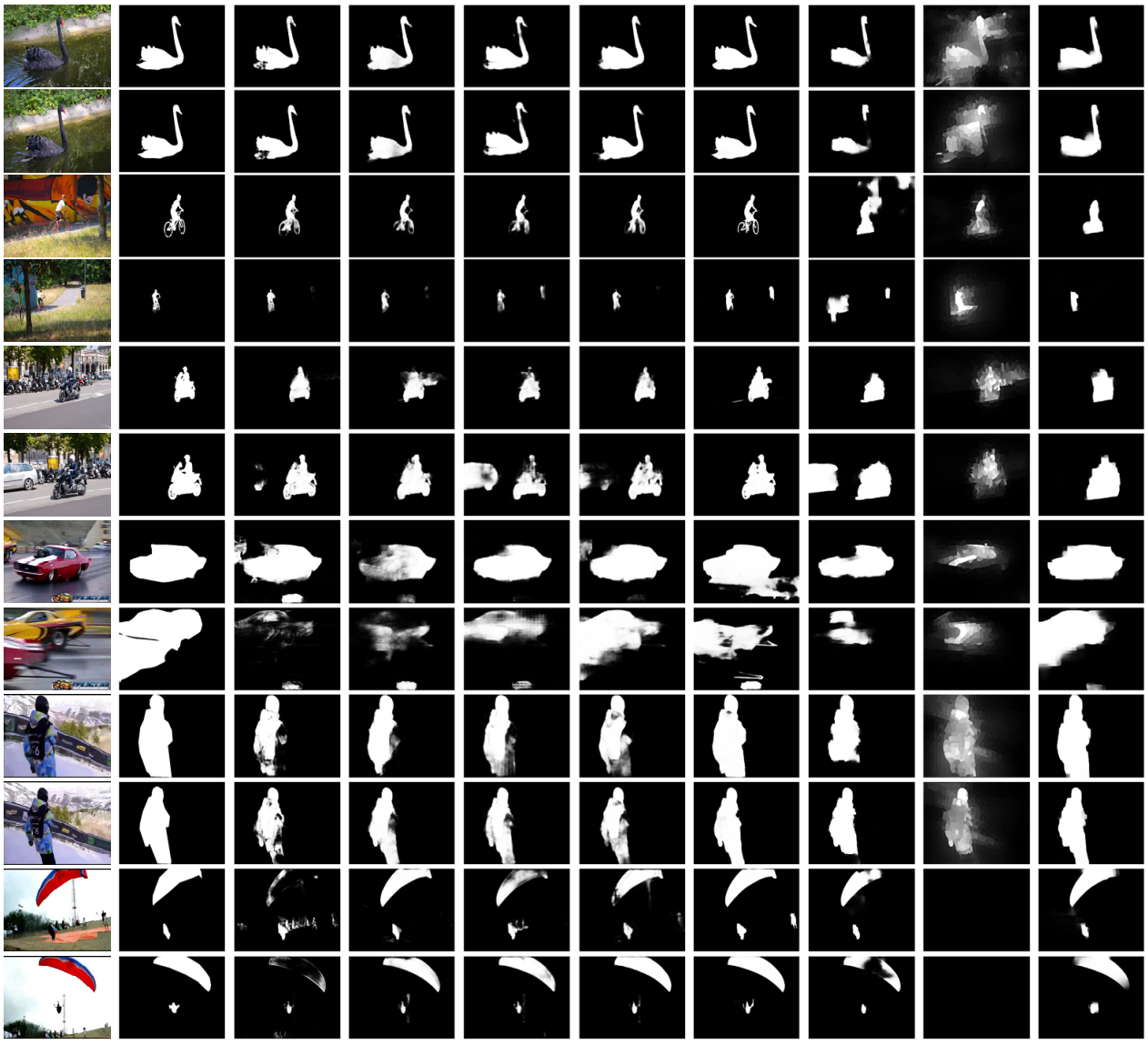

Figure 3. Qualitative comparison with state-of-the-art video salient object detection methods. MGA [7]; RCRNet [19]; SSAV [2]; PSCA [3]; TENet [13]; SSOD [21]; GF [16].