Supplemental Material for Video Segmentation with Background Motion Models

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1 IRLS Details and Algorithm Parameters

Algorithm 1 gives the procedure used to optimize the background motion model as described in Section 4. **GetWeights** computes the residuals from the given model H^k and uses Equation 3 to compute the weight for each track in T. Similarly, **GetCost** computes the total cost (Equation 4). Finally, **WLS** uses a weighted-least-squares variant of the four-point algorithm to re-estimate each homography H_i^k in the model using the computed weights.

Algorithm 1 IRLS for model fitting

```
procedure IRLS(H^0, T)
    s ← 1.0                                        ▷ step size
    k ← 0                                          ▷ iteration number
    w^0 ← GetWeights(H^0, T)                       ▷ initialize weights
    repeat
        w^{k+1} ← (1 − s)w^k + s∗GetWeights(H^k, T) ▷ update weights
        H^{k+1} ← WLS(w^{k+1}, T)                  ▷ update model
        cost ← GetCost(H^{k+1}, T)                 ▷ compute cost of new model
        if the cost decreased then
            k ← k + 1                              ▷ advance one iteration
            s ← min(4s, 1)                         ▷ increase step size
        else
            s ← s/4                                ▷ retry with a smaller step size
        end if
    until convergence
end procedure
```

Table 1 gives all parameters used in our method.

Parameter	Value	Description
	8	Track spacing (a parameter to [7]).
	5	Minimum track duration
τ	4	Inlier threshold (Equations 2–4).
λ_u	100	Unary cost weight (Equation 7).
λ_s	0.001	Smoothness cost weight (Equation 7).
$(s_{xy}, s_t, s_L, s_{uv})$	$(\frac{1}{35}, \frac{1}{10}, \frac{1}{7.3}, \frac{1}{8.5})$	Scales applied to lifted pixel coordinates before splatting.
$(w_{xy}, w_t, w_L, w_{uv})$	$(0.5, 0.5, 1.3, 1.5)$	Weights on dimension distances in smoothness term (Equation 7).
$r_{\text{textureless}}$	32	Distance before textureless prior is applied
$w_{\text{textureless}}$	32	Foreground cost applied for each synthetic observation
	8	Spacing of synthetic textureless prior observations
	0.25	Threshold on sliced segmentation

Table 1: A complete list of parameter settings used in our system.

2 Full results tables

This section includes tables for all relevant metrics from the DAVIS benchmark; see [6] for details on how the metrics are computed.

References

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[7] Narayanan Sundaram, Thomas Brox, and Kurt Keutzer. Dense point trajectories by gpu-accelerated large displacement optical flow. In *Proceedings of the 11th European Conference on Computer Vision: Part I*, ECCV'10, pages 438–451, Berlin, Heidelberg, 2010. Springer-Verlag. ISBN 3-642-15548-0, 978-3-642-15548-2.

Table 2: Jaccard (Mean)

	NLC [1]	CVOS [8]	TRC [2]	MSG [4]	KEY [3]	SAL [9]	FST [5]	Ours
bear	0.906	0.864	0.873	0.851	0.891	0.657	0.898	**0.935**
blackswan	**0.874**	0.422	0.569	0.526	0.842	0.222	0.732	0.231
bmx-bumps	**0.635**	0.368	0.350	0.353	0.309	0.188	0.241	0.388
bmx-trees	0.212	0.121	0.162	0.188	0.193	0.194	0.180	**0.416**
boat	0.007	0.056	0.130	0.144	0.065	0.271	**0.361**	0.317
breakdance	**0.673**	0.183	0.114	0.237	0.549	0.422	0.467	0.481
breakdance-flare	0.804	0.317	0.245	0.157	0.559	0.476	0.616	**0.825**
bus	0.629	0.664	0.684	0.885	0.785	0.739	0.825	**0.889**
camel	0.768	0.850	0.778	0.756	0.579	0.320	0.562	**0.909**
car-roundabout	0.509	**0.871**	0.552	0.630	0.640	0.500	0.808	0.833
car-shadow	0.645	0.759	0.449	**0.880**	0.589	0.538	0.698	0.786
car-turn	0.833	0.820	0.805	0.621	0.806	0.611	**0.851**	0.847
cows	**0.883**	0.562	0.833	0.799	0.337	0.623	0.791	0.814
dance-jump	0.718	0.341	0.303	0.065	**0.748**	0.291	0.598	0.678
dance-twirl	0.347	0.452	0.366	0.366	0.380	0.372	0.453	**0.786**
dog	0.809	0.753	0.786	0.331	0.692	0.566	0.708	**0.831**
dog-agility	**0.652**	0.193	0.138	0.110	0.132	0.055	0.280	0.050
drift-chicane	0.324	0.313	0.722	**0.758**	0.188	0.244	0.667	0.642
drift-straight	0.473	0.344	0.431	0.575	0.194	0.268	**0.683**	0.303
drift-turn	0.154	0.615	0.412	**0.638**	0.255	0.349	0.533	0.446
elephant	0.518	0.494	0.760	0.689	0.675	0.510	0.824	**0.851**
flamingo	0.539	0.783	0.731	0.794	0.692	0.570	0.817	**0.854**
goat	0.010	0.074	**0.793**	0.736	0.705	0.257	0.554	0.185
hike	0.918	0.878	0.756	0.603	0.895	0.683	0.889	**0.930**
hockey	0.810	0.817	0.674	0.713	0.515	0.566	0.468	**0.875**
horsejump-high	**0.834**	0.830	0.364	0.734	0.370	0.568	0.578	0.795
horsejump-low	0.651	**0.743**	0.705	0.682	0.630	0.388	0.526	0.740
kite-surf	0.453	0.357	0.501	0.419	**0.585**	0.193	0.272	0.135
kite-walk	**0.813**	0.447	0.052	0.597	0.197	0.725	0.649	0.691
libby	**0.635**	0.169	0.073	0.050	0.611	0.470	0.507	0.087
lucia	0.876	0.840	0.669	0.417	0.847	0.706	0.644	**0.913**
mallard-fly	**0.617**	0.380	0.293	0.033	0.585	0.227	0.601	0.144
mallard-water	0.761	0.245	0.190	0.045	**0.785**	0.085	0.087	0.045
motocross-bumps	0.614	0.603	0.502	0.466	0.689	0.351	0.617	**0.787**
motocross-jump	0.251	0.245	0.338	**0.618**	0.288	0.491	0.602	0.395
motorbike	0.714	0.387	0.723	0.737	0.572	0.335	0.558	**0.766**
paragliding	0.880	0.890	0.816	0.933	0.861	0.568	0.725	**0.933**
paragliding-launch	0.628	0.591	0.555	0.513	0.559	0.539	0.506	**0.636**
parkour	**0.901**	0.146	0.345	0.295	0.410	0.392	0.458	0.148
rhino	0.682	0.520	0.846	**0.902**	0.675	0.685	0.776	0.571
rollerblade	0.814	0.406	0.566	0.801	0.510	0.141	0.318	**0.845**
scooter-black	0.162	**0.759**	0.435	0.579	0.502	0.348	0.522	0.622
scooter-gray	0.586	0.327	0.357	0.345	0.363	0.421	0.325	**0.719**
soapbox	0.634	**0.832**	0.294	0.672	0.757	0.332	0.410	0.787
soccerball	0.829	0.242	0.350	0.370	**0.878**	0.378	0.843	0.809
stroller	**0.850**	0.619	0.720	0.678	0.759	0.466	0.580	0.429
surf	0.775	0.273	0.464	0.770	**0.893**	0.312	0.475	0.681
swing	**0.851**	0.533	0.413	0.622	0.710	0.569	0.431	0.804
tennis	**0.871**	0.494	0.196	0.590	0.762	0.480	0.388	0.820
train	0.729	**0.903**	0.876	0.887	0.450	0.620	0.831	0.868
Average	**0.641**	0.514	0.501	0.543	0.569	0.426	0.575	0.625
Best	13	5	1	5	5	0	3	18

Table 3: Jaccard (Recall)

	NLC [1]	CVOS [8]	TRC [2]	MSG [4]	KEY [3]	SAL [9]	FST [5]	Ours
bear	**1.000**	0.938	**1.000**	**1.000**	**1.000**	0.738	**1.000**	**1.000**
blackswan	**1.000**	0.042	0.979	0.708	**1.000**	0.000	**1.000**	0.000
bmx-bumps	**0.773**	0.500	0.398	0.307	0.182	0.148	0.239	0.466
bmx-trees	0.000	0.179	0.038	0.244	0.000	0.000	0.064	**0.295**
boat	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
breakdance	**0.976**	0.207	0.073	0.293	0.756	0.171	0.390	0.439
breakdance-flare	**1.000**	0.333	0.145	0.000	0.768	0.362	0.783	**1.000**
bus	0.718	0.705	0.731	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
camel	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.000	0.636	**1.000**
car-roundabout	0.616	**1.000**	0.575	0.644	0.849	0.521	**1.000**	**1.000**
car-shadow	0.763	**1.000**	0.105	**1.000**	0.632	0.658	0.974	**1.000**
car-turn	**1.000**	**1.000**	0.923	0.654	**1.000**	0.808	**1.000**	**1.000**
cows	**1.000**	0.686	**1.000**	**1.000**	0.392	**1.000**	**1.000**	**1.000**
dance-jump	**1.000**	0.431	0.328	0.000	**1.000**	0.052	0.793	**1.000**
dance-twirl	0.034	0.636	0.250	0.386	0.295	0.000	0.375	**1.000**
dog	**1.000**	0.810	**1.000**	0.448	**1.000**	0.828	**1.000**	**1.000**
dog-agility	**1.000**	0.087	0.000	0.000	0.000	0.000	0.217	0.000
drift-chicane	0.000	0.080	0.840	**1.000**	0.000	0.000	0.840	0.840
drift-straight	0.521	0.333	0.583	0.646	0.083	0.104	**0.979**	0.271
drift-turn	0.000	**0.790**	0.290	0.726	0.226	0.048	0.500	0.258
elephant	0.615	0.615	**1.000**	**1.000**	**1.000**	0.538	**1.000**	**1.000**
flamingo	0.372	0.974	**1.000**	**1.000**	**1.000**	0.885	**1.000**	**1.000**
goat	0.000	0.000	**1.000**	**1.000**	**1.000**	0.000	0.943	0.000
hike	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
hockey	**1.000**	**1.000**	**1.000**	0.973	0.630	0.877	0.342	**1.000**
horsejump-high	**1.000**	**1.000**	0.479	**1.000**	0.292	0.688	0.708	**1.000**
horsejump-low	0.897	0.983	**1.000**	**1.000**	**1.000**	0.103	0.776	**1.000**
kite-surf	0.188	0.562	0.583	0.292	**0.938**	0.000	0.021	0.000
kite-walk	**1.000**	0.500	0.000	0.949	0.295	**1.000**	**1.000**	0.833
libby	0.660	0.191	0.000	0.000	**0.745**	0.596	0.489	0.000
lucia	**1.000**	**1.000**	0.662	0.176	**1.000**	**1.000**	0.868	**1.000**
mallard-fly	**0.632**	0.456	0.338	0.000	0.588	0.015	0.618	0.000
mallard-water	**1.000**	0.269	0.000	0.000	**1.000**	0.000	0.000	0.000
motocross-bumps	0.741	0.741	0.552	0.603	0.793	0.069	0.707	**1.000**
motocross-jump	0.000	0.316	0.263	0.658	0.289	0.421	**0.816**	0.237
motorbike	**1.000**	0.512	**1.000**	**1.000**	0.488	0.220	0.732	**1.000**
paragliding	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.544	0.794	**1.000**
paragliding-launch	0.654	0.615	0.641	0.564	0.615	0.577	0.487	**0.667**
parkour	**1.000**	0.143	0.133	0.276	0.255	0.224	0.469	0.000
rhino	**1.000**	0.625	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.966
rollerblade	**1.000**	0.303	0.818	**1.000**	0.515	0.000	0.000	**1.000**
scooter-black	0.000	**1.000**	0.317	0.463	0.683	0.122	0.439	0.732
scooter-gray	0.822	0.466	0.425	0.438	0.192	0.233	0.260	**1.000**
soapbox	0.753	**1.000**	0.000	0.691	**1.000**	0.082	0.351	**1.000**
soccerball	0.913	0.283	0.370	0.391	**1.000**	0.239	**1.000**	0.913
stroller	**1.000**	0.775	**1.000**	0.989	**1.000**	0.303	0.719	0.135
surf	0.906	0.000	0.396	0.811	0.925	0.057	0.566	**0.943**
swing	**1.000**	0.655	0.638	0.724	**1.000**	0.793	0.483	**1.000**
tennis	**1.000**	0.324	0.147	0.735	0.809	0.397	0.221	**1.000**
train	**1.000**	0.987	**1.000**	**1.000**	0.321	0.885	**1.000**	**1.000**
Average	**0.731**	0.581	0.560	0.636	0.671	0.386	0.652	0.700
Best	28	13	16	18	23	7	17	31

Table 4: Boundary (F), mean

	NLC [1]	CVOS [8]	TRC [2]	MSG [4]	KEY [3]	SAL [9]	FST [5]	Ours
bear	0.850	0.845	0.832	0.781	0.775	0.495	0.860	**0.869**
blackswan	**0.820**	0.695	0.654	0.700	0.787	0.430	0.736	0.411
bmx-bumps	**0.734**	0.409	0.325	0.410	0.453	0.313	0.349	0.448
bmx-trees	0.330	0.118	0.189	0.263	0.366	0.206	0.348	**0.658**
boat	0.036	0.108	0.403	**0.485**	0.000	0.264	0.197	0.467
breakdance	**0.661**	0.191	0.121	0.231	0.463	0.300	0.411	0.382
breakdance-flare	0.808	0.335	0.301	0.230	0.585	0.512	0.694	**0.866**
bus	0.406	0.535	0.542	0.657	0.635	0.570	0.584	**0.800**
camel	0.719	0.873	0.698	0.629	0.437	0.432	0.590	**0.883**
car-roundabout	0.250	**0.678**	0.451	0.602	0.362	0.301	0.625	0.592
car-shadow	0.546	0.617	0.474	**0.858**	0.459	0.441	0.540	0.599
car-turn	0.634	0.703	**0.741**	0.677	0.632	0.485	0.731	0.658
cows	**0.807**	0.499	0.721	0.621	0.293	0.499	0.681	0.755
dance-jump	0.567	0.282	0.272	0.038	**0.569**	0.262	0.462	0.540
dance-twirl	0.365	0.444	0.376	0.325	0.317	0.301	0.471	**0.645**
dog	0.707	**0.761**	0.695	0.304	0.633	0.418	0.659	0.611
dog-agility	**0.551**	0.262	0.122	0.076	0.095	0.102	0.265	0.130
drift-chicane	0.312	0.397	0.823	**0.886**	0.192	0.206	0.731	0.726
drift-straight	0.385	0.330	0.408	**0.509**	0.053	0.167	0.470	0.170
drift-turn	0.185	**0.480**	0.310	0.459	0.018	0.231	0.442	0.301
elephant	0.251	0.359	0.546	0.505	0.324	0.231	0.569	**0.682**
flamingo	0.610	**0.806**	0.663	0.776	0.589	0.621	0.763	0.805
goat	0.133	0.241	**0.724**	0.657	0.552	0.187	0.400	0.376
hike	**0.943**	0.922	0.804	0.702	0.925	0.691	0.918	0.938
hockey	0.808	0.789	0.651	0.761	0.560	0.559	0.584	**0.889**
horsejump-high	**0.881**	0.841	0.405	0.748	0.392	0.613	0.621	0.824
horsejump-low	0.659	0.709	0.672	0.637	0.533	0.419	0.490	**0.722**
kite-surf	0.448	0.241	0.422	**0.521**	0.504	0.368	0.346	0.347
kite-walk	0.662	0.438	0.014	0.577	0.128	0.526	0.561	**0.791**
libby	**0.748**	0.185	0.086	0.118	0.730	0.529	0.718	0.231
lucia	0.872	0.801	0.663	0.491	0.819	0.691	0.568	**0.906**
mallard-fly	**0.660**	0.391	0.332	0.019	0.631	0.293	0.633	0.259
mallard-water	0.692	0.254	0.225	0.000	**0.733**	0.115	0.079	0.060
motocross-bumps	0.560	0.567	0.497	0.466	**0.674**	0.300	0.610	0.591
motocross-jump	0.303	0.186	0.307	0.393	0.237	0.388	**0.453**	0.339
motorbike	0.571	0.380	0.541	0.594	0.726	0.391	0.585	**0.754**
paragliding	0.744	0.744	0.724	**0.909**	0.681	0.541	0.675	0.857
paragliding-launch	0.243	0.182	0.157	0.196	0.253	0.169	0.185	**0.286**
parkour	**0.916**	0.158	0.421	0.401	0.374	0.359	0.478	0.231
rhino	0.431	0.469	0.739	**0.826**	0.429	0.487	0.634	0.467
rollerblade	**0.868**	0.475	0.687	0.822	0.351	0.211	0.411	0.784
scooter-black	0.228	0.557	0.304	**0.565**	0.420	0.257	0.395	0.479
scooter-gray	0.467	0.212	0.266	0.272	0.367	0.333	0.321	**0.564**
soapbox	0.658	**0.754**	0.389	0.633	0.719	0.307	0.355	0.674
soccerball	0.855	0.262	0.377	0.401	**0.924**	0.355	0.900	0.849
stroller	**0.874**	0.606	0.691	0.662	0.751	0.417	0.558	0.485
surf	0.673	0.515	0.637	0.804	**0.820**	0.395	0.445	0.585
swing	**0.778**	0.493	0.417	0.611	0.614	0.502	0.491	0.758
tennis	**0.927**	0.547	0.301	0.670	0.818	0.530	0.567	0.853
train	0.521	**0.831**	0.766	0.770	0.464	0.440	0.660	0.735
Average	**0.593**	0.490	0.478	0.525	0.503	0.383	0.536	**0.593**
Best	14	6	2	8	5	0	1	14

Table 5: F (boundary) recall

	NLC [1]	CVOS [8]	TRC [2]	MSG [4]	KEY [3]	SAL [9]	FST [5]	Ours
bear	**1.000**	0.938	**1.000**	**1.000**	**1.000**	0.662	**1.000**	**1.000**
blackswan	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.062	**1.000**	0.000
bmx-bumps	**0.795**	0.523	0.170	0.477	0.523	0.250	0.364	0.477
bmx-trees	0.179	0.192	0.167	0.308	0.115	0.000	0.154	**0.962**
boat	0.000	0.000	0.000	**0.247**	0.000	0.000	0.000	0.233
breakdance	**0.951**	0.220	0.110	0.293	0.317	0.000	0.049	0.049
breakdance-flare	**1.000**	0.348	0.130	0.000	0.855	0.594	0.884	**1.000**
bus	0.397	0.513	0.500	0.551	**1.000**	0.808	0.667	**1.000**
camel	**1.000**	**1.000**	**1.000**	0.955	0.125	0.091	0.773	**1.000**
car-roundabout	0.000	**1.000**	0.137	0.863	0.055	0.000	0.904	0.808
car-shadow	0.816	0.842	0.368	**1.000**	0.579	0.184	0.632	0.974
car-turn	**1.000**	0.936	0.987	0.936	0.808	0.449	**1.000**	**1.000**
cows	**1.000**	0.686	**1.000**	0.961	0.392	0.500	**1.000**	**1.000**
dance-jump	**0.828**	0.328	0.121	0.000	**0.828**	0.000	0.259	0.776
dance-twirl	0.114	0.614	0.091	0.318	0.000	0.011	0.466	**1.000**
dog	**1.000**	0.948	**1.000**	0.086	0.931	0.121	**1.000**	0.948
dog-agility	**0.652**	0.000	0.000	0.000	0.000	0.000	0.000	0.000
drift-chicane	0.040	0.380	0.840	**1.000**	0.000	0.000	0.900	**1.000**
drift-straight	0.333	0.167	0.458	**0.604**	0.000	0.000	0.458	0.000
drift-turn	0.000	**0.645**	0.194	0.339	0.000	0.000	0.387	0.000
elephant	0.000	0.462	0.795	0.615	0.077	0.000	0.821	**1.000**
flamingo	**1.000**	**1.000**	**1.000**	**1.000**	0.872	0.923	**1.000**	**1.000**
goat	0.000	0.023	**1.000**	0.989	0.568	0.000	0.057	0.000
hike	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.936	**1.000**	**1.000**
hockey	**1.000**	**1.000**	0.904	**1.000**	**1.000**	0.808	0.932	**1.000**
horsejump-high	**1.000**	**1.000**	0.500	0.979	0.354	0.854	0.875	**1.000**
horsejump-low	0.914	0.966	**1.000**	**1.000**	0.621	0.155	0.397	**1.000**
kite-surf	0.167	0.125	0.146	**0.625**	0.479	0.042	0.000	0.000
kite-walk	**1.000**	0.449	0.000	0.718	0.000	0.590	0.782	**1.000**
libby	0.851	0.255	0.000	0.000	**0.936**	0.660	**0.936**	0.000
lucia	**1.000**	**1.000**	0.868	0.382	**1.000**	0.985	0.750	**1.000**
mallard-fly	**0.750**	0.456	0.353	0.000	0.647	0.000	0.603	0.000
mallard-water	**1.000**	0.231	0.026	0.000	**1.000**	0.000	0.000	0.000
motocross-bumps	0.690	0.655	0.466	0.517	0.879	0.034	0.655	**0.914**
motocross-jump	0.132	0.158	0.158	0.447	0.184	0.316	**0.500**	0.105
motorbike	0.707	0.512	0.659	0.659	**1.000**	0.220	0.878	**1.000**
paragliding	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.456	0.779	**1.000**
paragliding-launch	0.038	0.013	0.000	0.000	0.038	0.000	0.000	**0.077**
parkour	**1.000**	0.184	0.439	0.347	0.235	0.224	0.500	0.000
rhino	0.011	0.625	0.977	**1.000**	0.000	0.398	**1.000**	0.273
rollerblade	**1.000**	0.576	**1.000**	**1.000**	0.121	0.000	0.121	**1.000**
scooter-black	0.000	**0.707**	0.122	0.537	0.195	0.000	0.122	0.488
scooter-gray	0.329	0.082	0.233	0.164	0.068	0.014	0.000	**0.767**
soapbox	0.763	**1.000**	0.186	0.691	**1.000**	0.021	0.000	0.990
soccerball	0.913	0.283	0.391	0.391	**1.000**	0.087	**1.000**	0.913
stroller	**1.000**	0.775	**1.000**	**1.000**	**1.000**	0.124	0.618	0.461
surf	0.887	0.830	0.642	**0.981**	0.887	0.283	0.453	0.906
swing	**1.000**	0.655	0.569	0.759	0.983	0.500	0.517	**1.000**
tennis	**1.000**	0.618	0.265	0.926	0.882	0.632	0.735	**1.000**
train	0.641	0.987	**1.000**	**1.000**	0.154	0.218	**1.000**	**1.000**
Average	0.658	0.578	0.519	0.613	0.534	0.264	0.579	**0.662**
Best	25	12	13	17	14	0	12	26

Table 6: Temporal Stability (T) mean. Note that nans appear as a result of running the code provided by [6].

	NLC [1]	CVOS [8]	TRC [2]	MSG [4]	KEY [3]	SAL [9]	FST [5]	Ours
bear	0.151	0.059	0.272	0.156	**0.068**	0.448	0.227	0.106
blackswan	0.110	0.058	0.219	0.145	**0.048**	0.660	0.225	0.069
bmx-bumps	nan	nan	nan	nan	nan	nan	nan	nan
bmx-trees	nan	nan	nan	nan	nan	nan	nan	nan
boat	0.557	1.213	0.350	0.163	**0.015**	0.382	0.177	0.485
breakdance	nan	nan	nan	nan	nan	nan	nan	nan
breakdance-flare	nan	nan	nan	nan	nan	nan	nan	nan
bus	0.178	0.146	0.194	0.154	**0.143**	0.369	0.270	0.244
camel	0.232	**0.123**	0.173	0.129	0.138	0.380	0.161	0.127
car-roundabout	0.352	**0.064**	0.382	0.291	0.160	0.536	0.242	0.152
car-shadow	0.361	**0.180**	0.452	0.206	0.314	0.793	0.353	0.207
car-turn	0.236	0.118	0.201	0.204	0.108	0.566	0.214	**0.100**
cows	0.147	**0.133**	0.148	0.195	0.412	0.511	0.281	0.133
dance-jump	0.318	0.459	0.576	**0.000**	0.214	0.586	0.241	0.316
dance-twirl	nan	nan	nan	nan	nan	nan	nan	nan
dog	nan	nan	nan	nan	nan	nan	nan	nan
dog-agility	nan	nan	nan	nan	nan	nan	nan	nan
drift-chicane	nan	nan	nan	nan	nan	nan	nan	nan
drift-straight	0.597	0.828	0.683	0.450	**0.291**	0.950	0.482	0.488
drift-turn	0.850	0.334	0.475	0.403	**0.150**	1.002	0.258	0.433
elephant	0.315	0.118	0.236	0.236	**0.085**	0.426	0.139	0.152
flamingo	**0.138**	0.173	0.215	0.382	0.112	0.486	0.175	0.170
goat	nan	nan	nan	nan	nan	nan	nan	nan
hike	0.158	0.125	0.230	0.251	**0.117**	0.412	0.247	0.132
hockey	0.228	**0.159**	0.228	0.211	0.162	0.377	0.276	0.238
horsejump-high	nan	nan	nan	nan	nan	nan	nan	nan
horsejump-low	nan	nan	nan	nan	nan	nan	nan	nan
kite-surf	0.942	0.249	0.432	0.507	**0.234**	0.568	0.404	0.197
kite-walk	0.221	0.127	**0.002**	0.328	0.366	0.356	0.301	0.427
libby	nan	nan	nan	nan	nan	nan	nan	nan
lucia	nan	nan	nan	nan	nan	nan	nan	nan
mallard-fly	nan	nan	nan	nan	nan	nan	nan	nan
mallard-water	0.242	0.394	0.641	0.000	**0.184**	1.070	0.230	0.596
motocross-bumps	0.542	**0.327**	0.566	0.481	0.344	0.903	0.329	0.415
motocross-jump	nan	nan	nan	nan	nan	nan	nan	nan
motorbike	nan	nan	nan	nan	nan	nan	nan	nan
paragliding	nan	nan	nan	nan	nan	nan	nan	nan
paragliding-launch	0.257	0.273	0.347	0.331	0.213	0.602	0.703	**0.207**
parkour	nan	nan	nan	nan	nan	nan	nan	nan
rhino	0.188	0.064	0.153	0.093	**0.056**	0.390	0.138	0.100
rollerblade	nan	nan	nan	nan	nan	nan	nan	nan
scooter-black	0.761	**0.320**	0.577	0.364	0.514	0.790	0.475	0.694
scooter-gray	nan	nan	nan	nan	nan	nan	nan	nan
soapbox	0.389	**0.154**	0.412	0.214	0.161	0.613	0.158	0.211
soccerball	nan	nan	nan	nan	nan	nan	nan	nan
stroller	0.206	**0.116**	0.235	0.346	0.128	0.546	0.184	0.294
surf	0.364	0.168	0.375	0.223	**0.086**	1.093	0.398	0.323
swing	nan	nan	nan	nan	nan	nan	nan	nan
tennis	nan	nan	nan	nan	nan	nan	nan	nan
train	0.575	0.056	0.110	**0.070**	0.270	0.396	0.159	0.109
Average	0.356	0.242	0.329	0.242	**0.189**	0.600	0.276	0.264
Best	1	9	1	2	12	0	0	2

[8] Brian Taylor, Vasiliy Karasev, and Stefano Soatto. Causal video object segmentation from persistence of occlusions. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, 2015.

[9] Wenguan Wang, Jianbing Shen, and F. Porikli. Saliency-aware geodesic video object segmentation. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.