

SegFlow: Joint Learning for Video Object Segmentation and Optical Flow

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1. Contents

This supplementary material provides additional results and analysis for both optical flow estimation and foreground object segmentation. In the following, we provide:

- Details of training data for optical flow on the KITTI [5] and MPI Sintel [1] datasets in Section 2
- Per-class evaluation of segmentation on DAVIS [9] in Section 3.
- Example results of optical flow (Figure 1-3) and object segmentation (Figure 4-8).

2. Optical Flow Estimation

In this section, we describe more details of training process on KITTI and Sintel in Table 3 of the manuscript.

KITTI. We finetune our model (SegFlow+ft) and FlowNetS [4] (FlowNetS+ft*) with the KITTI training set without data augmentation, and select the best model with 10-fold cross validation for comparisons.

Sintel. Similarly, we finetune our model (SegFlow+ft) and FlowNetS [4] (FlowNetS+ft*) on the Sintel training set using only original images and their flips, and select the best model using the validation set as in [4].

We show example results for comparisons between *SegFlow* and FlowNetS in Figure 1. In addition, we show visual comparisons of optical flow on DAVIS in Figure 2 and 3, in which our method generates more complete optical flow within the object corresponding to our segmentation results.

3. Video Object Segmentation

Table 1 presents the per-sequence evaluation (J_{mean}) on DAVIS compared to other state-of-the-art methods, including semi-supervised and unsupervised ones. we improve the J_{mean} by considering the prediction of the image and its flipping one, and averaging both outputs to obtain the final result, where we refer to as Ours². Without adding much computational cost, we further boost the performance with 1.3% in J_{mean} as shown in Table 1. We also present the results of MSK [6] with only using the image as the input (MSK-flo), and show that our method without flow performs better (Ours-flo v.s MSK-flo).

More comparisons between *SegFlow* and state-of-the-art methods are shown in Figure 4-8. To summarize the results in Table 1, we find that:

- *SegFlow* outperforms state-of-the-art unsupervised methods in most sequences.
- Online training is helpful for sequences with various appearance changes (Ours² v.s Ours-ol), such as non-rigid objects (e.g., camel, cows and soapbox), especially for sequences with dynamic backgrounds (e.g., 48.8% and 13.8% improvement for breakdance and dance-twirl respectively).
- Optical flow branch improves segmentation results (Ours² v.s Ours-flo) in most sequences (e.g., bmx-trees, breakdance, goat and libby), especially on the ones with large motion changes (e.g., 25% improvement for motocross-jump).

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Table 1. Per-sequence results on DAVIS validation Set.

Sequence	Semi-Supervised							Unsupervised			
	Ours ²	Ours	Ours-flo	OSVOS [2]	MSK [6]	MSK-flo [6]	OFL [10]	Ours-ol	FST [8]	NLC [3])	KEY [7]
blackswan	0.920	0.904	0.904	0.942	0.903	0.919	0.947	0.903	0.732	0.875	0.842
bmx-trees	0.457	0.450	0.437	0.555	0.575	0.321	0.149	0.437	0.180	0.212	0.193
breakdance	0.682	0.660	0.561	0.708	0.762	0.594	0.496	0.194	0.467	0.673	0.549
camel	0.791	0.782	0.760	0.851	0.801	0.804	0.867	0.760	0.562	0.768	0.579
car-roundabout	0.857	0.857	0.875	0.953	0.960	0.828	0.900	0.874	0.808	0.509	0.640
car-shadow	0.945	0.902	0.902	0.937	0.935	0.903	0.846	0.902	0.698	0.645	0.589
cows	0.906	0.894	0.888	0.946	0.882	0.919	0.910	0.727	0.791	0.883	0.337
dance-twirl	0.734	0.730	0.683	0.670	0.844	0.678	0.567	0.596	0.453	0.347	0.380
dog	0.930	0.923	0.912	0.907	0.909	0.868	0.897	0.918	0.708	0.809	0.692
drift-chicane	0.378	0.360	0.541	0.835	0.862	0.005	0.175	0.090	0.667	0.324	0.188
drift-straight	0.899	0.897	0.826	0.676	0.560	0.460	0.314	0.860	0.682	0.473	0.194
goat	0.861	0.854	0.844	0.880	0.845	0.858	0.865	0.836	0.554	0.010	0.705
horsejump-high	0.760	0.752	0.732	0.780	0.817	0.784	0.862	0.678	0.578	0.834	0.370
kite-surf	0.587	0.569	0.552	0.686	0.600	0.587	0.702	0.525	0.272	0.453	0.685
libby	0.700	0.686	0.655	0.808	0.775	0.788	0.594	0.670	0.507	0.635	0.611
motocross-jump	0.839	0.835	0.589	0.816	0.685	0.690	0.594	0.714	0.602	0.251	0.288
paragliding-launch	0.581	0.580	0.554	0.625	0.620	0.589	0.637	0.580	0.506	0.628	0.559
parkour	0.849	0.840	0.791	0.856	0.882	0.853	0.861	0.813	0.458	0.902	0.410
scooter-black	0.699	0.692	0.694	0.711	0.825	0.649	0.765	0.660	0.522	0.162	0.502
soapbox	0.837	0.789	0.779	0.812	0.899	0.861	0.689	0.737	0.410	0.634	0.757
mean	0.761	0.748	0.724	0.798	0.797	0.698	0.680	0.674	0.558	0.551	0.498

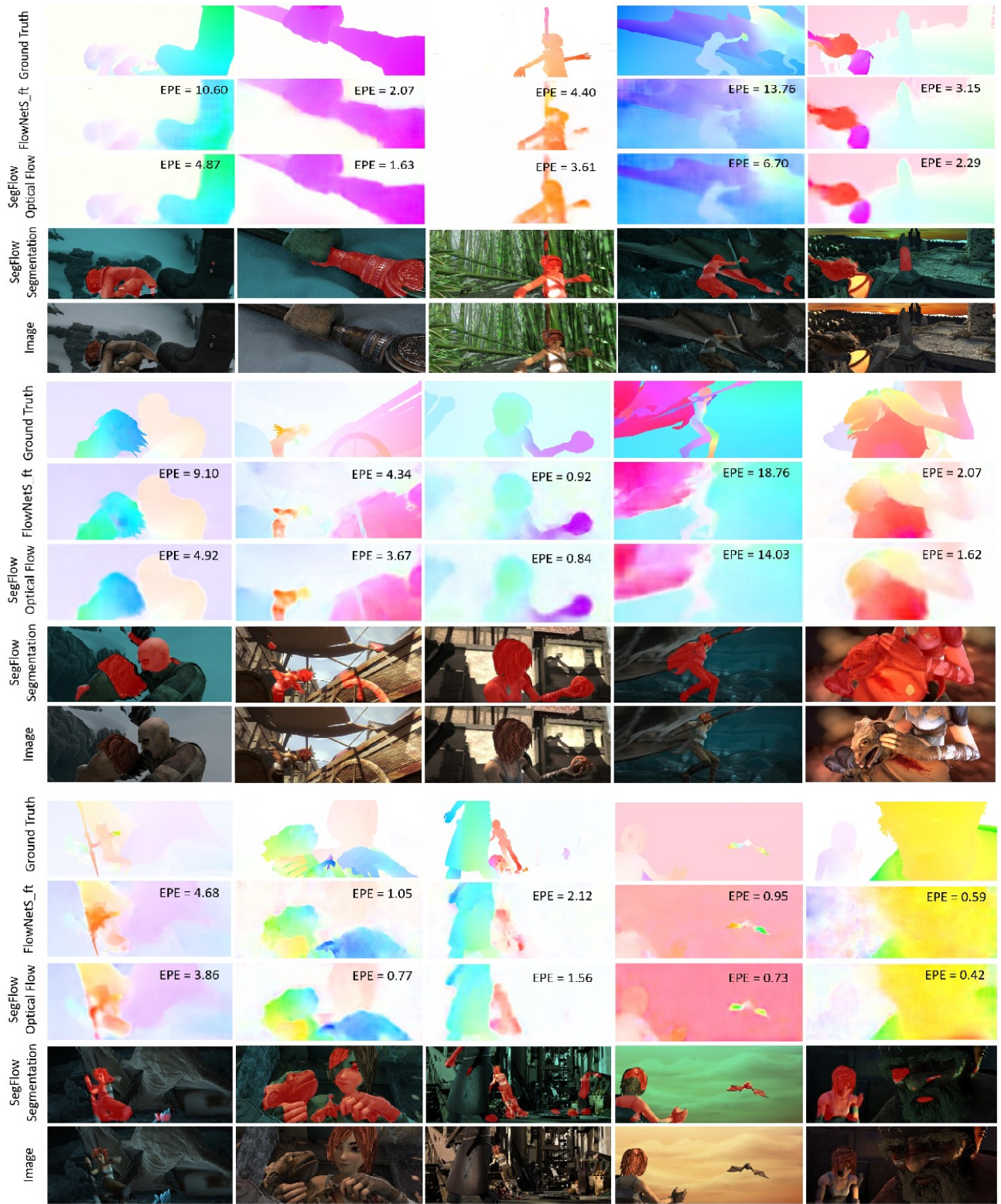


Figure 1. Example results on Sintel. For each set of results, row one to four shows the ground truth, optical flow predicted by FlowNetS+ft* (see Section 5.4 in paper for details), *SegFlow* and object segmentation generated by *SegFlow*, respectively.

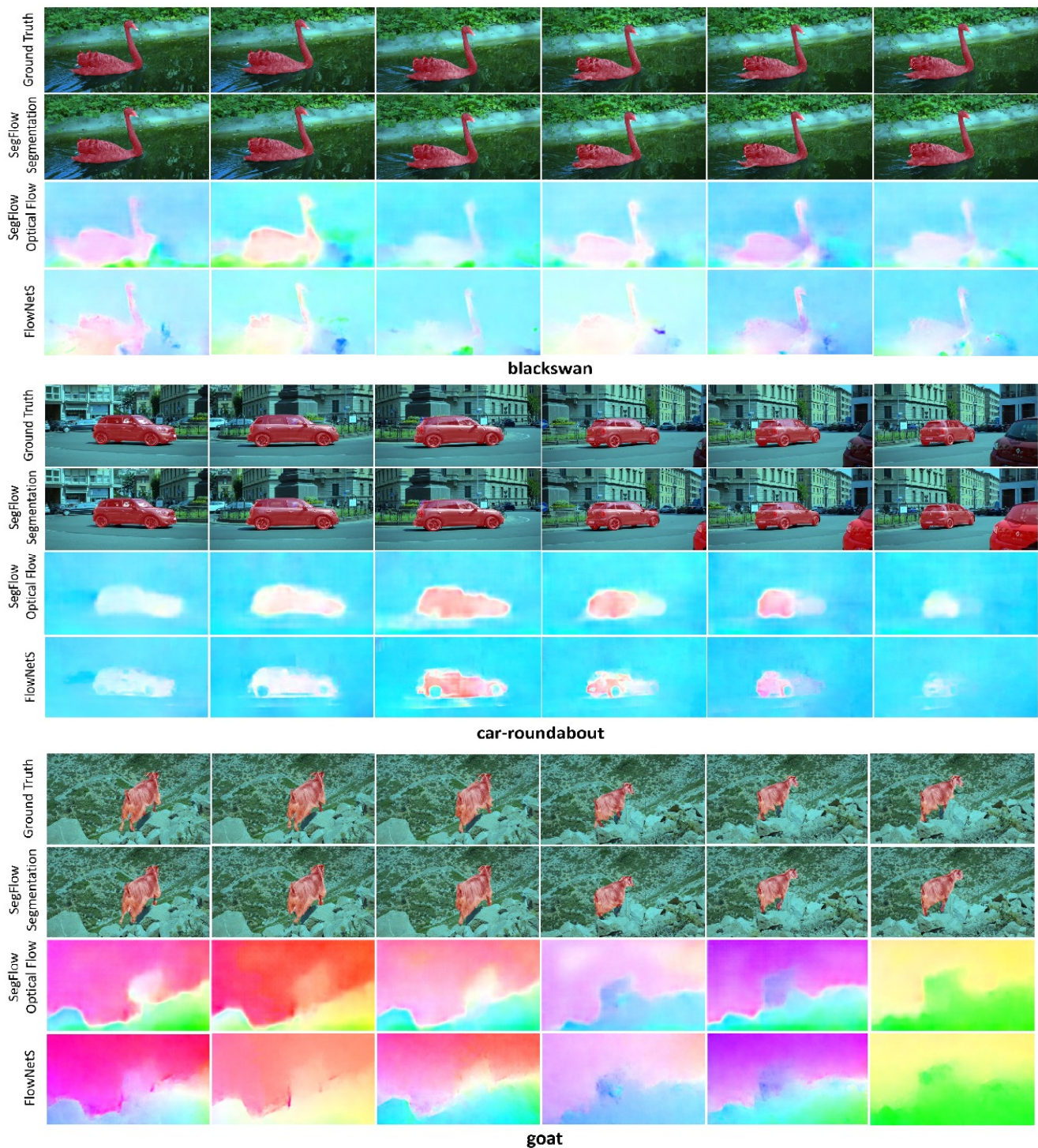


Figure 2. Example results on DAVIS. Row one to four of each sequence shows the annotations, our object segmentation and optical flow predicted by *SegFlow* and optical flow produced by FlowNetS [4], respectively.

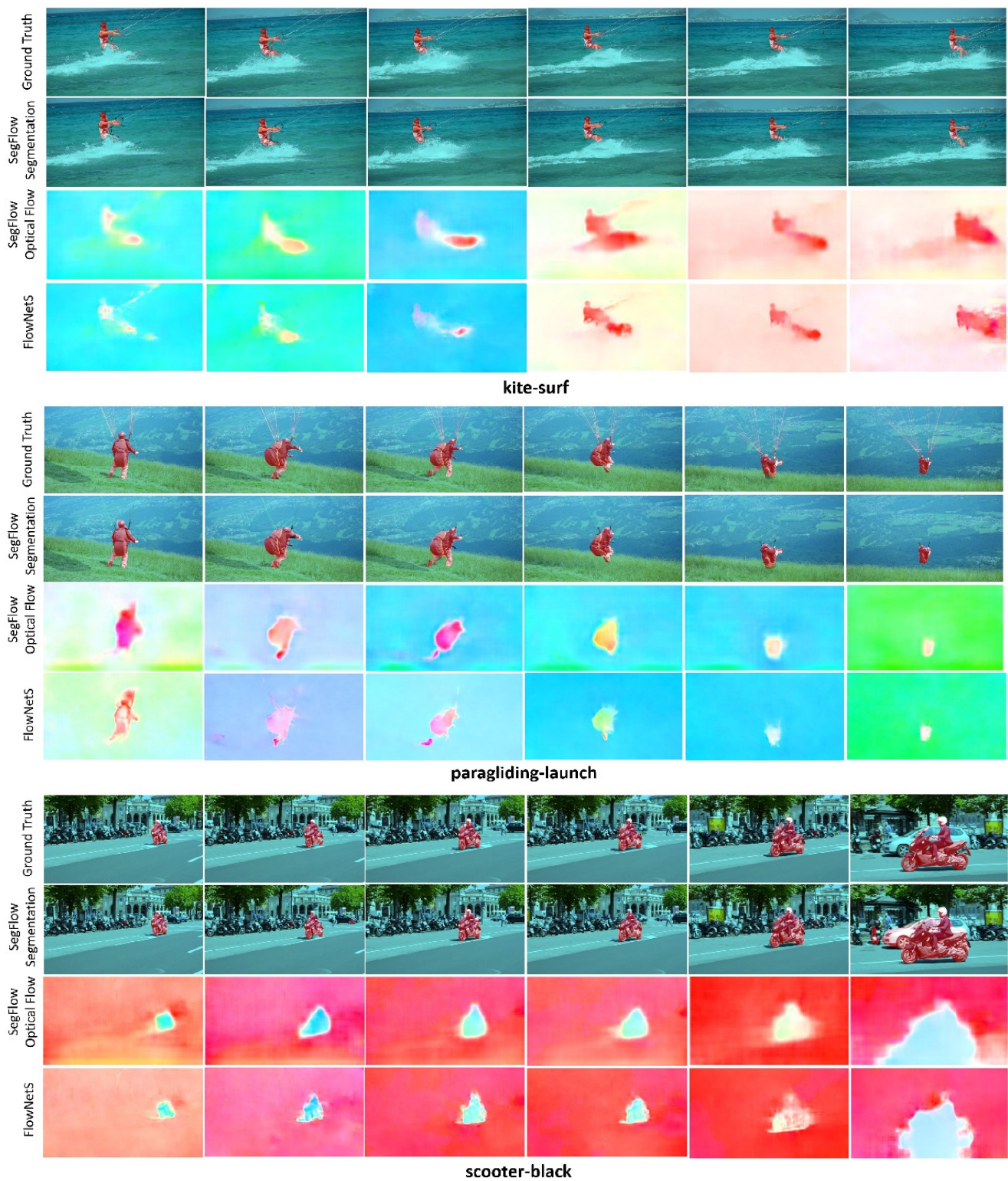


Figure 3. Example results on DAVIS. Row one to four of each sequence shows the annotations, our object segmentation and optical flow predicted by *SegFlow* and optical flow produced by FlowNetS [4], respectively.

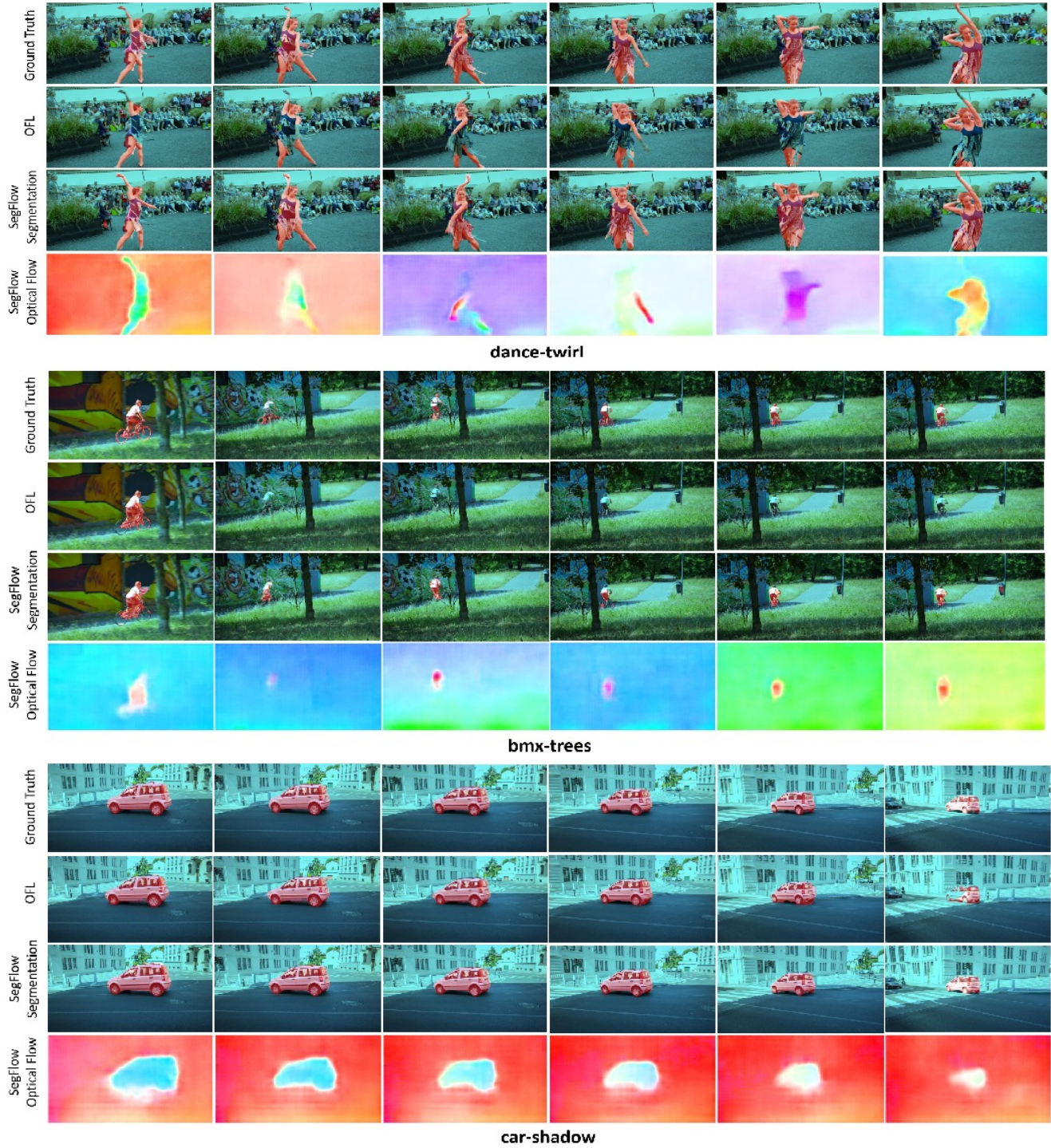


Figure 4. Example results on DAVIS. Row one to four of each sequence shows the annotations, object segmentation by OFL [10], object segmentation by *SegFlow*, and optical flow prediction by *SegFlow* respectively.



Figure 5. Example results on DAVIS. Row one to four of each sequence shows the annotations, object segmentation by OFL [10], object segmentation by *SegFlow*, and optical flow prediction by *SegFlow* respectively.



Figure 6. Example results on DAVIS dataset. Row one to four of each sequence shows the annotations, object segmentation by MSK [6], object segmentation by *SegFlow*, and optical flow prediction by *SegFlow* respectively.

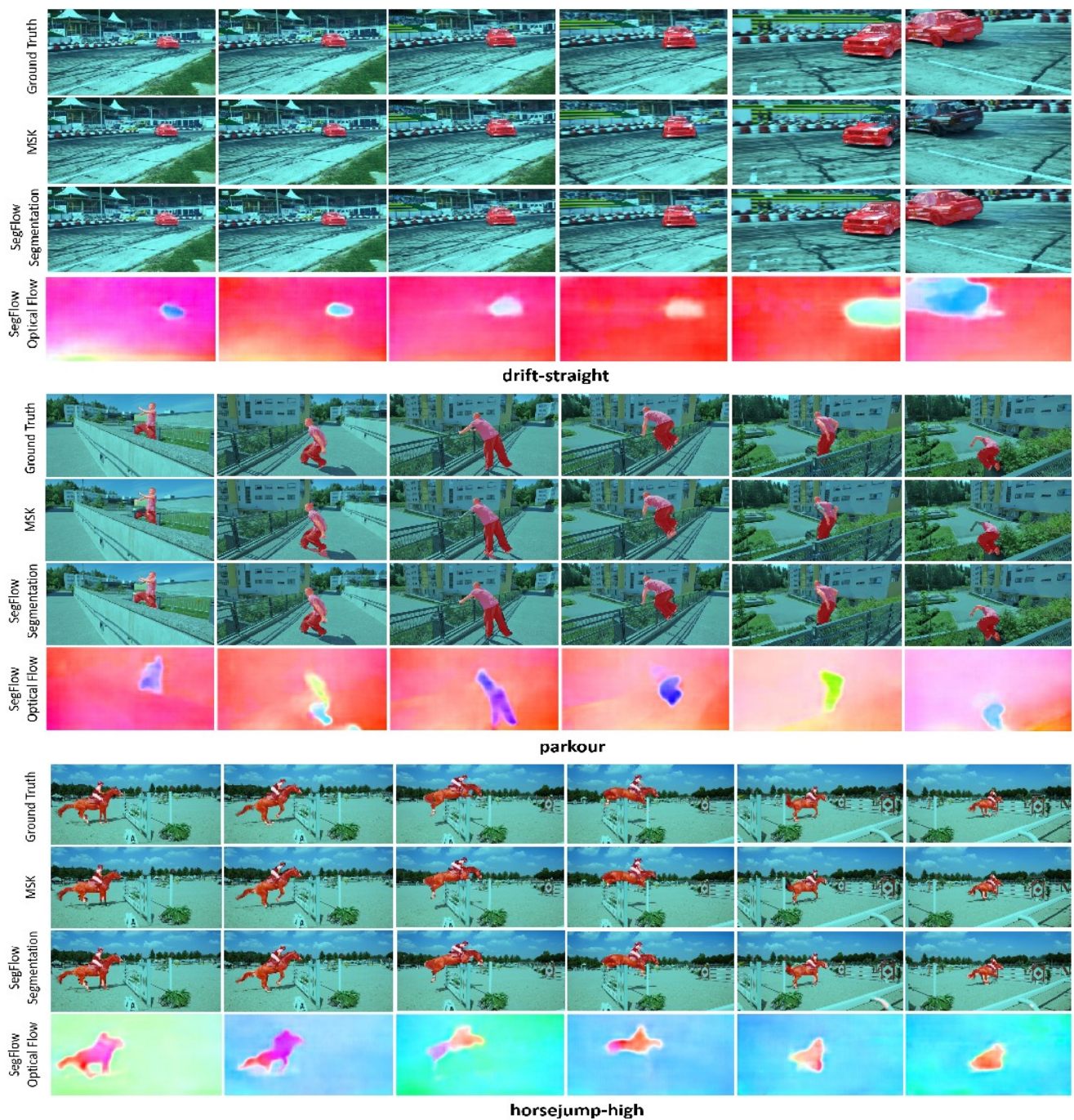


Figure 7. Example results on DAVIS. Row one to four of each sequence shows the annotations, object segmentation by MSK [6], object segmentation by *SegFlow*, and optical flow prediction by *SegFlow* respectively.

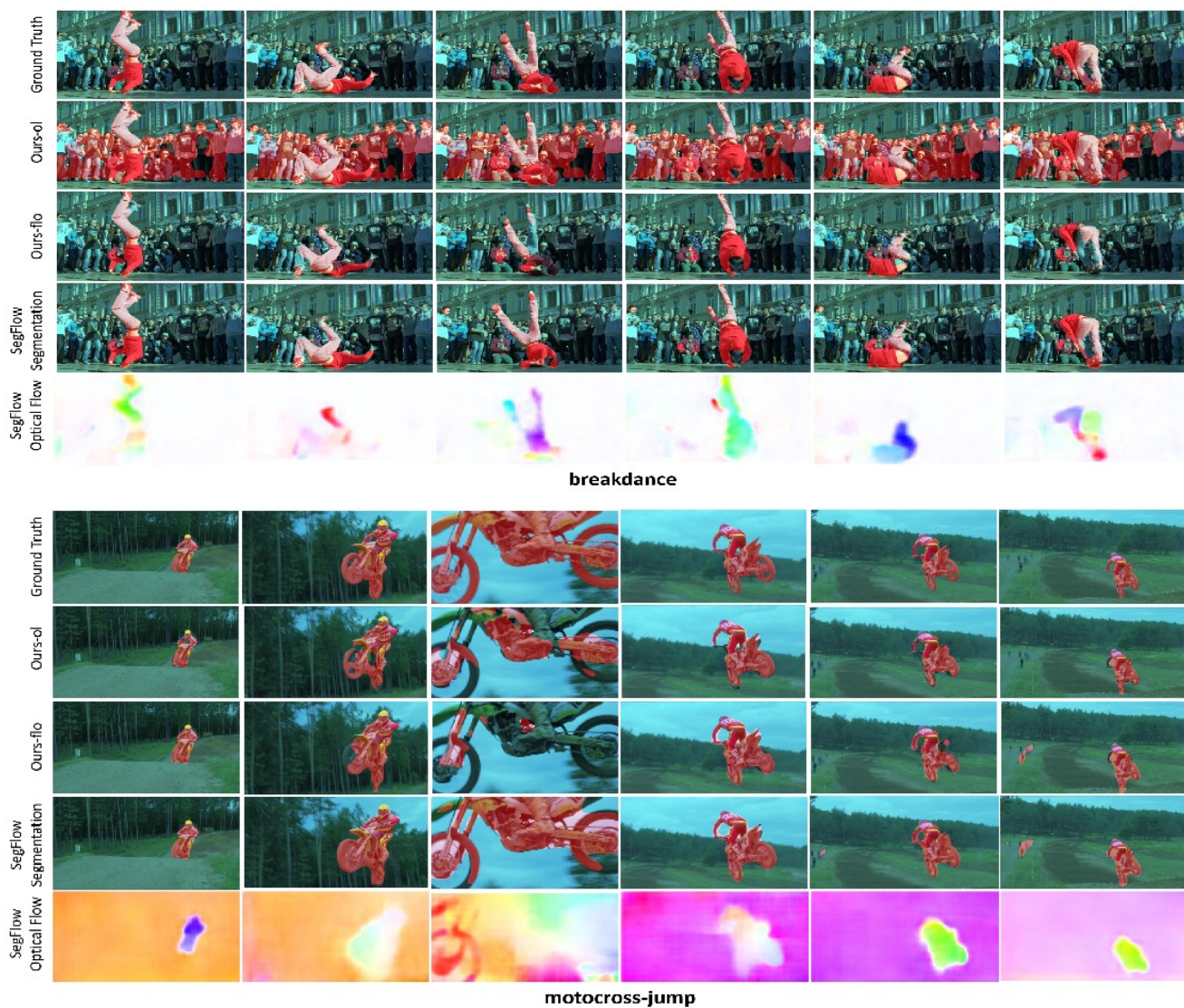


Figure 8. Example results on DAVIS. Row one to four of each sequence shows the annotations, object segmentation by *SegFlow* without online training (Ours-ol), *SegFlow* without optical flow branch (Ours-flo), *SegFlow*, and optical flow prediction by *SegFlow* respectively.

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