Supplementary Material

Beyond Correlation Filters: Learning Continuous Convolution Operators for Visual Tracking

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In this supplementary material of [6] we provide additional derivations and implementation details. Section 1 provides details about the derivation of eq. (5) in the paper. Section 2 contains detailed derivations of the Fourier coefficients of the desired convolution output y_j and the interpolation functions b_d, described in section 3.4 in the paper. Details about the numerical optimization is given in section 3. We provide detailed results on the OTB-2015 and Temple-Color datasets in sections 4 and 5 respectively. In our object tracking experiments, we use the same parameter settings for our method in all state-of-the-art comparisons (sections 5.2, 5.3 and 5.4), i.e. for *all* datasets and videos. Further, we use the same parameter settings for all feature point tracking experiments. Code, raw result files and a video of qualitative feature point tracking results on the MPI Sintel dataset are available at the project webpage http://www.cvl.isy.liu.se/research/objrec/visualtracking/conttrack/index.html.

1 Fourier Coefficients of the Interpolated Feature Map

We first derive the expression for the Fourier coefficients of the interpolated feature map $J_d\{x^d\}$, which is used to prove eq. (5) in the paper. The interpolation operator $J_d : \mathbb{R}^{N_d} \to L^2(T)$ for feature channel d is defined as (same as eq. (2) in the paper),

$$J_d\{x^d\}(t) = \sum_{n=0}^{N_d-1} x^d[n] b_d\left(t - \frac{T}{N_d}n\right). \tag{1}$$

Here, $b_d \in L^2(T)$ is the interpolation function for channel d. From the shift property [21], it follows that $b_d\big(t - \frac{T}{N_d}n\big)$ has Fourier coefficients $\exp\big(-i\frac{2\pi}{N_d}k\big)\hat{b}_d[k]$. By utilizing linearity, the Fourier coefficients of (1) are then derived as,

$$\widehat{J_d\{x^d\}}[k] = \sum_{n=0}^{N_d-1} x^d[n] e^{-i\frac{2\pi}{N_d}k} \hat{b}_d[k] = \hat{b}_d[k] \sum_{n=0}^{N_d-1} x^d[n] e^{-i\frac{2\pi}{N_d}k} = \hat{b}_d[k] X^d[k]. \tag{2}$$

Here, $X^d[k] := \sum_{n=0}^{N_d-1} x^d[n] e^{-i\frac{2\pi}{N_d}nk}$, $k \in \mathbb{Z}$ is the periodically extended discrete Fourier transform (DFT) of x^d. The Fourier coefficients of the confidence output (eq. (5) in the paper) are then derived from (2) here and eq. (1) in the paper by exploiting linearity and the first convolution property [21] (see section 3.1 in the paper) of the Fourier coefficients.

2 Fourier Coefficients of y_j and b_d

We construct the desired convolution output y_j and interpolation function b_d as periodic repetitions of functions defined on the real line. For an integrable function $g \in L^1(\mathbb{R})$, we define the T-periodic repetition (or periodic summation) as $g_T(t) = \sum_{n=-\infty}^{\infty} g(t - nT)$. The Fourier coefficients $\hat{g}_T[k]$ of g_T can then be obtained by evaluating the Fourier transform $\hat{g}(\xi) = \int_{-\infty}^{\infty} g(t) e^{-i2\pi\xi t}\,\mathrm{d}t$ of g at discrete locations using Poisson summation formula [21],

$$\hat{g}_T[k] = \frac{1}{T}\hat{g}\left(\frac{k}{T}\right) . \tag{3}$$

In the proposed learning framework, $y_j \in L^2(T)$ is the desired output of $S_f\{x_j\}$, i.e. the convolution operator applied to the sample x_j. Thus, in our formulation, the training sample x_j is labeled by an entire confidence function (or heat-map) y_j of the target presence at all continuous locations. The function value $y_j(t)$ represents the labeled confidence score at the location $t \in [0, T)$. As $y_j \in L^2(T)$ is arbitrary, it can be tailored for the specific application. For the visual tracking, a suitable approach is to construct y_j based on a Gaussian function. We let $y_j(t) = \sum_{n=-\infty}^{\infty} z_j(t - nT)$ be the periodic repetition of the Gaussian function,

$$z_j(t) = e^{-\frac{1}{2\sigma^2}(t-u_j)^2} . \tag{4}$$

Here, $u_j \in [0, T)$ is the estimated location of the target (or feature point) in the corresponding sample x_j and σ is a parameter. The Fourier transform of (4) is derived as $\hat{z}_j(\xi) = \sqrt{2\pi\sigma^2}\exp\left(-i2\pi u_j \xi\right)\exp\big(-2\sigma^2 \left(\pi\xi\right)^2\big)$ using the transform pair of a Gaussian function and the shift property (see e.g. [21]). The Fourier coefficients are thus computed using (3) as,

$$\hat{y}_j[k] = \frac{1}{T}\hat{z}_j\left(\frac{k}{T}\right) = \frac{\sqrt{2\pi\sigma^2}}{T}\exp\left(-2\sigma^2\left(\frac{\pi k}{T}\right)^2 - i\frac{2\pi}{T}u_j k\right) . \tag{5}$$

The interpolation functions b_d, used in the interpolation operator (1), are constructed using the standard cubic spline kernel [24],

$$b(t) = \begin{cases} (a+2)|t|^3 - (a+3)t^2 + 1 & |t| \le 1 \\ a|t|^3 - 5at^2 + 8a|t| - 4a & 1 < |t| \le 2 \\ 0 & |t| > 2 \end{cases} . \tag{6}$$

In our experiments, we use the value $a = -0.75$ for the shape parameter. The interpolation function for channel d is obtained by first rescaling b to the sample interval T/N_d. It is then shifted half an interval $T/(2N_d)$ to align the origin of the continuous coordinate system with the sampling intervals of the feature map. The resulting interpolation kernel c_d and its Fourier transform are given by,

$$c_d(t) = b\left(\frac{N_d}{T}\left(t - \frac{T}{2N_d}\right)\right) , \quad \hat{c}_d(\xi) = \frac{T}{N_d} e^{-i\pi\frac{T}{N_d}\xi}\hat{b}\left(\frac{T}{N_d}\xi\right) \tag{7}$$

Here, $\hat{c}_d$ is obtained through the shift and scaling property of the Fourier transform. The analytical expression for the Fourier transform of (6) is given by,

$$\hat{b}(\xi) = \frac{6(1-\cos 2\pi\xi) + 3a(1-\cos 4\pi\xi) - (6+8a)\pi\xi \sin 2\pi\xi - 2a\pi\xi \sin 4\pi\xi}{4\xi^4\pi^4} . \tag{8}$$

The Fourier coefficients of $b_d(t) = \sum_{-\infty}^{\infty} c_d(t - nT)$ are obtained through (3) as,

$$\hat{b}_d[k] = \frac{1}{T}\hat{c}_d\left(\frac{k}{T}\right) = \frac{1}{N_d}\exp\left(-i\frac{\pi}{N_d}k\right)\hat{b}\left(\frac{k}{N_d}\right) . \tag{9}$$

3 Conjugate Gradient Optimization

For the target tracking application we employ the Conjugate Gradient (CG) method [20] to iteratively optimize the filter coefficients $\hat{\mathbf{f}}$ by solving the normal equations (e.q. (8) in the paper),

$$\left(A^{\mathrm{H}}\Gamma A + W^{\mathrm{H}}W\right)\hat{\mathbf{f}} = A^{\mathrm{H}}\Gamma\hat{\mathbf{y}} . \tag{10}$$

Here, the matrix A originates from the data term of the loss (e.q. (7) in the paper) and consists of one diagonal block per feature dimension d and training sample j. The diagonal matrix Γ contains the sample weights α_j. The matrix W corresponds to a multi-channel convolution operation, where each channel d is convolved with the Fourier coefficients $\hat{w}$ of the penalty function. The vector $\hat{\mathbf{y}}$ is the concatenation of the Fourier coefficients of all label functions y_j (see section 3.3 in the paper for more details).

We perform 100 CG-iterations in the first frame to converge to a good initial estimate of the filter $\hat{\mathbf{f}}$. In the subsequent frames, we use 5 iterations per frame and initialize CG with the current filter (as computed in the previous frame). To further speed up the convergence, we initialize the previous search direction in CG to a forgetting factor times the final conjugate direction used in the previous frame. This forgetting factor is set to $(1-\lambda)^{10}$, where λ is the learning rate of the tracker. The CG method is commonly used with a preconditioner to improve the condition number of the matrix and thereby the convergence rate of the solver. We employ an approximate diagonal preconditioner, which is computed as an efficient weighted running average of the training samples.

Our Conjugate Gradient optimization has a number of advantages compared to the Gauss-Seidel approach used in [3,4] regarding complexity and implementation. First, CG does not require explicit evaluations of the matrix product $A^{\mathrm{H}}\Gamma A$. We therefore obtain a linear $\mathcal{O}(D)$ instead of quadratic $\mathcal{O}(D^2)$ complexity of the computations and memory consumption in the number of feature channels D. This is important for high-dimensional deep feature maps, as employed in this work. Secondly, CG can utilize the specific sparsity structure of the problem (10). We exploit that A can be permuted to a block-diagonal structure, containing one (dense) block matrix per Fourier coefficient $k = -K, \dots, K$.

The operations $\mathbf{v} \mapsto A\mathbf{v}$ and $\mathbf{v} \mapsto A^{\mathrm{H}}\mathbf{v}$ in CG is implemented solely using dense block-wise matrix-vector multiplications. We also use the fact that the matrices W and W^{H} correspond to convolution operations over all feature channels with the kernel $\hat{w}$ and its Hermitian adjoint respectively. The operation $\mathbf{v} \mapsto W^{\mathrm{H}}W\mathbf{v}$ in CG is performed as convolutions and thus W is not constructed explicitly. Since the Fourier coefficients of a real function obey the Hermitian symmetry, we only need to process half the Fourier coefficients $0 \leq k \leq K$. This effectively halves the computations and memory consumption of the training procedure. Finally, as the required operations in (10) are implemented as either block-wise dense matrix-vector multiplications, ordinary convolutions or element wise multiplications, our framework does not require explicit handling of sparse matrices (using e.g. sparse matrix libraries), which simplifies implementation.

4 Detailed Results on OTB-2015

In this supplementary material, detailed results on OTB-2015 [25] with 100 videos are provided. Videos and ground truth are available at `https://sites.google.com/site/benchmarkpami/`. Figure 1 contains the success plots for all 11 attributes and Table 2 shows the per-video overlap precision for all trackers in the comparison.

5 Detailed Results on Temple-Color

We also present detailed results on the Temple-Color dataset [17] with 128 videos. 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.

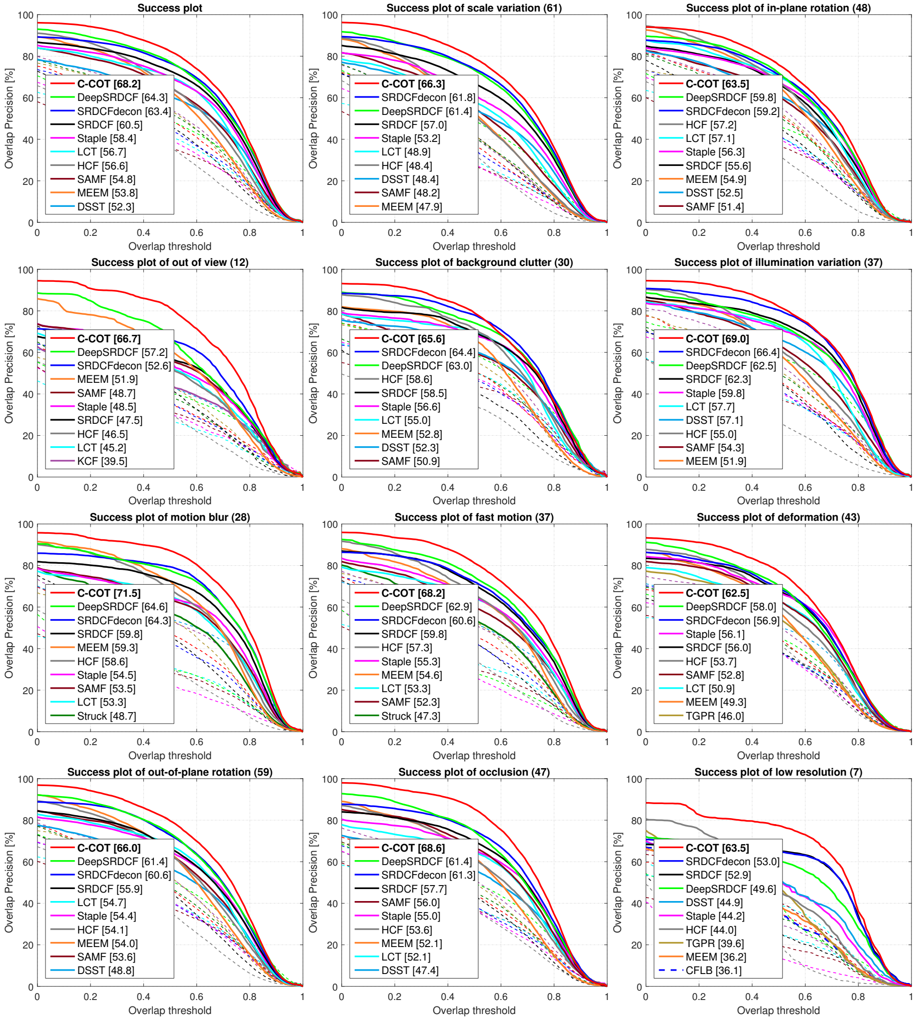

Fig. 1. Success plots on OTB-2015 [25] dataset. The overall success plot (top-left) is computed over the entire dataset (same as in figure 2a in the paper). We also show the success plots for all 11 attributes. The title of each attribute plot contains the name of the attribute and the number of videos associated with it. The area-under-the-curve (AUC) score is shown in the legend. For clarity, we only display the top 10 trackers in the legend. Our object tracking framework achieves the best results on all 11 attributes.

Table 1. A per-video comparison on the OTB-2015 dataset [25] with 100 videos. The results are shown in terms of overlap precision (OP) (in percent), which corresponds to the PASCAL criterion. The best and second best results for each video are shown in red and blue font respectively. Our object tracking framework achieves a significant gain of 5.1% in mean OP, compared to the second best tracker (DeepSRDCF).

Video	EDFT [8]	LSHT [12]	DFT [23]	ASLA [14]	TLD [15]	Struck [11]	CFLB [9]	ACT [7]	TGPR [10]	KCF [13]	DSST [2]	SAMF [16]	DAT [22]	MEEM [26]	LCT [19]	HCF [18]	Staple [1]	SRDCF [4]	SRDCFdecon [5]	DeepSRDCF [3]	**C-COT** [6]
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**	87.2	41.2	30.1	28.3	98.9
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	26.7	48.9	46.7	51.9	*53.3*
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	27.7	6.37	5.64	26.2	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*	96	54.5	54.5	84.8	**100**
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	*99.7*	**100**	**100**	**100**	98.8
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	69.5	*99.9*	*99.9*	*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**	**100**	**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**	98.9	**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**	**100**	**100**	**100**
BlurFace	24.1	11.8	29	15	**100**	44	31.4	**100**	*99.8*	**100**	**100**	**100**	26	**100**	**100**	**100**	*99.8*	**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	50.6	98.6	97.1	**100**	**100**
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	77.8	85.7	95.7	*96.6*	87.2
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	*99.7*	1.43	1.43	74.6	90.6
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*	**91.1**	1.02	1.02	85.3	65.5
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	41.5	**96**	39.7	89.5
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**	**100**	99.7	*99.8*	**100**
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	76.5	**100**	**100**	**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**	**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	17.3	**100**	**100**	**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**	**100**	**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**	**100**	**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	**100**	84.1	*85.3*	81	80.2
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	58.9	44.1	*85*	59.1	71.2
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	77	63.6	65.6	50.5	54
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	67.9	*82.1*	**92.9**	77.9	72.1
Coupon	**100**	**100**	**100**	**100**	38.8	**100**	**100**	**100**	37.9	**100**	**100**	**100**	*99.1*	39.4	**100**	**100**	**100**	**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**	**100**	**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	**100**	95.1	89.6	90.8	97.4
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**	**100**	**100**	**100**
Dancer2	**100**	**100**	**100**	**100**	84	**100**	**100**	**100**	**100**	**100**	**100**	**100**	*98.7*	*98.7*	**100**	**100**	**100**	**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	96.2	*98.9*	97.5	**100**	**100**
David2	**100**	**100**	54.2	83.6	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	11	**100**	**100**	*92.2*	**100**	**100**	**100**	**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**	**100**	96.4	**100**	*99.6*
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**	83.1	**100**	**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*	**19.1**	*18.6*	18.1	*18.6*	*18.6*
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	59.8	49.6	59.8	*79.5*	**83.5**
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**	**100**	**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	**99.8**	99.7	*99.7*	90.1	*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	58.4	30.1	22.1	*85*	**96.5**
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	67.3	*99.2*	97.4	97.2	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**	**100**	**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**	99.6	93.6	90.4	61.7	95.3
Fish	**100**	**100**	*86.1*	**100**	62	**100**	4.83	39.9	**100**	**100**	**100**	**100**	5.67	16.8	**100**	**100**	**100**	**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	71	66.3	67.8	76	74.5
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*	78.7	87.8	76.5	79	79
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**	95.9	39.2	39.2	39.2	37.8
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	**86.5**	62.6	53.1	54.3	43.6
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	31.3	55.9	70.4	**100**	**100**
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	45.2	*87.6*	**90.5**	79.5	74.6
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	46.6	77.6	79.8	**100**	*99.6*
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	7.4	*87.8*	71.5	**97.5**
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	7.43	**53.5**	*41.3*	35.5	6.13
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	95.4	*97.8*	**99.7**	94.9	94.2
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	3.18	*77.8*	39	**87.8**
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	91.8	**100**	91	60.3	75.3
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	34.4	96.5	**99.9**	99.2	*99.6*
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	**98.1**	92.2	47.1	89.5	*96.2*
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**	**100**	**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**	**100**	**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	42	46.2	46.6	12.1	**100**
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*	9.64	3.01	4.22	25.9	**88**
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	22.5	*97.1*	*97.1*	*97.1*	**97.4**
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**	18.6	99.3	98.7	94.1	**100**
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**	7.38	2.46	2.46	4.92	**9.84**
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*	21.4	95.8	95.5	**99.7**	99
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	90.5	64.3	39.3	**100**	**100**
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	26.8	26.3	**96.4**	90.5	*95.8*
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	62	**98.6**	*98.4*	97.9	96
Man	22.4	**100**	22.4	**100**	28.4	**100**	**100**	**100**	24.6	**100**	**100**	**100**	*47*	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
Matrix	9	2	6	7	7	11	13	1	10	13	18	32	8	36	31	*39*	33	37	29	35	**62**
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**	98.5	99.7	*99.9*	**100**	**100**
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**	6.71	7.32	7.32	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**	**100**	99.1	**100**	*99.6*	97.8
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	27.9	13.6	12.5	11.9	31.4
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	69.1	**97.5**	*94.7*	93.7	93.1
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	75.3	16.5	55.5	96.4	**99.4**
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	1.64	1.1	94.2	98.1	4.93
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**	**100**	**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	**100**	98.6	*98.9*	3.55	3.55
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**	76.9	68.8	61.3	79.4	75
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*	35.2	46	61.1	52.4	76.8
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	50.7	53.8	47	43.8	38.5
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	53.5	56.9	**60**	*59.4*
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	12.1	**57.3**	22.4	27.7	29.8
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*	12.3	4.94	4.94	11.1	30.9
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	24.5	57.9	**84.7**	*84.4*	77.3
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**	**100**	*99.4*	*99.4*	98.9	**100**
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	26.3	95.7	93.9	**96.8**	*96*
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**	**98.4**	98.2	83.3	97
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	65.8	83.3	85.8	90	95
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	98	*99.1*	96.6	**99.7**	**99.7**
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	87.4	**95.3**	*94.5*	64.4	89.3
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	**90**	79.7	58.3	70.8	*84.1*
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	*51.6*	40.3	36.3	41.1	48.4
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	*99.3*	96.5	95.3	96.3	99.1
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	97.7	43.5	99.4	71.3	*99.6*
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	**66.4**	52.8	*57.6*	49.8	42.1
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**	**99.8**	**99.8**	95.4
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**	**100**	43.4	**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	93.1	92.3	93.3	**99.2**	*98*
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	69.9	72.9	76.7	*77.3*	**82.4**

Table 2. A per-video comparison on the Temple-Color dataset [17] with 128 videos. The results are shown in terms of overlap precision (OP) (in percent), which corresponds to the PASCAL criterion. The best and second best results for each video are shown in red and blue font respectively. Our approach achieves a significant gain of 4.6% in mean OP, compared to the second best tracker (SRDCFdecon).

Video	EDFT [8]	LSHT [12]	DFT [23]	ASLA [14]	TLD [15]	Struck [11]	CFLB [9]	ACT [7]	TGPR [10]	KCF [13]	DSST [2]	SAMF [16]	DAT [22]	MEEM [26]	LCT [19]	HCF [18]	Staple [1]	SRDCF [4]	SRDCFdecon [5]	DeepSRDCF [3]	**C-COT** [6]
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	*50*	**85.1**	45.3	44.6	44.6
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	95.3	90.9	83.4	95.9	**99**
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	88.8	77.4	78.9	86.4	89.3
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	*88.9*	65.2	78.3	54.9	**89.2**
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**	2.3	1.28	5.12	11.3	2.05
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	63.4	57.5	**91.5**	83.1	*90.8*
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*	*69.3*	*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**	4.09	*5.02*	*5.02*	*5.02*	4.09
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**	87	41.4	96.1	28.3	98.9
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	33.3	56.9	*67.5*	48.8	**73.2**
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	39.3	35.4	47.7	43.1	45.1
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	91.4	82.8	87.5	64.6	*92.7*
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	85.6	43.3	57.8	41.1	47.8
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	86	**96.7**	94.8	75.6	72
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**	**100**	98.9	**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	13.8	53.8	*90.3*	**90.4**	85.2
Biker	19	19	19	52	26.3	21.8	19	43	63.1	19	93.9	93.9	19	41.3	19	47.5	**100**	96.6	*97.2*	91.6	52.5
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	2.77	15	22.4	19.4	*63.4*
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	88.9	57.6	65.7	96	**100**
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	92.8	92.1	**96.8**	90.1	83.4
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	4.77	50.7	50.4	**57.3**	*55.4*
Boat	44.4	39.8	44.9	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	61.7	58.3	59.5	60.9	60.9
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	**100**	1.43	1.43	74.6	90.6
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**	**100**	*99.8*	**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	10.2	**90.4**	10.2	*82.4*	9.92
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	88.1	97.5	96.7	**99.2**	95.4
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**	**100**	**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	**99.6**	80.6	*85.7*	81	80.2
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	28.3	**93.2**	28.1	28.3
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	*99.8*	99.1	99.1	99.1	99.5
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**	**100**	**100**	*99.8*
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	*80.2*	**83.2**	71.8	18.8	78.2
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	78	61.5	56.4	50.5	54
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	67.9	*92.9*	**94.3**	77.9	72.1
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**	**100**	**100**	**100**
Cup	**100**	**100**	**100**	**100**	**100**	**100**	*46.2*	**100**	**100**	**100**	**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	1.48	1.18	1.18
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	96.2	98.7	*98.9*	**100**	**100**
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**	**100**	*99.6*	**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**	**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	18.6	22.1	22.1	24.7	18.6
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	**99.7**	99.6	99.5	90.1	*99.7*
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*	32.1	29.5	16.1	25	5.36
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	*99.9*	99.5	**100**	97.3	**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**	**100**	**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	4.35	4.52	**80**	*79.8*	78.9
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	85.1	*89.9*	84.5	**93.2**	83.1
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	**65.6**	17.7	11.5	20.4	43.1
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	14.5	14.1	55	14.8	32.5
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**	**100**	39.2	52.7	39.2	37.8
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	64.4	17.4	81.8	**100**	*99.6*
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	11.6	7.4	7.27	**85.9**	77.7
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	92.2	*98.9*	97.4	**99.3**	**99.3**
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	*97.1*	64.9	65.2	95.5	95.5
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*	87.1	44.9	69.6	21.9	57.3
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	16.8	18.9	14.8	*82*
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	97.5	*99.8*	99.5	99.5	**100**
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	75.7	67.3	87.6	**98.8**	94
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	66	83	82	79.7	90.3
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**	94.7	**98.4**	90.8	94.1	96.7
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	64.4	41.6	55.2	52.8	*85*
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*	9.64	56	9.64	25.9	**88**
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	22.5	*97.1*	*97.1*	*97.1*	**97.4**
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**	18.6	97.7	**100**	94.1	**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**	**100**	**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	44.8	33.9	33.1	12.8	*92.4*
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	90.3	98	**99.1**	93.8	97.4
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*	99.6	99.1	98.1	*99.8*	**100**
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	11	16.7	*31.8*	22.7	**62.7**
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	26.8	**98.8**	91.3	90.5	*95.8*
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	84.5	97.4	91.9	97.9	96
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**	**84.4**	*82.3*	**84.4**	81
Matrix	9	1	6	11	7	11	2	1	9	13	17	32	8	36	31	*39*	15	30	25	35	**62**
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	51.1	53.3	*68.4*	65.4	**69.9**
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	92.1	86.3	54.5	54.2	53.9
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	55.4	90.7	57.8	85.8	82.4
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	43.7	65	4.85	35.9	18.4
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**	6.71	7.32	6.71	7.32	7.32
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	23.8	*67.5*	23.6	23.8
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**	**100**	98.2	98.7	*99.6*	97.8
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	92.5	*97.1*	94.6	**99.6**	**99.6**
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	**70**	22.2	54.7	38.6	50.2
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	72.5	**100**	*99.3*	*99.3*	**100**
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*	**100**	36.5	38.1	44.2	41.4
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	4.22	48.8	91.6	97	95.8
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	0.752	2.26	4.51	72.9	75.9
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	2.42	0.806	8.06	12.9	*40.3*
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*	7.99	12.6	13.1	11.1	12.6
Ring	**100**	5.97	75.6	*99.5*	**100**	**100**	**100**	**100**	28.4	**100**	**100**	**100**	4.98	**100**	**100**	**100**	**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	**100**	*99.8*	**100**	98.5	98.5
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	1.64	95.6	96.2	*98.1*	4.93
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**	**100**	**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	**100**	3.55	3.55	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	90.2	93.9	94.4	93	95.8
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	**91.1**	12.8	*66.9*	57	11.8
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	**83**	21.5	44.8	43.8	38.5
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	67.8	44.3	11	10.6	**87.3**
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	*84.6*	84.1	**86.3**	62.1	79.2
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	**56.3**	37.4	34.8	5.43	22.7
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*	12.3	6.17	8.64	11.1	30.9
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**	**100**	*99.6*	99.4
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	37.7	6.5	38.1	26.9	34.2
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	24	*82.1*	22.2	**84.4**	77.3
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	42.7	52.1	*58.7*	55	**68.9**
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**	**100**	22.3	98.3	98.9	**100**
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	78.3	77.7	78.8	78.8	75.5
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	98.3	97.7	98.3	97.7	97.7
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	85.7	**100**	**100**	**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	52.7	43.6	67.8	37.9	*75*
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	*41.7*	8.18	6.14	15.1	30.2
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	40.9	48.7	20.4	12.9	45.5
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	31.1	8.89	6.67	13.3	12.6
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	1.52	2.02	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	1.04	1.74	2.08	3.13	3.13
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	14.1	92.1	89.9	69.2	79.1
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*	**100**	98.7	98.4	95.4	**100**
Tennis	85.3	5.88	10.3	*96.6*	16.2	86.3	96.1	62.7	9.8	8.82	67.2	69.6	**97.5**	81.4	8.82	8.82	54.9	86.8	89.7	88.7	88.7
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**	*99.5*	**100**	**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	97.7	98.3	*98.6*	**98.9**	84.5
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	86.8	*92.3*	**93.4**	64.4	89.3
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	*97.7*	95.1	**98.5**	96.6	97.3
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	8.89	19.8	9.38	9.63
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	98.9	96.7	97.2	96.3	*99.1*
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	*99.3*	**99.8**	**99.8**	95.4
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**	**100**	43.4	**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	93.1	92.6	93.6	**99.2**	*98*
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	8.09	9.36	**35.3**	10.2	10.2
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	28.6	29.1	29.1	**85**	*80.8*
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	2.49	5.47	4.98	**70.1**	5.47
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	63	62.2	*65.8*	65.4	**70.4**

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