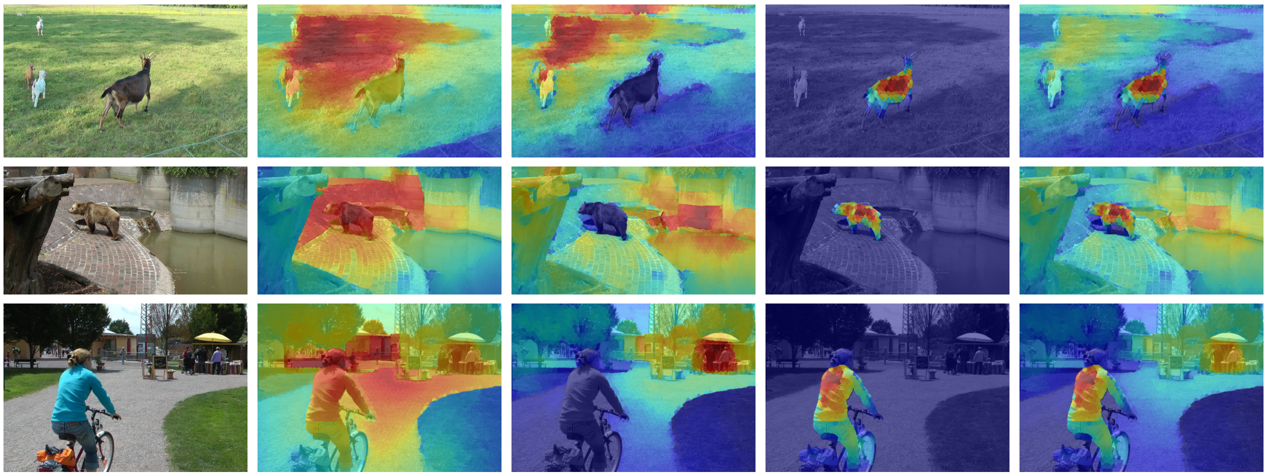
Candidate Proposals Pruning

Section 5.2 of the paper explains our approach to rebalance the set of proposals by selecting only those with higher discriminative power, i.e. those that do not overlap both with foreground and background. The original and newly generated distribution of proposals is visualized in Figure 1.



(a) Source (b) GOP (c) Background (d) Foreground (e) Resampled

Figure 1: Left to right: distribution of object proposals on arbitrary frames. Colormaps are computed as the sum of the object proposals normalized to range [0,1]. Starting from a source image (a) we generate a set of geodesic object proposals with resulting distribution over the image (b). Note that many proposals fall on background regions. An SVM classifier (Section 5.1) resamples the set of proposals into foreground (c) and background (d). The new set (e), corresponding to the union of (c) and (d), is now balanced and contains proposals with higher discriminative power (Section 5.2).

Evaluation

In this section we provide additional comparisons of the proposed method against several state-of-the-art approaches on the *Freiburg-Berkeley Motion Segmentation Dataset* (FBMS [1]). The dataset is split into FBMS-Training (Table 1,2) and FBMS-Test (Table 3,4). It consists of 59 videos in total. Due to running-time and memory constraints of the prior approaches that we compare to, we limit the length of video to 75 frames. Furthermore sequences characterized by slow motion have been accelerated temporally by subsampling frames. The speed-up factor is reported next to the sequence name.

References

[1] T. Brox and J. Malik, “Object segmentation by long term analysis of point trajectories,” in *Proc. ECCV*, 2010.

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[3] A. Papazoglou and V. Ferrari, “Fast object segmentation in unconstrained video,” in *Proc. ICCV*, 2013.

[4] D. Zhang, O. Javed, and M. Shah, “Video object segmentation through spatially accurate and temporally dense extraction of primary object regions,” in *Proc. CVPR*, 2013.

[5] A. Faktor and M. Irani, “Video segmentation by non-local consensus voting,” in *Proc. BMVC*, 2014.

Sequence		FCP	CRF	SVM	SEA [2]	FST [3]	DAG [4]	NLC [5]
bear01	3x	0.85	0.71	0.74	0.62	0.75	0.79	**(0.90)**
bear02	3x	0.84	0.54	0.70	0.77	**(0.85)**	0.15	0.42
cars2	1x	**(0.90)**	0.71	0.47	0.79	0.00	0.59	0.43
cars3	1x	0.87	0.81	0.31	0.78	**(0.89)**	0.00	0.39
cars6	1x	**(0.87)**	0.60	0.68	0.77	0.77	0.74	0.76
cars7	1x	**(0.84)**	0.43	0.28	0.82	0.72	0.75	0.74
cars8	1x	**(0.93)**	0.66	0.70	0.77	0.84	0.79	0.46
cars9	1x	**(0.80)**	0.61	0.38	0.75	0.45	0.00	0.31
cats02	3x	0.70	0.50	0.67	0.73	**(0.77)**	0.35	0.59
cats04	3x	0.75	0.00	0.11	**(0.82)**	0.00	0.00	0.29
cats05	3x	0.13	0.00	**(0.50)**	0.17	0.17	0.06	0.19
cats07	3x	0.81	0.58	0.43	0.72	0.00	0.00	**(0.89)**
ducks01	3x	0.00	0.00	0.00	0.00	0.00	0.00	**(0.00)**
horses01	3x	0.83	0.85	0.76	0.70	0.73	0.00	**(0.90)**
horses03	3x	0.38	0.64	0.54	0.72	0.72	0.69	**(0.76)**
horses06	3x	0.74	0.79	0.63	0.47	0.81	0.58	**(0.81)**
lion02	3x	**(0.46)**	0.28	0.27	0.30	0.41	0.00	0.36
marple1	3x	0.75	0.73	**(0.84)**	0.76	0.28	0.73	0.09
marple10	3x	0.09	0.07	0.13	0.26	0.07	**(0.30)**	0.16
marple11	3x	0.56	0.13	0.38	0.67	0.02	0.51	**(0.75)**
marple13	3x	0.71	0.73	0.71	0.71	0.61	0.38	**(0.81)**
marple3	3x	0.82	**(0.86)**	0.81	0.79	0.32	0.72	0.08
marple5	3x	0.78	0.22	0.50	**(0.81)**	0.71	0.65	0.69
marple8	1x	**(0.75)**	0.60	0.47	0.62	0.71	0.02	0.44
meerkats01	3x	**(0.59)**	0.21	0.39	0.40	0.59	0.37	0.37
people04	3x	**(0.86)**	0.83	0.85	0.83	0.49	0.79	0.55
people05	3x	**(0.79)**	0.56	0.61	0.64	0.62	0.61	0.45
rabbits01	3x	0.82	0.71	0.14	0.59	**(0.88)**	0.17	0.27
rabbits05	3x	0.88	0.82	0.49	0.86	0.84	**(0.88)**	0.85
Average (29)		**(0.69)**	0.52	0.50	0.64	0.52	0.40	0.51
Unsupervised		N	N	N	N	Y	Y	Y

Table 1: *Intersection-over-union* comparisons on the FBMS-Training dataset. The columns SVM and CRF correspond to the results obtained using either only our SVM-based classification, or only our CRF-based labeling, respectively. Our full approach FCP combing SVM and CRF substantially outperforms the individual components and compares favorably to several state-of-the-art approaches. Note that results on this table are biased by instances of unsupervised methods that do not detect the dominant object. For a more informative comparison refer to Table 2.

Sequence	FCP	CRF	SVM	SEA [2]	FST [3]	DAG [4]	NLC [5]
bear01	0.85	0.71	0.74	0.62	0.75	0.79	**(0.90)**
bear02	0.84	0.54	0.70	0.77	**(0.85)**	0.15	0.42
cars6	**(0.87)**	0.60	0.68	0.77	0.77	0.74	0.76
cars7	**(0.84)**	0.43	0.28	0.82	0.72	0.75	0.74
cars8	**(0.93)**	0.66	0.70	0.77	0.84	0.79	0.46
cats02	0.70	0.50	0.67	0.73	**(0.77)**	0.35	0.59
horses03	0.38	0.64	0.54	0.72	0.72	0.69	**(0.76)**
horses06	0.74	0.79	0.63	0.47	0.81	0.58	**(0.81)**
marple1	0.75	0.73	**(0.84)**	0.76	0.28	0.73	0.09
marple13	0.71	0.73	0.71	0.71	0.61	0.38	**(0.81)**
marple3	0.82	**(0.86)**	0.81	0.79	0.32	0.72	0.08
marple5	0.78	0.22	0.50	**(0.81)**	0.71	0.65	0.69
meerkats01	**(0.59)**	0.21	0.39	0.40	0.59	0.37	0.37
people04	**(0.86)**	0.83	0.85	0.83	0.49	0.79	0.55
people05	**(0.79)**	0.56	0.61	0.64	0.62	0.61	0.45
rabbits01	0.82	0.71	0.14	0.59	**(0.88)**	0.17	0.27
rabbits05	0.88	0.82	0.49	0.86	0.84	**(0.88)**	0.85
Average (17)	**(0.77)**	0.62	0.61	0.71	0.68	0.60	0.56
Unsupervised	N	N	N	N	Y	Y	Y

Table 2: *Intersection-over-union* comparisons on a subset of the FBMS-Training dataset. Sequences for which at least one of the unsupervised methods did not detect the object have been removed. The columns SVM and CRF correspond to the results obtained using either only our SVM-based classification, or only our CRF-based labeling, respectively.

Sequence		FCP	CRF	SVM	SEA [2]	FST [3]	DAG [4]	NLC [5]
camel01	1x	0.77	**(0.80)**	0.62	0.73	0.00	0.00	0.00
cars1	1x	0.69	0.80	0.68	**(0.83)**	0.82	0.10	0.27
cars10	1x	0.80	0.74	0.77	**(0.89)**	0.01	0.00	0.04
cars4	1x	**(0.85)**	0.21	0.44	0.50	0.84	0.00	0.22
cars5	1x	0.73	0.31	0.33	**(0.74)**	0.00	0.00	0.36
cats01	3x	**(0.83)**	0.68	0.76	0.62	0.80	0.34	0.71
cats03	3x	0.39	0.00	0.11	0.17	**(0.53)**	0.32	0.12
cats06	3x	0.48	0.13	0.48	**(0.70)**	0.10	0.44	0.59
dogs01	3x	0.55	0.22	0.39	0.38	0.53	**(0.56)**	0.54
dogs02	3x	**(0.79)**	0.60	0.60	0.71	0.00	0.73	0.37
farm01	3x	0.83	0.70	0.77	**(0.88)**	0.72	0.00	0.57
giraffes01	3x	0.64	0.65	0.61	**(0.75)**	0.13	0.00	0.55
goats01	3x	0.82	0.84	0.78	0.53	**(0.84)**	0.79	0.58
horses02	3x	0.61	0.49	0.50	0.50	0.00	**(0.78)**	0.31
horses04	3x	**(0.78)**	0.74	0.73	0.65	0.69	0.00	0.18
horses05	3x	**(0.77)**	0.66	0.47	0.69	0.34	0.44	0.38
lion01	3x	**(0.84)**	0.74	0.80	0.73	0.80	0.77	0.67
marple12	3x	0.61	0.46	0.45	**(0.77)**	0.69	0.10	0.59
marple2	3x	0.59	0.57	0.71	**(0.78)**	0.65	0.56	0.60
marple4	1x	**(0.88)**	0.73	0.87	0.69	0.15	0.45	0.19
marple6	3x	0.77	0.64	0.77	**(0.86)**	0.24	0.18	0.48
marple7	3x	0.65	0.64	0.65	**(0.72)**	0.51	0.20	0.08
marple9	3x	0.83	0.80	0.69	**(0.96)**	0.39	0.01	0.25
people03	1x	**(0.86)**	0.62	0.73	0.85	0.73	0.05	0.81
people1	1x	0.68	0.64	0.22	0.58	0.54	0.69	**(0.85)**
people2	1x	0.81	0.78	0.76	0.77	**(0.92)**	0.48	0.77
rabbits02	3x	0.66	0.11	0.33	0.42	0.65	0.32	**(0.71)**
rabbits03	3x	0.43	0.40	0.23	0.42	0.41	0.22	**(0.44)**
rabbits04	3x	0.29	0.00	0.12	0.23	**(0.38)**	0.12	0.20
tennis	3x	0.48	0.27	0.41	0.55	0.30	0.51	**(0.64)**
Average (30)		**(0.69)**	0.53	0.56	0.65	0.46	0.31	0.44
Unsupervised		N	N	N	N	Y	Y	Y

Table 3: *Intersection-over-union* of the FBMS-Test dataset. The columns SVM and CRF correspond to the results obtained using either only our SVM-based classification, or only our CRF-based labeling, respectively. Similarly to Table 1, our full approach FCP combing SVM and CRF substantially outperforms the individual components and compares favorably to several state-of-the-art approaches. Note that results on this table are biased by instances of unsupervised methods that do not detect the dominant object. For a more informative comparison refer to Table 4.

Sequence	FCP	CRF	SVM	SEA [2]	FST [3]	DAG [4]	NLC [5]
cars1	0.69	0.80	0.68	**(0.83)**	0.82	0.10	0.27
cats01	**(0.83)**	0.68	0.76	0.62	0.80	0.34	0.71
cats03	0.39	0.00	0.11	0.17	**(0.53)**	0.32	0.12
dogs01	0.55	0.22	0.39	0.38	0.53	**(0.56)**	0.54
goats01	0.82	0.84	0.78	0.53	**(0.84)**	0.79	0.58
horses05	**(0.77)**	0.66	0.47	0.69	0.34	0.44	0.38
lion01	**(0.84)**	0.74	0.80	0.73	0.80	0.77	0.67
marple2	0.59	0.57	0.71	**(0.78)**	0.65	0.56	0.60
marple4	**(0.88)**	0.73	0.87	0.69	0.15	0.45	0.19
marple6	0.77	0.64	0.77	**(0.86)**	0.24	0.18	0.48
people1	0.68	0.64	0.22	0.58	0.54	0.69	**(0.85)**
people2	0.81	0.78	0.76	0.77	**(0.92)**	0.48	0.77
rabbits02	0.66	0.11	0.33	0.42	0.65	0.32	**(0.71)**
rabbits03	0.43	0.40	0.23	0.42	0.41	0.22	**(0.44)**
rabbits04	0.29	0.00	0.12	0.23	**(0.38)**	0.12	0.20
tennis	0.48	0.27	0.41	0.55	0.30	0.51	**(0.64)**
Average (16)	**(0.65)**	0.51	0.53	0.58	0.56	0.43	0.51
Unsupervised	N	N	N	N	Y	Y	Y

Table 4: *Intersection-over-union* comparisons on a subset of the FBMS-Test dataset. Sequences for which at least one of the unsupervised methods did not detect the object have been removed. The columns SVM and CRF correspond to the results obtained using either only our SVM-based classification, or only our CRF-based labeling, respectively.