Supplementary Material

Adaptive Decontamination of the Training Set: A Unified Formulation for Discriminative Visual Tracking

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In this supplementary material of [3], we first prove the result $\alpha_k \to \rho_k$ in the case when $\mu \to 0$ (stated on page 4 in [3]). The derivation is performed in section 1. In section 2 we present the per-video and all attribute results on the OTB-2015 dataset [19]. Finally, section 3 contains per-video results on the Temple-Color dataset [14].

1. Derivation of $\alpha_k \to \rho_k$ When $\mu \to 0$

Here, we derive that the computed sample weights α_k converge to the prior weights ρ_k when the flexibility parameter μ is reduced in our joint formulation. That is, we derive that $\alpha_k \to \rho_k$ when $\mu \to 0$ for fixed model parameters $\theta \in \Omega$. Our joint optimization problem is given by (corresponds to eq. (3) in the paper),

$$\text{minimize} \quad J(\theta,\alpha) = \sum_{k=1}^{t} \alpha_k \sum_{j=1}^{n_k} L(\theta; x_{jk}, y_{jk}) + \frac{1}{\mu} \sum_{k=1}^{t} \frac{\alpha_k^2}{\rho_k} + \lambda R(\theta) \tag{1a}$$

$$\text{subject to} \quad \alpha_k \geq 0\,,\ k = 1, \dots, t \tag{1b}$$

$$\sum_{k=1}^{t} \alpha_k = 1. \tag{1c}$$

Here, the prior weights are positive $\rho_k > 0$ and sum up to one,

$$\sum_{k=1}^{t} \rho_k = 1 \tag{2}$$

We let the model parameters θ be fixed and define the total loss in frame k by,

$$L_k = \sum_{j=1}^{n_k} L(\theta; x_{jk}, y_{jk}). \tag{3}$$

Minimizing the joint formulation (1) with respect to the weights α_k is then equivalent to solving the following quadratic programming problem,

$$\text{minimize} \quad J_2(\alpha) = \sum_{k=1}^{t} L_k \alpha_k + \frac{1}{\mu} \sum_{k=1}^{t} \frac{\alpha_k^2}{\rho_k} \tag{4a}$$

$$\text{subject to} \quad \alpha_k \geq 0\,,\ k = 1, \dots, t \tag{4b}$$

$$\sum_{k=1}^{t} \alpha_k = 1. \tag{4c}$$

We temporarily ignore the inequality constraint (4b) and introduce Lagrange multipliers for the constraint (4c),

$$\mathcal{L}(\alpha,\eta) = \sum_{k=1}^{t} L_k \alpha_k + \frac{1}{\mu}\sum_{k=1}^{t} \frac{\alpha_k^2}{\rho_k} - \eta \cdot \left(\sum_{k=1}^{t} \alpha_k - 1\right). \tag{5}$$

Here, η denotes the Lagrange multiplier. Differentiation w.r.t. α_k gives,

$$\frac{\partial \mathcal{L}}{\partial \alpha_k} = L_k + \frac{2}{\mu}\frac{\alpha_k}{\rho_k} - \eta\,,\ k = 1,\dots,t. \tag{6}$$

The stationary point is computed by setting the partial derivatives to zero,

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \alpha_k} &= 0 \iff \\ \alpha_k &= \frac{\mu\eta}{2}\rho_k - \frac{\mu}{2} L_k \rho_k\,,\ k = 1,\dots,t\end{aligned} \tag{7}$$

The Lagrange multiplier η is computed by summing both sides of (7) over k and using (4c) and (2),

$$\begin{aligned}\sum_{k=1}^{t} \alpha_k &= \sum_{k=1}^{t}\left(\frac{\mu\eta}{2}\rho_k - \frac{\mu}{2}L_k\rho_k\right) \iff \\ 1 &= \frac{\mu\eta}{2} - \frac{\mu}{2}\sum_{k=1}^{t} L_k\rho_k \iff \\ \eta &= \frac{2}{\mu} + \sum_{k=1}^{t} L_k \rho_k.\end{aligned} \tag{8}$$

Using the result (8) in (7) gives,

$$\alpha_k = \rho_k + \frac{\mu}{2}\cdot\left(\rho_k \sum_{l=1}^{t} L_l \rho_l - L_k \rho_k\right) \tag{9}$$

From (9) it follows that $\alpha_k \to \rho_k$ when $\mu \to 0$. To show that the inequality constraint (4b) also holds in the limit $\mu \to 0$, we define the constant

$$\delta = \min_k \rho_k \cdot \left|\rho_k \sum_{l=1}^{t} L_l\rho_l - L_k\rho_k\right|^{-1}. \tag{10}$$

This choice ensures that $\alpha_k > 0$, $\forall k$ for $0 < \mu < \delta$. The inequality constraint (4b) is thus satisfied for $0 < \mu < \delta$. This proves that the limit $\mu \to 0$ of (9) is also the limit of the solution α_k of (4). Hence, $\alpha_k \to \rho_k$ in (4) when $\mu \to 0$.

2. Detailed Results on OTB-2015

We provide detailed results on OTB-2015 [19] with 100 videos. The videos and ground truth are available at `https://sites.google.com/site/benchmarkpami/`. Figure 1 contains the success plots for all 11 attributes. Table 2 shows the per-video overlap precision for all trackers.

3. Detailed Results on Temple-Color

We also report detailed results on the Temple-Color dataset [14] with 128 videos. The videos and ground truth are available at `http://www.dabi.temple.edu/~hbling/data/TColor-128/TColor-128.html`. The per-video overlap precision for all trackers in our comparison are reported in table 2.

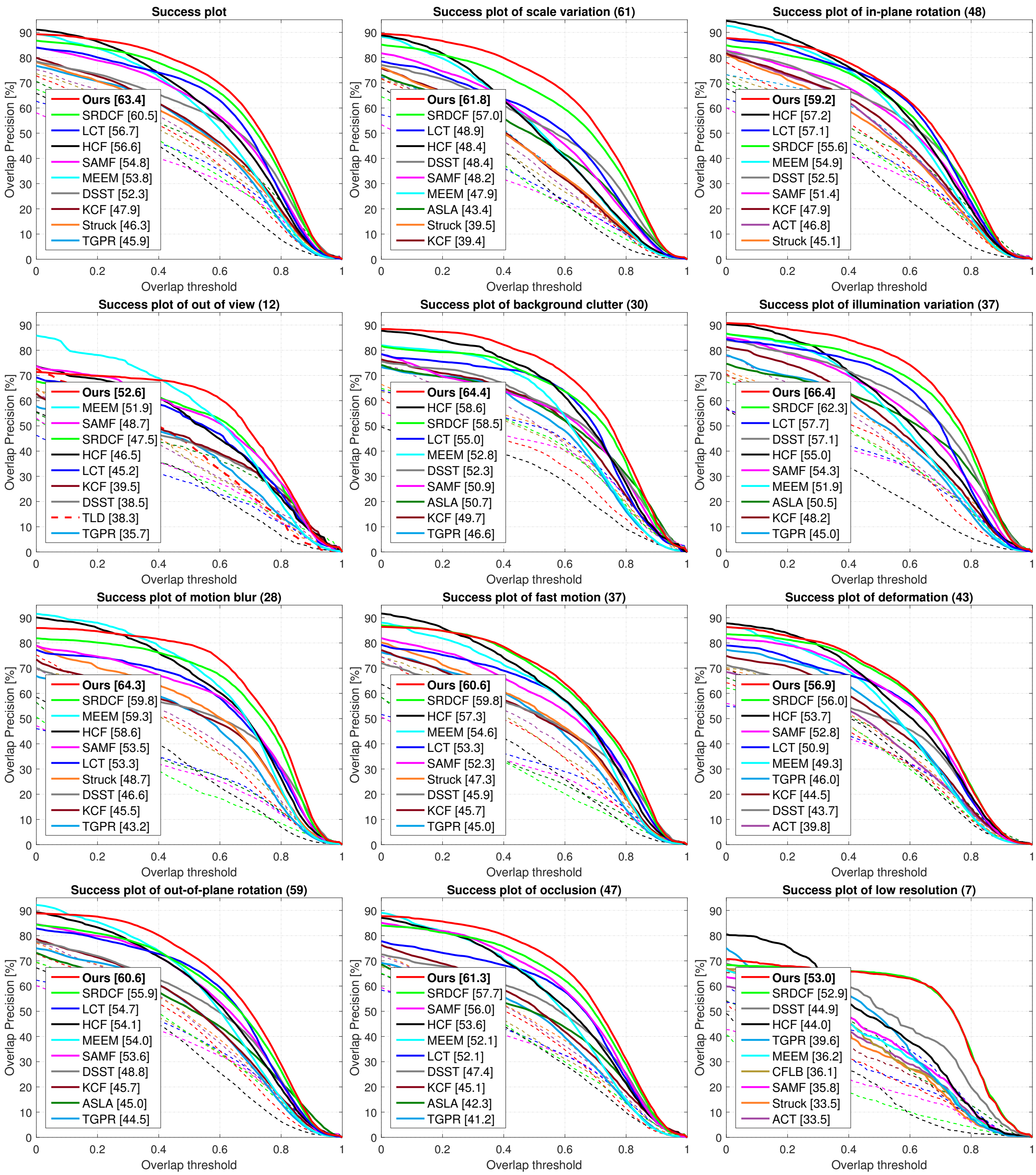

Figure 1. Success plots on OTB-2015 [19]. We show the total success plot (top-left) and the success plots for all 11 attributes. The title of each attribute plot contain the name of the attribute and the number of videos associated with it. The area-under-the-curve score is shown in the legend. For clarity, only the top 10 trackers in each plot are displayed in the legend. Our approach obtains the best results on all 11 attributes.

Video	EDFT[5]	LSHT[9]	DFT[18]	ASLA[11]	TLD[12]	Struck[8]	CFLB[6]	ACT[4]	TGPR[7]	KCF[10]	DSST[1]	SAMF[13]	DAT[17]	MEEM[20]	LCT[16]	HCF[15]	SRDCF[2]	**Ours**
Basketball	31	4.55	71.6	65.2	31.3	11	9.1	48.7	91.3	89.8	69.8	96.7	89.5	83	*99.2*	**99.9**	41.2	30.1
Biker	26.7	8.89	26.7	46.7	32.6	26.7	48.1	26.7	**87.4**	26.7	28.1	31.9	44.4	26.7	45.9	25.9	*48.9*	46.7
Bird1	26.7	4.41	26.2	2.45	0.49	15.4	0.98	2.45	**31.1**	6.37	6.62	5.64	*30.1*	4.41	**31.1**	19.9	6.37	5.64
Bird2	94.9	85.9	71.7	50.5	42.4	52.5	47.5	**99**	85.9	46.5	47.5	*98*	**99**	**99**	77.8	**99**	54.5	54.5
BlurBody	11.7	26	11.4	15	44	98.8	41.3	53.9	98.5	58.7	62.3	95.8	37.1	98.8	*99.4*	99.1	**100**	**100**
BlurCar1	1.48	1.21	7.68	2.29	13.6	*99.9*	50.4	69.9	94.5	**100**	98.8	**100**	1.48	**100**	**100**	99.7	*99.9*	*99.9*
BlurCar2	7.35	21.9	17.4	12.3	84.8	93.8	94.7	94.7	93.8	94.7	**100**	*99.8*	48.7	94.7	**100**	94.7	**100**	**100**
BlurCar3	5.6	30.8	11.8	12	93.6	**100**	56	32.8	93.3	*99.4*	**100**	**100**	25.2	**100**	**100**	**100**	**100**	**100**
BlurCar4	96.8	33.7	**100**	21.8	42.6	**100**	**100**	**100**	*99.7*	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
BlurFace	24.1	11.8	29	15	**100**	44	31.4	**100**	*99.8*	**100**	**100**	**100**	26	**100**	**100**	**100**	**100**	**100**
BlurOwl	4.28	9.83	10.8	11.4	63.9	98.6	94.1	20.8	13.6	22.8	22	23.1	**99.8**	*99*	89.4	96.5	98.6	97.1
Board	19.4	86.5	19.9	50.9	14.1	79.9	68.1	73.7	11.3	85.5	84.2	**97.1**	2.01	82.5	85.4	94.7	85.7	*95.7*
Bolt	1.71	32.6	4	1.43	17.7	2.29	2.29	**100**	1.43	94.3	**100**	*99.7*	96	88	98.9	98	1.43	1.43
Bolt2	0.683	52.9	0.683	0.683	0.683	4.44	34.5	27	0.683	0.683	1.02	0.683	*63.5*	0.683	0.683	**88.4**	1.02	1.02
Box	16.4	33.7	30.9	57.2	61.6	58.7	32.5	33.6	35.8	35.7	39.6	*92.9*	5.86	83.5	8.96	33.7	41.5	**96**
Boy	98	50.7	48.3	43.5	82.9	97.5	98.5	95	99	99.2	**100**	**100**	96.3	99.2	**100**	99	**100**	*99.7*
Car1	5.39	5.39	5.39	*81.6*	38.7	5.39	6.27	5.39	7.75	5.39	60.5	36.3	5.39	5.39	20.8	5.39	**100**	**100**
Car2	**100**	98.2	13.4	**100**	**100**	**100**	*99.7*	**100**	9.2	**100**	**100**	**100**	7.34	**100**	**100**	**100**	**100**	**100**
Car24	17.3	17.2	7.19	**100**	*99*	17	17.3	17.3	18.3	17.3	17.3	15.7	16.4	17.2	85.3	17.3	**100**	**100**
Car4	27.5	27.6	25.8	**100**	24	39.9	25	27.6	40.7	36.4	**100**	**100**	0.152	26.4	*98.9*	39.6	**100**	**100**
CarDark	68.4	60.6	33.6	**100**	53.7	**100**	97.7	**100**	**100**	69.2	**100**	58.3	2.04	**100**	*99.2*	88.3	**100**	**100**
CarScale	44.8	44.8	44.8	71	68.7	43.3	44.8	44.8	40.5	44.4	*84.5*	59.9	44.4	44.8	79	44.4	84.1	**85.3**
ClifBar	29.7	28.2	23.9	37.7	42.2	21.6	25.6	31.8	9.32	30.1	**88.6**	25.6	29.4	60.6	70.3	41.7	44.1	*85*
Coke	14.4	49.8	8.59	14.4	57.4	*94.2*	70.4	64.3	88	72.2	83.2	79.7	47.8	**95.5**	91.4	91.4	63.6	65.6
Couple	21.4	9.29	8.57	22.1	22.9	60.7	63.6	10.7	58.6	24.3	10.7	45.7	63.6	75.7	52.9	74.3	*82.1*	**92.9**
Coupon	**100**	**100**	**100**	**100**	38.8	**100**	**100**	**100**	37.9	**100**	**100**	**100**	*99.1*	39.4	**100**	**100**	**100**	**100**
Crossing	75	40	64.2	**100**	45.8	95.8	*98.3*	88.3	*98.3*	95	**100**	**100**	97.5	*98.3*	**100**	95	**100**	**100**
Crowds	91	54.3	91	89	89	68.2	90.8	96.8	86.7	**100**	90.2	*99.7*	1.73	83.8	96.2	99.4	95.1	89.6
Dancer	89.3	88.4	89.8	**100**	88.9	85.8	89.3	90.7	*91.6*	*91.6*	**100**	**100**	73.8	80.9	**100**	*91.6*	**100**	**100**
Dancer2	**100**	**100**	**100**	**100**	84	**100**	**100**	**100**	**100**	**100**	**100**	**100**	*98.7*	*98.7*	**100**	**100**	**100**	**100**
David	55.4	28.2	23.4	94.9	61.1	23.6	23.8	62.6	80.5	62.2	**100**	95.8	39.1	62.6	92.8	60.1	*98.9*	97.5
David2	**100**	**100**	54.2	83.6	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	11	**100**	**100**	*92.2*	**100**	**100**
David3	87.3	74.6	74.2	49.6	32.1	33.7	53.6	87.7	98.8	*99.2*	52.8	**100**	**100**	94	98	**100**	**100**	96.4
Deer	63.4	4.23	31	4.23	28.2	**100**	**100**	**100**	**100**	81.7	78.9	*88.7*	9.86	**100**	81.7	**100**	**100**	**100**
Diving	**18.6**	16.7	**18.6**	17.7	16.7	*18.1*	**18.6**	**18.6**	*18.1*	**18.6**	*18.1*	**18.6**	**18.6**	17.2	**18.6**	**18.6**	**18.6**	*18.1*
Dog	19.7	15	19.7	*66.1*	**72.4**	15.7	13.4	13.4	22.8	14.2	60.6	47.2	18.1	14.2	33.9	13.4	49.6	59.8
Dog1	64.4	54.3	52.1	*89.9*	75.6	65.2	58.4	65.3	66.9	65.1	**100**	72.8	6.52	62.9	**100**	65.2	**100**	**100**
Doll	49.3	23	35	92.2	69.3	68.9	72.4	49.6	86.4	55.2	**99.7**	65.2	18.3	72.9	99.4	72.9	*99.7*	**99.7**
DragonBaby	22.1	19.5	11.5	15.9	13.3	8.85	6.19	23	38.1	30.1	6.19	63.7	39.8	**80.5**	31	*78.8*	30.1	22.1
Dudek	82.3	89.9	80.1	90.5	67	98.1	95.5	96.1	94.6	97.6	98.1	98.2	18.1	95.3	**99.9**	97.6	*99.2*	97.4
FaceOcc1	67.2	79.4	80.3	27.2	56.4	**100**	*98.8*	**100**	96.2	**100**	**100**	**100**	90.6	**100**	**100**	94.2	**100**	**100**
FaceOcc2	99.4	*99.8*	99.5	**100**	78.9	**100**	97.8	62.4	93.5	99.6	**100**	98.6	1.11	91.9	*99.8*	**100**	93.6	90.4
Fish	**100**	**100**	*86.1*	**100**	62	**100**	4.83	39.9	**100**	**100**	**100**	**100**	5.67	16.8	**100**	**100**	**100**	**100**
FleetFace	54.7	65.5	55.6	64.5	44.1	*78.1*	57.3	58.7	64.2	66.9	66.5	70.3	5.23	77.8	**94.3**	61.8	66.3	67.8
Football	97.5	77.3	84.3	77.1	74.9	89.8	68	63.8	*98.3*	70.2	79	78.5	0.276	95.6	**100**	*98.3*	87.8	76.5
Football1	**100**	91.9	**100**	43.2	36.5	32.4	32.4	40.5	68.9	94.6	39.2	35.1	79.7	90.5	*97.3*	**100**	39.2	39.2
Freeman1	12.6	18.4	17.8	32.8	23.3	20.2	14.7	13.8	22.7	16.3	35.3	28.2	19	22.1	**65.3**	29.8	*62.6*	53.1
Freeman3	28.9	15.7	33	**91.7**	64.6	17.6	31.3	33	1.09	27.8	31.3	26.1	30.7	33	31.1	29.6	55.9	*70.4*
Freeman4	17	20.1	18	17	21.6	18.7	15.9	17.3	19.1	18.4	41.7	16.6	23.7	28.3	41.3	45.9	*87.6*	**90.5**
Girl	48.6	14.4	25.2	86.8	72.6	97	29	49.8	17.4	74.2	30.6	**100**	46.2	90.4	*97.6*	97.4	77.6	79.8
Girl2	7.13	8.13	7	15.5	27.6	35.9	7.27	7	7.27	7	7.27	77.5	55.4	*78.6*	7.47	7.47	7.4	**87.8**
Gym	7.04	31.2	6.91	4.95	35.6	11.1	3.13	26.9	35.5	34.3	1.56	35.1	29.3	37.9	2.35	40.8	**53.5**	*41.3*
Human2	9.31	16.8	9.13	93.2	48.8	71.5	54.4	17.6	19.5	18.3	55.8	56.9	29	83.4	94.5	80.4	*97.8*	**99.7**
Human3	0.53	1.24	0.53	0.648	0.53	1.06	0.53	2.53	0.471	0.471	2.77	0.471	6.77	*65.8*	0.471	3.24	3.18	**77.8**
Human4	19.3	19	19.3	9.15	13.6	21.1	19.5	19.2	59.4	51.3	90.4	*93.6*	60	49.5	79.3	60.9	**100**	91
Human5	34.2	5.05	7.57	*98.9*	60	33.9	34.2	24	28.5	23.6	24.3	24	1.4	34.2	8.27	24	96.5	**99.9**
Human6	22.5	20.1	21.2	43.9	30.4	22.3	22.5	22.6	21.6	22.5	45.6	25	22.5	22.3	26.9	22.5	**92.2**	*47.1*
Human7	23.2	26.4	16	29.2	*94*	41.2	41.2	33.2	50.4	40.8	42.4	44.8	15.6	41.2	28.4	40.8	**100**	**100**
Human8	13.3	7.81	13.3	8.59	9.38	13.3	4.69	25.8	11.7	30.5	**100**	67.2	29.7	30.5	*99.2*	30.5	**100**	**100**
Human9	14.8	23	13.4	18.7	20.3	4.92	22.6	19.7	19	23.9	23.9	19	16.7	19.7	**47.2**	23.9	46.2	*46.6*
Ironman	4.22	2.41	3.61	15.1	8.43	4.82	7.23	24.7	8.43	15.1	13.3	11.4	4.82	*51.8*	9.64	**60.8**	3.01	4.22
Jogging	22.1	91.2	21.5	22.8	96.4	95.8	17.3	22.5	22.5	22.5	22.5	*96.7*	22.5	91.5	*96.7*	96.4	**97.1**	**97.1**
Jogging	15	15.6	15.6	18.2	95.4	16.3	97.7	18.2	99.3	16	18.2	*99.7*	19.5	86	97.1	**100**	99.3	98.7
Jump	5.74	4.92	5.74	7.38	4.1	**9.84**	8.2	*9.02*	8.2	7.38	8.2	8.2	3.28	8.2	6.56	**9.84**	2.46	2.46
Jumping	91.7	7.67	11.8	5.75	92.3	88.5	4.79	4.79	10.2	28.1	6.07	24.6	5.43	*99*	92.7	**99.4**	95.8	95.5
KiteSurf	*98.8*	41.7	83.3	31	38.1	53.6	95.2	**100**	90.5	32.1	39.3	44	89.3	*98.8*	45.2	45.2	64.3	39.3
Lemming	44.8	40.7	47.4	16.7	63.4	63.8	79.3	29	29.5	44.2	27.2	*90*	74.4	88	89.1	26.7	26.3	**96.4**
Liquor	23.3	60.1	22.9	68.8	75.5	40.5	40	28	37.7	98.1	40.9	81.2	42.7	98.3	49.9	81.2	**98.6**	*98.4*
Man	22.4	**100**	22.4	**100**	28.4	**100**	**100**	**100**	24.6	**100**	**100**	**100**	*47*	**100**	**100**	**100**	**100**	**100**
Matrix	9	2	6	7	7	11	13	1	10	13	18	32	8	36	31	**39**	*37*	29
Mhyang	91.2	97.1	77.5	**100**	90.3	**100**	90.3	91.7	93.7	**100**	99	**100**	76.4	96.9	99.1	**100**	99.7	*99.9*
MotorRolling	6.1	9.15	6.1	9.76	*17.7*	15.2	7.32	15.9	11.6	7.93	6.71	7.93	8.54	9.76	6.1	**59.8**	7.32	7.32
MountainBike	**100**	**100**	35.1	92.1	25	94.7	96.5	**100**	**100**	98.7	**100**	93	12.3	81.1	*99.1*	**100**	*99.1*	**100**
Panda	0.415	0.415	0.415	0.415	0.415	0.415	26.3	0.415	**68.7**	14.6	13.4	23.6	*65*	39.2	26.7	20.4	13.6	12.5
RedTeam	34.9	28.5	27	77.2	35.3	39.8	39.1	40.5	40.7	37.6	70	56.9	30.3	39.2	69.8	29.6	**97.5**	*94.7*
Rubik	76.8	43.9	35.5	*91*	47.4	31.9	14.6	81.8	11.3	81.4	77.2	50.9	39	64.5	**98.5**	72.9	16.5	55.5
Shaking	17.5	69.9	82.5	23.3	3.29	52.9	0.822	67.9	53.2	1.37	**100**	1.37	3.01	93.2	*99.2*	85.5	1.1	94.2
Singer1	27.6	27.6	27.6	**100**	*98.6*	29.9	29.9	27.6	21.9	27.6	**100**	57.3	28.5	27.4	72.6	27.6	**100**	**100**
Singer2	79	**100**	69.7	76.2	11.2	3.83	55.5	3.55	97.5	96.7	**100**	3.55	1.37	3.83	**100**	4.1	98.6	*98.9*
Skater	40.6	*83.8*	42.5	41.3	50	73.8	78.8	51.9	81.9	81.3	30	71.9	69.4	65	42.5	**88.8**	68.8	61.3
Skater2	4.83	2.76	6.44	32.9	35.2	48.7	11.7	73.6	57.2	62.1	29.2	61.6	78.4	**85.5**	72.2	*83.4*	46	61.1
Skating1	15.5	18.3	16.3	*73.3*	9	31.3	34	35.5	52.8	36.3	52.3	52.5	9	38.3	**82**	37.5	53.8	47
Skating2	2.96	22	12.3	37.2	5.92	17.8	3.17	17.3	32.1	27.9	38.1	48.2	34.5	13.1	8.25	46.9	*53.5*	**56.9**
Skating2	12.9	14.2	4.44	15.2	2.33	19.5	18	15	16.5	27.9	10.4	*34.7*	2.96	3.59	2.33	25.2	**57.3**	22.4
Skiing	9.88	3.7	6.17	12.3	7.41	4.94	6.17	9.88	9.88	7.41	4.94	4.94	**51.9**	32.1	9.88	*42*	4.94	4.94
Soccer	17.6	9.18	21.9	10.5	11.2	18.1	16.8	32.9	13.8	39.3	38.8	33.9	13.5	21.4	15.3	46.7	*57.9*	**84.7**
Subway	**100**	82.3	*99.4*	97.1	57.7	97.7	22.3	22.3	98.9	**100**	22.3	**100**	90.9	97.7	**100**	**100**	*99.4*	*99.4*
Surfer	86.2	40.4	1.86	2.13	82.7	81.4	28.5	94.7	**96**	39.9	29	85.9	22.3	38.3	93.9	43.6	*95.7*	93.9
Suv	5.19	52.8	5.19	79.2	95.8	47.3	56.3	53.4	53.7	**98.4**	**98.4**	**98.4**	12	79	**98.4**	*98.3*	**98.4**	98.2
Sylvester	55	92.9	40.6	44.9	84.8	*96.3*	**98.9**	74.2	94.5	82.1	69.4	78.4	29.4	92.1	92.9	84.7	83.3	85.8
Tiger1	33.2	7.74	67.9	15.8	23.2	83.7	25.8	87.1	33	85.7	59.3	83.1	14.3	91.7	90.5	81.4	**99.1**	*96.6*
Tiger2	26.3	11.2	80.5	12.6	20.3	69.3	25.5	66	76.2	36.4	29.6	49.3	44.7	49.3	72.3	55.6	**95.3**	*94.5*
Toy	38.7	28	40.6	50.9	77.9	35.8	32.8	39.5	30.3	43.2	**90**	68.3	1.11	38.7	79	41	*79.7*	58.3
Trans	41.9	40.3	35.5	40.3	39.5	41.1	38.7	**54.8**	33.9	47.6	32.3	*50.8*	38.7	44.4	35.5	43.5	40.3	36.3
Trellis	47.6	44.3	51.8	85.8	40.6	54	1.23	66.3	86.8	84	*97.7*	**100**	71	81.2	92.3	83.5	96.5	95.3
Twinnings	34	26.3	32.7	47.8	54.8	54.1	24.2	57.3	59.9	54.4	**100**	96.6	53.7	57.7	74.3	62.6	43.5	*99.4*
Vase	16.2	15.9	15.9	17.7	34.3	15.5	15.1	16.2	15.9	16.2	43.9	21	15.5	16.2	20.7	16.2	*52.8*	**57.6**
Walking	55.1	54.4	55.1	**99.8**	35.2	52.4	54.9	49	81.8	51.5	**99.8**	**99.8**	53.6	53.6	*98.3*	53.2	**99.8**	**99.8**
Walking2	38.2	38.4	38.2	39.8	20.8	43	43.2	38.4	*78*	38	**100**	51	35.6	37.8	40.6	41.4	**100**	**100**
Woman	93.3	83.9	*93.5*	88.6	32.8	*93.5*	90.3	92.8	**93.6**	**93.6**	93.3	92	16.6	93	93.1	*93.5*	92.3	93.3
Average	41.4	40	35.9	49	46.5	52.9	44.9	49.6	54	54.9	60.6	64.7	36.4	63.4	70.1	65.5	*72.9*	**76.7**

Table 1. Per-video results on the OTB-2015 dataset [19] with 100 videos. The results are shown in terms of overlap precision (in percent), which corresponds to the PASCAL criterion. The two best results for each sequence are shown in red and blue respectively. Our approach achieves a significant gain of 3.8% in average overlap precision, compared to the best existing tracker (SRDCF).

Video	EDFT[5]	LSHT[9]	DFT[18]	ASLA[11]	TLD[12]	Struck[8]	CFLB[6]	ACT[4]	TGPR[7]	KCF[10]	DSST[1]	SAMF[13]	DAT[17]	MEEM[20]	LCT[16]	HCF[15]	SRDCF[2]	Ours
Airport	38.5	28.4	40.5	44.6	43.9	41.9	1.35	40.5	42.6	42.6	*47.3*	43.2	42.6	41.2	42.6	42.6	**85.1**	45.3
Baby	29.7	13.2	29.7	90.9	61.5	27.4	29.7	29.7	32.1	27.4	**97**	*91.2*	29.7	27	29.1	29.1	90.9	83.4
Badminton	17.8	91.9	17.6	92.7	72.9	58	7.25	54.7	**96.5**	*96.4*	72.2	85.1	83.9	90.8	95.3	89.8	77.4	78.9
Badminton	7.09	0.142	4.26	29.6	3.55	64	59.4	49.6	85.7	9.93	41.8	*86*	**86.4**	68.5	80.6	82.7	65.2	78.3
Ball	2.3	1.28	2.3	2.56	1.28	6.91	2.56	1.53	2.3	1.53	1.28	1.79	11.8	*25.1*	1.28	**28.6**	1.28	5.12
Ball	6.04	0.864	13.1	20.2	10.4	0.345	0.173	42	40.4	36.1	6.04	44.2	67.2	53	54.1	*87*	57.5	**91.5**
Ball	*69.3*	29.2	*69.3*	59	**84.4**	58	68.4	63.2	*69.3*	56.1	*69.3*	*69.3*	*69.3*	*69.3*	68.4	67.9	*69.3*	*69.3*
Ball	*5.02*	1.49	4.83	0.372	0.372	2.97	2.42	0.372	4.65	1.3	2.23	1.3	4.65	4.65	3.35	**5.39**	*5.02*	*5.02*
Basketball	31	87.9	71.6	16.7	33.8	49	8.97	48.7	88.7	89.8	12.1	96.7	89.5	83	*99*	**99.9**	41.4	96.1
Basketball	11.7	10.5	12.1	11.5	7.46	11.9	11.1	14.5	9.68	19	16.7	34.7	11.1	13.5	19.4	19.4	*56.9*	**67.5**
Basketball	6.59	12.3	9.01	15.2	6.81	16.5	9.23	10.8	10.8	22.9	16.5	**53**	46.2	5.27	*51*	33.2	35.4	47.7
Basketball	49.4	57.1	9.3	22	4.76	61	59.6	67.6	64.4	69.8	34.7	76.6	72.3	**94.1**	59	76.4	82.8	*87.5*
Bee	57.8	78.9	14.4	38.9	**98.9**	83.3	37.8	43.3	91.1	20	26.7	22.2	*95.6*	54.4	28.9	28.9	43.3	57.8
Bicycle	25.5	55.4	21	*95.2*	24.7	30.6	19.9	20.3	35.4	19.6	60.9	78.6	47.2	44.6	19.2	33.6	**96.7**	94.8
Bike	71.4	4.12	39.5	97.1	12.9	75.9	11.5	74.7	91	76.7	*99.6*	**100**	74.2	75.7	76.7	76.7	**100**	**100**
Bike	2.34	2.34	2.34	13.4	15.8	2.34	2.34	2.34	2.46	2.34	13.5	10.1	2.34	2.34	2.34	9.98	*53.8*	**90.3**
Biker	19	19	19	52	26.3	21.8	19	43	63.1	19	93.9	93.9	19	41.3	19	47.5	*96.6*	**97.2**
Bikeshow	2.77	2.22	21.9	3.05	1.39	2.77	12.7	18.3	46.5	21.6	7.48	35.7	**76.7**	46	2.22	*56.2*	15	22.4
Bird	94.9	16.2	94.9	9.09	43.4	49.5	47.5	**99**	57.6	54.5	52.5	55.6	**99**	*98*	76.8	*98*	57.6	65.7
Board	19.2	83.1	20.1	13.7	5.35	81.9	*93.8*	83.9	10.9	92	81.6	82.4	79.9	89.3	92.3	92.8	92.1	**96.8**
Boat	5.04	5.04	5.04	6.1	16.2	5.04	5.04	5.04	5.04	5.04	5.57	39.3	4.51	5.04	5.04	5.04	**50.7**	*50.4*
Boat	44.4	39.8	44.8	60.4	42.5	52.9	51.2	53.6	45.4	44.9	*66.5*	**69.4**	27.2	51.2	44.4	52.4	58.3	59.5
Bolt	1.71	1.14	4	1.43	17.7	1.43	2.29	**100**	2.29	94.3	**100**	*99.7*	96	88	98.6	98	1.43	1.43
Boy	98	42.5	48.3	43.9	96.5	97.5	98.5	95	95.5	*99.2*	**100**	**100**	96.3	*99.2*	99	99	**100**	**100**
Busstation	10.5	9.37	10.5	10.2	10.5	*56.2*	10.5	11	10.5	10.5	10.2	10.2	9.92	11.3	10.5	10.2	**90.4**	10.2
Busstation	24.6	34.7	24.8	24.1	33.9	29.1	91.9	26.3	90.1	87.8	92.4	23.8	93.9	**98.7**	88.1	90.4	*97.5*	96.7
CarDark	68.4	50.1	33.6	**100**	27.5	**100**	*98.7*	**100**	**100**	69.2	**100**	58.3	2.04	**100**	97.7	88.3	**100**	**100**
CarScale	44.8	44.8	44.8	71.8	75.4	43.3	44.8	44.8	47.6	44.4	*84.5*	59.9	44.4	44.8	44.8	44.4	80.6	**85.7**
Carchasing	28.1	28.1	28.1	28.3	*32.1*	27.7	28.1	28.7	28.1	28.3	28.3	28.3	25	28.1	28.7	28.7	28.3	**93.2**
Carchasing	*99.5*	96	**100**	100	72	98.8	**100**	97.4	97.7	91.6	*99.5*	96.5	84.8	98.3	98.6	96	99.1	99.1
Carchasing	6.33	6.33	6.33	6.79	*81.7*	6.33	6.33	6.33	6.33	6.33	**100**	7.69	6.33	6.33	6.33	6.33	**100**	**100**
Charger	17.1	28.9	18.1	22.1	50.3	19.1	13.1	36.6	30.5	19.5	*79.5*	56.4	41.9	22.1	29.5	29.5	**83.2**	71.8
Coke	14.4	4.12	8.59	14.4	47.1	*94.5*	63.2	64.3	91.8	72.2	83.8	79.7	47.8	**95.5**	91.4	91.4	61.5	56.4
Couple	21.4	10.7	8.57	10.7	5	60.7	63.6	10.7	10.7	24.3	10.7	45.7	63.6	75.7	50	74.3	*92.9*	**94.3**
Crossing	75	11.7	64.2	**100**	45.8	95.8	*98.3*	88.3	*98.3*	95	**100**	**100**	97.5	*98.3*	96.7	95	**100**	**100**
Cup	**100**	**100**	**100**	**100**	**100**	**100**	*46.2*	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
Cup	1.48	1.18	1.18	1.18	*2.66*	1.18	1.18	1.18	1.18	**6.21**	1.18	1.18	1.18	1.18	1.48	1.18	1.48	1.48
David	55.4	43.7	23.4	95.3	91.1	24	23.8	62.6	62.6	62.2	**100**	95.8	39.1	62.6	62.6	60.1	98.7	*98.9*
David3	87.3	35.3	74.2	52.4	32.1	33.7	64.7	87.7	*99.6*	99.2	53.6	**100**	**100**	94	96.4	**100**	**100**	*99.6*
Deer	63.4	4.23	31	4.23	78.9	**100**	**100**	**100**	**100**	81.7	84.5	*88.7*	9.86	**100**	81.7	**100**	**100**	**100**
Diving	19	18.2	21.2	*29.4*	16.5	21.2	29	20.8	14.3	**30.3**	28.1	17.7	*29.4*	18.2	**30.3**	28.6	22.1	22.1
Doll	49.3	46.7	35	98.7	69	52.7	72.5	49.6	51.3	55.2	**99.6**	67	18.3	72.9	72.9	72.9	**99.6**	*99.5*
Eagle	20.5	11.6	33	38.4	36.6	28.6	33	35.7	45.5	2.68	2.68	2.68	18.8	**85.7**	2.68	*74.1*	29.5	16.1
Electricalbike	97.8	1.47	59.5	**100**	93.4	97.1	97.1	97.8	99.6	97.1	*99.9*	*99.9*	1.83	96.7	96.8	94.5	99.5	**100**
FaceOcc1	67.2	**100**	80.3	29	51.1	**100**	*98.8*	**100**	98	**100**	**100**	**100**	90.6	**100**	**100**	94.2	**100**	**100**
Face	3.71	3.55	3.71	4.35	*43.9*	3.06	3.06	3.87	3.71	4.35	4.35	4.35	3.23	3.55	3.71	3.71	4.52	**80**
Face	20.3	22.3	28.4	8.78	8.78	25	39.2	8.78	8.78	10.1	52.7	**89.9**	10.1	73.6	8.78	79.1	**89.9**	*84.5*
Fish	4.99	5.49	5.24	5.24	6.73	29.7	2.74	6.98	*65.1*	4.24	4.99	32.7	**65.6**	58.9	5.99	61.1	17.7	11.5
Fish	15.2	15.2	34.2	15	19.4	14.1	14.8	15.2	14	14.8	15	15.4	**72.3**	*57.4*	14.5	15.4	14.1	55
Football1	**100**	85.1	**100**	47.3	35.1	32.4	32.4	40.5	94.6	94.6	39.2	35.1	79.7	90.5	*97.3*	**100**	39.2	52.7
Girl	48.6	57	25.2	29.4	80.2	96.8	36.4	49.8	83.6	74.2	23.8	**100**	46.2	90.4	95.4	*97.4*	17.4	81.8
Girlmov	6.2	28.9	5.67	41.2	21.1	17.3	7.2	5.93	6.33	7.4	6.93	45.2	*83.7*	**85.3**	7.4	7.4	7.4	7.27
Guitar	95.9	88.1	91.4	90.3	97	97.4	96.6	97.8	97.8	*98.5*	97.4	97.4	17.2	94.4	97.8	96.3	**98.9**	97.4
Guitar	94.9	**98.1**	**98.1**	51.4	17.3	68.1	79.9	**98.1**	63.9	91.1	54.6	**98.1**	80.5	*96.5*	90.4	92.3	64.9	65.2
Gym	11	5.48	17.9	43.9	42.8	38.3	17.6	19.2	80.7	77.4	78.2	85.4	**88.9**	77.8	83.7	*87.9*	44.9	69.6
Hand	*69.3*	59	60.2	16.4	12.3	26.6	14.3	16.8	32.4	13.1	16.8	16.8	59	16.8	**88.5**	15.6	16.8	18.9
Hand	86.3	30.7	93.3	2.24	8.73	4.74	1.25	2.24	97	92.8	13.5	97	99.3	98	97.8	94.3	**99.8**	*99.5*
Hand	*92*	0.398	34.3	47.4	52.6	39.4	41.4	53	*92*	61.8	61.4	83.3	87.6	**95.6**	*92*	84.5	67.3	87.6
Hurdle	75.7	51.3	26.3	11.3	14.3	53.7	3.67	88.3	87.7	*90.7*	63.3	87.7	**95.3**	86.3	69	89.3	83	82
Hurdle	56.6	15.5	39.5	48	2.63	0.658	54.6	88.5	84.5	94.7	67.8	*97*	64.5	**98.4**	90.1	**98.4**	**98.4**	90.8
Iceskater	14.2	12	14	71.4	49.2	82.2	43.8	52.2	67	**85.6**	27	82.6	72.2	69.6	76.4	*82.8*	41.6	55.2
Ironman	4.22	3.61	3.61	12.7	8.43	6.02	7.23	24.7	7.23	15.1	14.5	11.4	4.82	51.8	9.64	**60.8**	*56*	9.64
Jogging1	22.1	35.2	21.5	22.1	96.1	22.1	16	22.5	22.5	22.5	22.5	*96.7*	22.5	91.5	*96.7*	96.4	**97.1**	**97.1**
Jogging2	15	13.4	15.6	15.6	87	16.3	97.7	18.2	99	16	18.2	*99.7*	19.5	86	97.1	**100**	97.7	**100**
Juice	48	45.8	47.8	**100**	*99.5*	48	51	48	**100**	48	**100**	**100**	45.8	47.8	48	48	**100**	**100**
Kite	8.06	2.07	80	14.7	11.2	1.24	22.9	44.8	*91.3*	41.5	44.2	30.2	43	**96.7**	34.3	43.6	33.9	33.1
Kite	78.1	54.4	28.1	54.4	82.1	16.3	84.5	89.4	95.6	55.2	64.6	*98.9*	86.8	88.1	91.3	87.4	98	**99.1**
Kite	57.6	97.3	38.3	77.5	**100**	98.7	98.9	57.6	88.8	97.7	97.7	96.4	96.2	98.3	**100**	*99.8*	99.1	98.1
Kobe	18.9	14.4	16.2	13.9	6.19	5.33	16	17.9	20.6	14.9	16.3	17.7	*26.3*	15.8	15.8	17	16.7	**31.8**
Lemming	44.8	58.7	47.4	16.8	63.8	64.3	79.3	29	26.9	44.2	27.2	90.7	74.4	88	78.3	26.7	**98.8**	*91.3*
Liquor	23.3	0.517	22.9	58.6	63	40.6	40	28	42.2	*98.1*	40.9	44.1	42.7	**98.3**	80.8	81.2	97.4	91.9
Logo	12.8	12.8	12.8	19.8	74.6	13.6	13.6	12.8	11.8	12.8	53.4	35.7	10.7	12.6	12.5	11	**84.4**	*82.3*
Matrix	9	1	6	11	7	11	2	1	9	13	17	32	8	*36*	31	**39**	30	25
Messi	41.2	30.9	47.4	20.6	21	27.9	20.2	4.78	*62.1*	19.9	25.4	22.4	40.4	54	47.1	44.1	53.3	**68.4**
Michaeljackson	36.4	36.9	36.1	89.1	49.1	50.6	62.3	53.9	94.1	**100**	14.2	90.1	52.9	*96.9*	64.4	87.3	86.3	54.5
Microphone	93.1	15.7	62.7	18.1	61.8	**100**	19.6	**100**	95.1	*99.5*	69.6	98.5	87.7	99	**100**	99	90.7	57.8
Microphone	*99*	4.85	28.2	24.3	9.71	0.971	4.85	12.6	15.5	17.5	41.7	10.7	**100**	74.8	13.6	11.7	65	4.85
MotorRolling	6.1	6.1	6.1	8.54	12.8	*16.5*	7.32	15.9	15.9	7.93	6.71	7.93	8.54	9.76	6.1	**59.8**	7.32	6.71
Motorbike	23.8	2.84	23.8	**99.8**	9.59	23.6	23.8	23.8	24	23.8	23.8	23.8	23.1	30	23.8	64.7	23.8	*67.5*
MountainBike	**100**	97.4	35.1	63.6	20.2	97.4	97.4	**100**	**100**	*98.7*	**100**	93	12.3	81.1	96.5	**100**	98.2	*98.7*
Panda	61	2.49	22	44.4	78.8	61	51.9	52.3	3.73	2.49	2.49	2.9	51.9	94.2	36.5	53.1	**97.1**	*94.6*
Plane	27.1	12.7	12.1	9.95	21.6	18.7	27.4	22.5	32.2	29.6	33.1	**58.3**	14.1	14.1	30.6	33.4	22.2	*54.7*
Plate	68.3	52.1	71.8	92.3	**100**	2.11	59.9	73.9	67.6	72.5	68.3	68.3	73.9	74.6	70.4	66.2	**100**	*99.3*
Plate	98.9	43.6	95	85.1	74.6	0.552	**100**	**100**	**100**	**100**	*99.4*	95	74.6	97.8	**100**	*99.4*	36.5	38.1
Pool	**99.4**	4.22	*98.2*	97	5.42	97	**99.4**	4.22	4.22	3.61	4.22	4.22	4.22	96.4	3.61	4.22	48.8	91.6
Pool	**99.2**	12.8	25.6	3.76	91.7	8.27	*98.5*	0.752	0.752	0.752	0.752	0.752	15.8	*98.5*	0.752	0.752	2.26	4.51
Pool	5.65	0.806	1.61	0.806	1.61	0.806	0.806	1.61	0.806	1.61	0.806	1.61	1.61	**71**	1.61	1.61	0.806	*8.06*
Railwaystation	2.91	3.15	2.91	2.91	22.3	7.26	3.39	3.39	3.15	3.39	3.15	3.15	**94.4**	8.23	3.39	*75.8*	12.6	13.1
Ring	**100**	5.97	75.6	*99.5*	100	**100**	**100**	**100**	28.4	**100**	**100**	**100**	4.98	**100**	**100**	**100**	**100**	**100**
Sailor	71.1	9.95	12.4	11.7	11.9	46.5	96.3	98	10.2	39.6	41	98.3	99.3	*99.8*	41	97.5	*99.8*	**100**
Shaking	17.5	48.5	82.5	36.7	3.29	46	0.822	67.9	64.1	1.37	**100**	1.37	3.01	93.2	94.2	85.5	95.6	*96.2*
Singer1	27.6	27.6	27.6	**100**	*97.2*	29.9	29.9	27.6	22.8	27.6	**100**	57.8	28.5	27.4	27.6	27.6	**100**	**100**
Singer2	79	65.3	69.7	**100**	9.56	3.83	55.5	3.55	*99.5*	96.7	**100**	3.55	1.37	3.83	**100**	4.1	3.55	3.55
Singer	98.1	93	31.8	21	9.35	70.6	15.4	17.3	98.6	86.9	14	**100**	96.3	98.6	*99.5*	90.2	93.9	94.4
Singer	27.7	27.6	8.51	18.6	*59.5*	13.8	7.81	8.31	9.81	8.91	7.81	23.2	5.51	27.1	24.9	7.71	12.8	**66.9**
Skating1	15.5	10.5	16.3	**74**	44.5	31.3	34	35.5	50	36.3	52.3	*52.5*	9	38.3	35	37.5	21.5	44.8
Skating2	17.4	16.3	16.1	15	21.5	33.4	2.26	18.2	68.2	65.5	4.81	70	32.2	75.7	**78.9**	*78.6*	44.3	11
Skating	50.6	41.1	11.5	6.85	14.7	31.5	5.13	9.05	57.7	28.6	7.82	9.05	67.7	74.8	45	33.7	*84.1*	**86.3**
Skating	27	25.2	5.63	7.65	4.83	6.24	5.43	5.43	28.6	8.65	5.63	**41.9**	32.4	37.8	12.9	*39.6*	37.4	34.8
Skiing	9.88	3.7	6.17	9.88	7.41	4.94	7.41	9.88	9.88	7.41	4.94	4.94	**51.9**	32.1	11.1	*42*	6.17	8.64
Skiing	77.9	47.9	13.3	90.2	83.2	75.5	37.6	58.9	74.4	73.4	*99.6*	**100**	80.4	73.4	78.9	65.2	**100**	**100**
Skyjumping	13.3	3.41	14.9	5.76	*41.2*	18.7	21.5	3.94	36.6	6.4	14.9	36.1	**46.4**	31.4	3.09	32.7	6.5	38.1
Soccer	17.6	15.3	21.9	13.8	8.93	14	13.5	32.9	13.5	39.3	15.3	33.9	13.5	21.4	15.3	*46.7*	**82.1**	22.2
Spiderman	12	12	11.1	12	8.55	10.8	6.27	11.7	11.7	9.12	33.3	45	3.7	12	12	12	*52.1*	**58.7**
Subway	**100**	97.1	*99.4*	21.7	97.7	97.1	22.3	22.3	97.7	**100**	22.3	**100**	90.9	97.7	**100**	**100**	22.3	98.3
Suitcase	39.1	75	41.8	39.7	**91.3**	38.6	39.1	*80.4*	39.1	*80.4*	69	78.3	39.1	78.8	78.3	79.3	77.7	78.8
Sunshade	37.8	10.5	47.1	55.2	69.2	*98.8*	**100**	**100**	97.7	98.3	98.3	97.1	91.3	**100**	96.5	98.3	97.7	98.3
SuperMario	18.8	33.1	18.8	35.3	39.1	*99.2*	73.7	17.3	3.01	14.3	18.8	14.3	12.8	*99.2*	16.5	63.2	85.7	**100**
Surf	8.17	9.9	8.42	19.3	7.92	10.9	16.6	7.92	31.4	4.21	6.93	**83.9**	67.8	*69.6*	51.7	59.4	43.6	67.8
Surf	9.46	11.5	6.91	10.5	2.56	26.1	11.5	11.8	32.2	10.2	30.7	8.44	**49.9**	*39.9*	13.6	9.97	8.18	6.14
Surf	18.3	21.9	12.2	32.6	21.9	25.8	55.2	*60.9*	**64.9**	10.4	15.4	14.3	57	42.3	44.4	54.5	48.7	20.4
Surf	11.9	31.1	7.41	12.6	9.63	8.89	7.41	8.89	*37*	23.7	20.7	7.41	**40.7**	20	14.8	12.6	8.89	6.67
TableTennis	3.54	0.505	1.52	3.03	**7.58**	3.54	*5.05*	1.52	0.505	2.02	1.01	2.02	3.03	1.52	2.02	1.52	1.52	1.52
TennisBall	*4.17*	1.04	3.13	2.43	2.78	0.347	2.43	1.74	0.347	0.347	**6.25**	0.347	2.78	1.74	1.04	0.347	1.74	2.08
Tennis	17	73.1	36.8	95.6	79.7	67.6	59	87.2	**98.2**	94.3	61.5	91.6	*97.8*	94.5	96	94.1	92.1	89.9
Tennis	91.8	*99.7*	96.4	89.8	38.7	98.4	70.5	41	*99.7*	**100**	**100**	**100**	99.3	**100**	**100**	*99.7*	98.7	98.4
Tennis	85.3	5.88	10.3	*96.6*	16.2	86.3	96.1	6.27	9.8	8.82	67.2	69.6	**97.5**	81.4	8.82	8.82	86.8	89.7
Thunder	85.6	53.3	50.7	8.27	1.33	0.533	22.1	*99.5*	98.9	95.5	70.1	**100**	96.3	**100**	69.3	**100**	**100**	**100**
Tiger1	37	14.1	96.3	17.5	15.3	84.2	35	36.2	96.6	98	61.6	58.8	29.1	82.5	92.9	87.3	*98.3*	**98.6**
Tiger2	26.3	19.5	80.5	12.3	29	66	25.5	66	87.1	36.4	29.6	49.3	44.7	49.3	72.6	55.6	*92.3*	**93.4**
Torus	96.2	92	57.2	23.1	6.06	9.09	17.8	95.8	96.2	96.2	94.7	95.8	87.5	96.2	89.8	*96.6*	95.1	**98.5**
Toyplane	8.89	0.247	6.17	8.4	*27.7*	8.89	9.88	9.63	**46.9**	9.63	9.63	9.63	8.64	8.89	9.88	24.2	8.89	19.8
Trellis	47.6	48.3	51.8	66.6	59.8	31.8	1.23	66.3	83	84	*97.7*	**100**	71	81.2	81.4	83.5	96.7	97.2
Walking	55.1	52.4	55.1	**99.8**	30.1	52.4	54.9	49	65.5	51.5	**99.8**	**99.8**	53.6	53.6	53.9	53.2	*99.3*	**99.8**
Walking2	38.2	37.4	38.2	41.4	25.8	43	43.2	38.4	*89.6*	38	**100**	51	35.6	37.8	38	41.4	**100**	**100**
Woman	93.3	35	*93.5*	63.7	28.8	*93.5*	*93.5*	92.8	*93.5*	**93.6**	93.3	92	16.6	93	93.1	*93.5*	92.6	**93.6**
Yo	10.2	5.53	5.11	4.26	*21.7*	10.6	9.36	4.26	4.68	5.11	5.11	6.38	8.51	17.4	10.2	8.09	9.36	**35.3**
Yo	20	19.8	19.8	29.5	**52**	*44.7*	20	20	0.441	20.9	20	20.3	20	34.1	20.7	18.7	29.1	29.1
Yo	7.96	1.49	4.48	2.49	**69.7**	*50.2*	1.99	2.49	2.49	2.49	2.49	2.49	0.995	5.47	2.99	2.99	5.47	4.98
Average	41.2	30.4	34	38.8	38.4	40.9	37.8	42.1	51.6	46.5	47.5	56.1	48.2	*62.2*	52.8	58.2	62.2	**65.8**

Table 2. Per-video results on the Temple-Color dataset [14] with 128 videos. The results are shown in terms of overlap precision (in percent), which corresponds to the PASCAL criterion. The two best results for each sequence are shown in red and blue respectively. Our approach achieves a significant gain of 3.6% in average overlap precision, compared to the best existing trackers (MEEM and SRDCF).

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