Hierarchical Convolutional Features for Visual Tracking
Supplementary Document

Chao Ma
SJTU
chaoma@sjtu.edu.cn

Jia-Bin Huang
UIUC
jbhuang1@illinois.edu

Xiaokang Yang
SJTU
xkyang@sjtu.edu.cn

Ming-Hsuan Yang
UC Merced
mhyang@ucmerced.edu

1. Comparisons with the State-of-the-art Trackers

We quantitatively evaluate the proposed tracking algorithm on the 100 benchmark sequences [10] with comparisons to 12 state-of-the-art trackers, which can be broadly categorized into three classes:

1. Deep learning tracker DLT [8];
2. Correlation trackers including the CSK [5], STC [12], and KCF [6] trackers;
3. Representative tracking algorithms using single or multiple online classifiers, including the MIL [1], Struck [3], CT [13], LSHT [4], TLD [7], SCM [14], MEEM [11], and TGPR [2] trackers.

These trackers can be downloaded from the authors' websites listed in Table 1 or the tracker benchmark code library [9, 10].

Table 1. Links to publicly available implementations.

DLT [8]	http://winsty.net/dlt.html
CSK [5]	http://home.isr.uc.pt/~henriques/circulant/
STC [12]	http://www4.comp.polyu.edu.hk/~cslzhang/STC/STC.htm
KCF [6]	http://home.isr.uc.pt/~henriques/circulant/
MIL [1]	http://vision.ucsd.edu/project/tracking-online-multiple-instance-learning
Struck [3]	http://www.samhare.net/research/struck
CT [13]	http://www4.comp.polyu.edu.hk/~cslzhang/CT/CT.htm
LSHT [4]	http://www.shengfenghe.com/visual-tracking-via-locality-sensitive-histograms.html
TLD [7]	http://personal.ee.surrey.ac.uk/Personal/Z.Kalal/tld.html
SCM [14]	http://faculty.ucmerced.edu/mhyang/project/cvpr12_scm.htm
MEEM [11]	http://cs-people.bu.edu/jmzhang/MEEM/MEEM.html
TGPR [2]	http://www.dabi.temple.edu/~hbling/code/TGPR.htm

2. Visual Tracking Benchmark Evaluation

In this section, we report complete results of the distance precision rate and overlap success rate in Section 2.1. We then present center location errors for each sequence in Section 2.2. Finally, we report the robustness evaluation results in Section 2.3.

2.1. Distance Precision Rate (DPR) and Overlap Sucess Rate (OSR)

Distance Precision Rate (DPR) Table 2 shows the distance precision rate (DPR) at a threshold of 20 pixels over the first 50 benchmark sequences in [9]. Table 3 shows the distance precision rate of the additional sequences in the 100 sequence dataset in [10].

Overlap Success Rate (OSR) Table 4 shows the overlap success rate (OSR) at a threshold of 0.5 over the first 50 benchmark sequences in [9]. Table 5 shows the overlap success rate of the additional sequences in the 100 sequence dataset in [10].

Table 2. Distance precision rate at a threshold of 20 pixels on the first 50 benchmark sequences [9]. The proposed algorithm performs favorably against the state-of-the-art algorithms.

Sequences	**Ours**	**DLT**	**KCF**	**STC**	**Struck**	**SCM**	**CT**	**LSHT**	**CSK**	**MIL**	**TLD**	**MEEM**	**TGPR**
basketball	1.000	0.086	0.923	0.560	0.120	0.661	0.299	0.051	1.000	0.284	0.028	0.892	0.993
bolt	1.000	0.026	0.989	0.046	0.020	0.031	0.011	0.371	0.034	0.014	0.306	0.966	0.026
boy	1.000	1.000	1.000	0.761	1.000	0.440	0.930	0.593	0.844	0.846	1.000	1.000	1.000
car4	0.997	1.000	0.953	0.967	0.992	0.974	0.281	0.569	0.355	0.354	0.874	0.686	1.000
carDark	1.000	0.715	1.000	1.000	1.000	1.000	0.005	0.623	1.000	0.379	0.639	1.000	1.000
carScale	0.627	0.714	0.806	0.647	0.647	0.647	0.718	0.639	0.651	0.627	0.853	0.651	0.806
coke	0.962	0.340	0.838	0.155	0.948	0.430	0.113	0.540	0.873	0.151	0.684	0.945	0.942
couple	0.921	0.307	0.257	0.086	0.736	0.114	0.693	0.121	0.086	0.679	1.000	1.000	0.107
crossing	1.000	1.000	1.000	0.533	1.000	1.000	1.000	0.550	1.000	1.000	0.617	1.000	0.950
david	1.000	0.321	1.000	0.837	0.329	1.000	0.815	0.752	0.499	0.699	1.000	0.904	0.987
david2	1.000	0.711	1.000	1.000	1.000	1.000	0.004	1.000	1.000	0.978	1.000	1.000	1.000
david3	1.000	0.698	1.000	0.925	0.337	0.496	0.413	0.754	0.659	0.738	0.111	0.996	1.000
deer	1.000	0.042	0.817	0.042	1.000	0.028	0.042	0.028	1.000	0.127	0.732	1.000	1.000
dog1	1.000	0.996	1.000	0.700	0.996	0.976	0.950	0.851	1.000	0.919	1.000	0.982	1.000
doll	0.978	0.957	0.968	0.763	0.919	0.978	0.684	0.387	0.579	0.732	0.983	0.985	0.971
dudek	0.905	0.918	0.877	0.554	0.897	0.883	0.418	0.646	0.807	0.688	0.597	0.792	0.681
faceocc1	0.600	0.462	0.730	0.250	0.575	0.933	0.330	0.642	0.947	0.221	0.203	0.683	0.831
faceocc2	0.994	0.850	0.972	0.974	1.000	0.860	0.681	0.990	1.000	0.740	0.856	0.986	0.979
fish	1.000	0.401	1.000	1.000	1.000	0.863	0.882	1.000	0.042	0.387	1.000	1.000	1.000
fleetface	0.590	0.434	0.460	0.481	0.639	0.529	0.438	0.577	0.567	0.358	0.506	0.591	0.393
football	1.000	0.296	0.796	0.801	0.751	0.765	0.798	0.793	0.798	0.790	0.804	0.992	1.000
football1	1.000	0.608	0.959	0.514	1.000	0.568	0.351	0.973	0.757	1.000	0.554	1.000	0.986
freeman1	0.979	0.380	0.402	0.371	0.801	0.982	0.396	0.966	0.555	0.939	0.540	0.997	0.985
freeman3	0.811	1.000	0.911	0.596	0.789	1.000	0.209	0.346	0.572	0.048	0.767	0.985	0.122
freeman4	0.943	0.346	0.534	0.233	0.375	0.509	0.064	0.873	0.187	0.201	0.410	0.565	0.519
girl	1.000	0.776	0.864	0.594	1.000	1.000	0.608	0.212	0.554	0.714	0.918	1.000	0.904
ironman	0.645	0.127	0.217	0.151	0.114	0.157	0.096	0.036	0.133	0.108	0.120	0.506	0.096
jogging-1	0.974	0.228	0.235	0.228	0.241	0.228	0.231	0.967	0.228	0.231	0.974	0.964	0.225
jogging-2	1.000	0.173	0.163	0.186	0.254	1.000	0.166	0.166	0.186	0.186	0.857	0.971	0.997
jumping	1.000	0.962	0.342	0.054	1.000	0.153	0.096	0.134	0.051	0.997	1.000	1.000	0.109
lemming	0.258	0.298	0.487	0.312	0.628	0.166	0.677	0.406	0.436	0.823	0.859	0.911	0.275
liquor	0.816	0.357	0.976	0.403	0.390	0.276	0.209	0.598	0.223	0.199	0.588	0.925	0.657
matrix	0.620	0.010	0.170	0.100	0.120	0.350	0.020	0.110	0.010	0.180	0.160	0.640	0.110
mhyang	1.000	1.000	1.000	1.000	1.000	1.000	0.819	0.987	1.000	0.460	0.978	1.000	1.000
motorRolling	0.945	0.043	0.049	0.073	0.085	0.037	0.037	0.049	0.043	0.043	0.116	0.061	0.061
mountainBike	1.000	0.811	1.000	1.000	0.921	0.969	0.175	1.000	1.000	0.667	0.259	0.917	1.000
shaking	0.868	0.926	0.019	0.981	0.192	0.814	0.047	0.712	0.564	0.282	0.405	0.995	0.641
singer1	1.000	1.000	0.843	1.000	0.641	1.000	0.840	0.413	0.670	0.501	1.000	0.470	0.219
singer2	0.041	0.036	0.948	0.571	0.036	0.112	0.005	0.986	0.036	0.404	0.071	0.038	0.954
skating1	1.000	0.763	1.000	0.690	0.465	0.768	0.090	0.535	0.988	0.130	0.318	0.693	0.700
skiing	0.988	0.123	0.074	0.136	0.037	0.136	0.086	0.123	0.099	0.074	0.123	1.000	0.111
soccer	0.816	0.138	0.791	0.135	0.253	0.268	0.219	0.099	0.135	0.191	0.115	0.314	0.143
subway	1.000	0.023	1.000	0.246	0.983	1.000	0.989	1.000	0.240	0.994	0.251	1.000	1.000
suv	0.979	1.000	0.979	0.805	0.572	0.978	0.250	0.524	0.568	0.123	0.909	0.743	0.531
sylvester	0.852	0.770	0.843	0.897	0.995	0.946	0.901	0.949	0.910	0.651	0.949	0.954	0.946
tiger1	0.811	0.433	0.851	0.261	0.175	0.126	0.215	0.074	0.255	0.095	0.456	0.822	0.269
tiger2	0.567	0.329	0.356	0.145	0.630	0.112	0.364	0.093	0.110	0.414	0.386	0.488	0.792
trellis	1.000	0.339	1.000	0.738	0.877	0.873	0.387	0.450	0.810	0.230	0.529	0.968	0.981
walking	1.000	0.748	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.964	1.000	1.000
walking2	1.000	1.000	0.434	0.794	0.982	1.000	0.432	0.400	0.468	0.406	0.426	0.392	0.996
woman	0.940	0.938	0.938	0.615	1.000	0.940	0.204	0.940	0.250	0.206	0.191	0.963	0.940
Average	**0.891**	**0.548**	**0.741**	**0.547**	**0.656**	**0.649**	**0.406**	**0.561**	**0.545**	**0.475**	**0.608**	**0.830**	**0.705**

Table 3. Distance precision rate at a threshold of 20 pixels on additional benchmark sequences [10]. The average scores are computed from the 100 sequences. The proposed algorithm performs favorably against the state-of-the-art algorithms.

Sequences	Ours	DLT	KCF	STC	Struck	SCM	CT	LSHT	CSK	MIL	TLD	MEEM	TGPR
biker	0.521	0.958	0.507	0.514	0.556	0.500	0.099	0.303	0.514	0.514	0.514	0.535	0.514
bird1	0.392	0.588	0.069	0.015	0.150	0.517	0.578	0.235	0.029	0.461	0.010	0.289	0.811
bird2	0.980	0.202	0.475	0.505	0.545	0.899	0.101	0.980	0.515	0.646	0.859	1.000	0.737
blurBody	0.991	0.045	0.584	0.165	0.814	0.093	0.009	0.117	0.428	0.015	0.449	0.886	0.790
blurCar1	0.995	0.026	0.995	0.962	0.996	0.022	0.057	0.009	0.012	0.049	0.821	0.993	0.035
blurCar2	0.961	0.749	0.938	0.990	0.916	0.099	0.164	0.137	0.925	0.166	0.979	0.959	0.962
blurCar3	1.000	0.252	0.994	0.406	1.000	0.157	0.207	0.232	0.549	0.328	0.952	1.000	0.042
blurCar4	1.000	0.563	0.997	0.574	0.997	0.179	0.021	0.095	1.000	0.037	0.803	0.976	0.937
blurFace	1.000	0.191	1.000	0.629	0.436	0.112	0.116	0.089	0.996	0.191	1.000	0.990	0.990
blurOwl	0.962	0.070	0.228	0.114	0.989	0.190	0.071	0.057	0.162	0.100	0.713	0.995	0.512
board	0.870	0.570	0.656	0.092	0.752	0.441	0.069	0.126	0.089	0.170	0.011	0.605	0.053
bolt2	0.952	0.973	0.017	0.980	0.109	0.014	0.638	0.666	1.000	1.000	0.014	0.017	0.020
box	0.394	0.396	0.415	0.390	0.239	0.153	0.630	0.369	0.080	0.140	0.742	0.370	0.294
car1	0.391	1.000	0.739	0.275	0.334	1.000	0.145	0.229	0.260	0.241	0.417	0.196	0.337
car2	1.000	1.000	1.000	1.000	1.000	1.000	0.411	0.998	1.000	0.074	1.000	1.000	0.074
car24	1.000	1.000	1.000	0.926	0.170	1.000	0.549	0.587	0.863	0.548	1.000	1.000	0.992
clifBar	0.915	0.464	0.445	0.468	0.182	0.121	0.201	0.081	0.210	0.169	0.208	0.941	0.146
coupon	1.000	0.382	1.000	1.000	1.000	1.000	0.459	1.000	1.000	0.410	0.740	0.394	0.388
crowds	1.000	0.916	1.000	1.000	0.911	1.000	0.012	1.000	1.000	0.086	1.000	1.000	1.000
dancer	1.000	0.964	1.000	0.907	0.987	1.000	0.956	0.947	1.000	0.947	0.951	0.916	0.964
dancer2	1.000	1.000	1.000	1.000	1.000	1.000	0.973	1.000	1.000	0.933	0.853	0.980	0.993
diving	0.753	0.256	0.535	0.340	0.521	0.540	0.042	0.186	0.367	0.288	0.158	0.209	0.214
dog	1.000	0.961	0.992	1.000	0.945	0.953	0.992	0.764	1.000	0.882	1.000	1.000	0.992
dragonBaby	0.867	0.372	0.336	0.221	0.106	0.283	0.257	0.168	0.212	0.115	0.257	0.823	0.752
girl2	0.076	0.074	0.071	0.071	0.272	0.343	0.108	0.073	0.071	0.073	0.077	0.801	0.577
gym	0.988	0.146	0.795	0.549	0.597	0.342	0.192	0.919	0.522	0.828	0.641	0.913	0.858
human2	0.540	0.556	0.171	0.154	0.432	0.354	0.117	0.148	0.129	0.107	0.257	0.180	0.738
human3	0.035	0.009	0.006	0.019	0.010	0.009	0.020	0.020	0.016	0.019	0.008	0.866	0.010
human4	0.852	0.205	0.534	0.193	0.211	0.192	0.198	0.208	0.204	0.192	0.118	0.504	0.508
human5	0.245	0.891	0.265	0.321	0.990	0.933	0.244	0.163	0.244	0.334	1.000	0.997	0.993
human6	0.381	0.446	0.290	0.299	0.255	0.322	0.260	0.284	0.294	0.293	0.458	0.663	0.295
human7	1.000	0.436	0.472	0.332	1.000	0.368	0.312	0.372	0.656	1.000	1.000	1.000	0.856
human8	1.000	0.219	1.000	0.297	0.195	1.000	0.078	0.086	0.289	0.156	0.188	1.000	0.188
human9	1.000	0.321	0.725	0.190	0.282	0.203	0.246	0.672	0.197	0.449	0.213	0.498	0.639
jump	0.082	0.066	0.057	0.074	0.082	0.074	0.008	0.057	0.074	0.033	0.066	0.066	0.066
kiteSurf	0.464	0.286	0.333	0.286	0.905	0.333	0.452	0.583	0.345	0.595	0.464	1.000	0.440
man	1.000	1.000	1.000	1.000	1.000	1.000	0.246	1.000	1.000	0.231	1.000	1.000	0.970
panda	0.973	0.996	0.364	0.529	1.000	0.993	0.984	0.586	0.159	0.995	0.729	1.000	1.000
redTeam	1.000	1.000	1.000	0.798	1.000	1.000	1.000	0.995	1.000	1.000	0.721	1.000	1.000
rubik	0.897	0.359	0.969	0.305	0.307	0.216	0.122	0.422	0.338	0.794	0.989	0.536	0.156
skater	0.994	0.981	0.938	0.625	0.994	0.781	0.394	0.975	0.731	0.931	0.925	0.925	0.963
skater2	0.903	0.237	0.694	0.333	0.726	0.694	0.028	0.030	0.655	0.308	0.379	0.913	0.352
skating2-1	0.725	0.040	0.383	0.066	0.190	0.061	0.082	0.199	0.080	0.099	0.034	0.273	0.268
skating2-2	0.444	0.114	0.490	0.091	0.292	0.283	0.089	0.256	0.095	0.032	0.025	0.178	0.262
surfer	1.000	0.585	0.910	0.324	0.971	0.707	0.279	0.455	0.016	0.715	1.000	0.987	0.992
toy	0.830	0.214	0.985	0.055	0.897	0.258	0.380	0.727	0.491	0.365	0.934	0.745	0.690
trans	0.298	0.185	0.306	0.371	0.226	0.250	0.194	0.516	0.266	0.137	0.419	0.210	0.250
twinnings	0.989	0.998	0.907	0.409	1.000	0.725	0.746	0.731	0.979	0.994	0.623	0.987	0.994
vase	0.624	0.413	0.793	0.649	0.513	0.376	0.679	0.295	0.760	0.539	0.531	0.476	0.779
Average	**0.837**	**0.526**	**0.692**	**0.507**	**0.635**	**0.572**	**0.359**	**0.497**	**0.516**	**0.439**	**0.592**	**0.781**	**0.643**

Table 4. Overlaps success rate at a threshold of 0.5 on the first 50 benchmark sequences [9]. The proposed algorithm performs favorably against the state-of-the-art algorithms.

Sequences	**Ours**	**DLT**	**KCF**	**STC**	**Struck**	**SCM**	**CT**	**LSHT**	**CSK**	**MIL**	**TLD**	**MEEM**	**TGPR**
basketball	0.999	0.057	0.898	0.236	0.102	0.611	0.259	0.047	0.874	0.274	0.025	0.861	0.850
bolt	0.980	0.017	0.934	0.043	0.017	0.014	0.006	0.326	0.017	0.011	0.146	0.283	0.014
boy	0.990	1.000	0.992	0.663	0.975	0.439	0.688	0.502	0.842	0.385	0.935	0.990	0.990
car4	0.396	1.000	0.367	0.225	0.398	0.973	0.275	0.276	0.276	0.276	0.792	0.349	0.398
carDark	0.883	0.682	0.723	0.997	1.000	0.997	0.003	0.608	0.992	0.178	0.529	1.000	1.000
carScale	0.444	0.706	0.444	0.528	0.433	0.651	0.448	0.448	0.448	0.448	0.437	0.373	0.421
coke	0.914	0.326	0.722	0.089	0.942	0.337	0.093	0.450	0.739	0.117	0.289	0.921	0.914
couple	0.743	0.286	0.243	0.086	0.543	0.107	0.686	0.071	0.086	0.671	1.000	0.757	0.107
crossing	0.950	0.992	0.925	0.175	0.942	1.000	0.983	0.400	0.317	0.983	0.517	0.958	0.808
david	0.601	0.270	0.622	0.584	0.236	0.913	0.427	0.291	0.236	0.229	0.970	0.597	0.771
david2	0.922	0.475	1.000	0.752	1.000	0.911	0.002	0.996	1.000	0.324	0.952	1.000	1.000
david3	1.000	0.504	0.992	0.333	0.337	0.484	0.349	0.679	0.627	0.683	0.103	0.933	0.988
deer	1.000	0.042	0.817	0.042	1.000	0.028	0.042	0.028	1.000	0.127	0.732	1.000	1.000
dog1	0.652	0.884	0.653	0.573	0.653	0.847	0.652	0.547	0.653	0.650	0.673	0.653	0.713
doll	0.729	0.960	0.552	0.100	0.688	0.987	0.531	0.229	0.218	0.433	0.624	0.730	0.714
dudek	0.976	0.978	0.976	0.724	0.980	0.976	0.852	0.886	0.947	0.857	0.842	0.978	0.879
faceocc1	0.942	0.591	1.000	0.243	1.000	1.000	0.854	0.796	1.000	0.765	0.834	1.000	0.982
faceocc2	1.000	0.736	0.996	0.980	1.000	0.874	0.744	1.000	1.000	0.936	0.829	0.996	0.993
fish	1.000	0.372	1.000	0.372	1.000	0.863	0.889	1.000	0.042	0.387	0.964	1.000	1.000
fleetface	0.618	0.421	0.669	0.463	0.666	0.706	0.638	0.629	0.676	0.537	0.567	0.777	0.610
football	0.983	0.293	0.682	0.619	0.660	0.586	0.785	0.773	0.657	0.738	0.412	0.959	0.970
football1	1.000	0.324	0.959	0.351	0.878	0.405	0.081	0.716	0.392	0.784	0.392	0.838	0.811
freeman1	0.298	0.334	0.160	0.169	0.215	0.807	0.101	0.181	0.144	0.153	0.212	0.212	0.218
freeman3	0.296	0.852	0.274	0.207	0.200	0.930	0.002	0.135	0.330	0.009	0.580	0.309	0.067
freeman4	0.459	0.155	0.184	0.170	0.155	0.244	0.004	0.180	0.170	0.021	0.269	0.329	0.332
girl	0.974	0.666	0.756	0.302	0.980	0.882	0.178	0.146	0.398	0.294	0.764	0.948	0.882
ironman	0.608	0.060	0.157	0.042	0.048	0.133	0.090	0.024	0.127	0.048	0.066	0.434	0.060
jogging-1	0.964	0.221	0.225	0.208	0.225	0.212	0.225	0.827	0.225	0.225	0.967	0.909	0.225
jogging-2	1.000	0.156	0.160	0.173	0.248	0.990	0.140	0.160	0.182	0.163	0.831	0.909	0.990
jumping	0.994	0.700	0.281	0.048	0.799	0.121	0.006	0.067	0.048	0.476	0.847	0.987	0.096
lemming	0.267	0.243	0.431	0.153	0.640	0.166	0.680	0.395	0.429	0.811	0.594	0.853	0.268
liquor	0.812	0.363	0.982	0.251	0.406	0.321	0.209	0.597	0.278	0.201	0.582	0.978	0.681
matrix	0.390	0.010	0.130	0.100	0.120	0.300	0.020	0.020	0.010	0.110	0.070	0.380	0.040
mhyang	1.000	1.000	1.000	0.860	1.000	0.997	0.730	0.969	1.000	0.389	0.893	0.997	0.982
motorRolling	0.598	0.073	0.079	0.140	0.159	0.073	0.055	0.098	0.073	0.073	0.171	0.110	0.110
mountainBike	1.000	0.320	0.991	0.873	0.855	0.961	0.171	1.000	1.000	0.575	0.259	0.838	1.000
shaking	0.855	0.926	0.014	0.852	0.167	0.896	0.041	0.699	0.581	0.227	0.400	0.956	0.433
singer1	0.276	1.000	0.276	0.507	0.299	1.000	0.248	0.276	0.296	0.276	0.991	0.271	0.228
singer2	0.041	0.036	0.970	0.459	0.036	0.164	0.011	1.000	0.036	0.475	0.101	0.038	1.000
skating1	0.375	0.485	0.363	0.230	0.370	0.423	0.100	0.188	0.368	0.103	0.228	0.385	0.535
skiing	0.420	0.111	0.062	0.111	0.037	0.086	0.074	0.025	0.074	0.074	0.074	0.321	0.086
soccer	0.467	0.138	0.390	0.115	0.156	0.237	0.202	0.099	0.138	0.156	0.122	0.301	0.130
subway	1.000	0.017	0.994	0.223	0.909	0.994	0.766	0.840	0.223	0.794	0.229	0.966	0.994
suv	0.983	1.000	0.985	0.513	0.575	0.984	0.231	0.529	0.575	0.130	0.839	0.749	0.535
sylvester	0.847	0.512	0.819	0.610	0.929	0.886	0.828	0.930	0.717	0.546	0.928	0.913	0.923
tiger1	0.814	0.298	0.857	0.052	0.183	0.129	0.246	0.077	0.264	0.097	0.456	0.917	0.272
tiger2	0.556	0.181	0.364	0.090	0.649	0.112	0.370	0.082	0.107	0.447	0.173	0.496	0.816
trellis	0.835	0.318	0.840	0.580	0.784	0.854	0.350	0.439	0.591	0.244	0.473	0.819	0.793
walking	0.532	0.464	0.515	0.721	0.566	0.959	0.502	0.459	0.519	0.541	0.383	0.517	0.738
walking2	0.414	1.000	0.378	0.442	0.434	1.000	0.384	0.384	0.388	0.380	0.340	0.352	0.706
woman	0.935	0.802	0.936	0.258	0.935	0.858	0.159	0.781	0.245	0.188	0.166	0.333	0.935
Average	**0.740**	**0.478**	**0.622**	**0.365**	**0.559**	**0.616**	**0.341**	**0.457**	**0.443**	**0.373**	**0.521**	**0.696**	**0.628**

Table 5. Overlaps success rate at a threshold of 0.5 on additional benchmark sequences [10]. The average scores are computed on the entire 100 sequences. The proposed algorithm performs favorably against the state-of-the-art algorithms.

Sequences	Ours	DLT	KCF	STC	Struck	SCM	CT	LSHT	CSK	MIL	TLD	MEEM	TGPR
biker	0.246	0.500	0.254	0.204	0.254	0.444	0.007	0.070	0.254	0.246	0.310	0.254	0.366
bird1	0.199	0.017	0.064	0.029	0.105	0.159	0.390	0.123	0.022	0.343	0.005	0.083	0.542
bird2	0.990	0.141	0.465	0.374	0.525	0.889	0.101	0.970	0.525	0.596	0.707	1.000	0.727
blurBody	0.991	0.090	0.587	0.060	0.988	0.174	0.015	0.257	0.590	0.024	0.629	0.988	0.973
blurCar1	0.997	0.030	1.000	0.028	0.999	0.028	0.084	0.012	0.012	0.049	0.849	1.000	0.038
blurCar2	0.947	0.863	0.947	0.311	0.938	0.144	0.232	0.198	0.947	0.352	0.998	0.947	0.932
blurCar3	1.000	0.252	0.994	0.070	1.000	0.182	0.218	0.235	0.549	0.328	0.952	1.000	0.045
blurCar4	1.000	0.771	1.000	0.134	1.000	0.326	0.037	0.316	1.000	0.037	0.882	1.000	0.984
blurFace	1.000	0.203	1.000	0.525	0.436	0.132	0.150	0.120	1.000	0.195	1.000	1.000	1.000
blurOwl	0.965	0.071	0.228	0.074	0.986	0.216	0.084	0.067	0.165	0.116	0.735	0.995	0.512
board	0.946	0.605	0.854	0.219	0.789	0.663	0.483	0.605	0.476	0.380	0.107	0.761	0.129
bolt2	0.884	0.413	0.007	0.515	0.041	0.007	0.420	0.522	0.338	0.966	0.007	0.007	0.010
box	0.337	0.396	0.357	0.128	0.234	0.176	0.718	0.347	0.071	0.165	0.760	0.339	0.241
car1	0.054	0.999	0.054	0.088	0.054	0.987	0.008	0.054	0.054	0.054	0.319	0.054	0.078
car2	1.000	1.000	1.000	0.559	1.000	1.000	0.114	0.985	1.000	0.074	1.000	1.000	0.074
car24	0.173	0.976	0.173	0.706	0.170	1.000	0.169	0.173	0.173	0.172	0.483	0.173	0.715
clifBar	0.417	0.288	0.301	0.165	0.061	0.042	0.070	0.032	0.087	0.028	0.051	0.606	0.104
coupon	1.000	0.382	1.000	1.000	1.000	1.000	0.520	1.000	1.000	0.933	0.740	0.394	0.388
crowds	0.991	0.352	0.997	0.507	0.769	0.735	0.003	0.380	0.994	0.075	0.994	0.879	0.919
dancer	0.916	0.929	0.916	0.249	0.849	0.991	0.840	0.876	0.907	0.889	0.360	0.827	0.964
dancer2	1.000	0.480	1.000	0.920	1.000	1.000	1.000	1.000	1.000	1.000	0.853	1.000	0.993
diving	0.186	0.153	0.186	0.288	0.181	0.177	0.005	0.172	0.186	0.186	0.167	0.172	0.181
dog	0.134	0.472	0.142	0.394	0.157	0.213	0.197	0.173	0.142	0.197	0.709	0.142	0.173
dragonBaby	0.788	0.336	0.301	0.204	0.088	0.230	0.239	0.159	0.212	0.088	0.257	0.805	0.735
girl2	0.075	0.073	0.070	0.069	0.199	0.232	0.331	0.082	0.071	0.199	0.080	0.686	0.562
gym	0.408	0.042	0.343	0.207	0.219	0.145	0.029	0.316	0.091	0.329	0.205	0.287	0.378
human2	0.804	0.554	0.183	0.116	0.699	0.546	0.209	0.166	0.178	0.206	0.525	0.472	0.953
human3	0.032	0.005	0.005	0.033	0.006	0.005	0.019	0.012	0.006	0.013	0.005	0.741	0.005
human4	0.609	0.027	0.513	0.184	0.211	0.120	0.192	0.187	0.196	0.183	0.109	0.496	0.504
human5	0.240	0.281	0.236	0.243	0.341	0.415	0.237	0.043	0.243	0.285	0.512	0.339	0.348
human6	0.225	0.437	0.225	0.208	0.223	0.283	0.217	0.133	0.226	0.213	0.346	0.223	0.237
human7	0.408	0.432	0.408	0.328	0.408	0.368	0.152	0.232	0.312	0.412	0.844	0.412	0.400
human8	0.305	0.109	0.305	0.242	0.133	1.000	0.008	0.086	0.203	0.156	0.133	0.305	0.133
human9	0.239	0.125	0.239	0.170	0.049	0.203	0.003	0.174	0.180	0.187	0.193	0.197	0.305
jump	0.098	0.057	0.074	0.090	0.098	0.074	0.008	0.057	0.082	0.057	0.074	0.082	0.082
kiteSurf	0.452	0.286	0.310	0.274	0.905	0.321	0.345	0.405	0.321	0.381	0.429	0.988	0.393
man	1.000	1.000	1.000	1.000	1.000	1.000	0.216	1.000	1.000	0.209	1.000	1.000	0.254
panda	0.204	0.427	0.146	0.221	0.360	0.392	0.366	0.475	0.136	0.551	0.385	0.391	0.735
redTeam	0.296	0.956	0.376	0.277	0.398	0.391	0.351	0.287	0.397	0.187	0.283	0.408	0.517
rubik	0.729	0.112	0.814	0.116	0.268	0.195	0.108	0.344	0.254	0.538	0.622	0.441	0.156
skater	0.888	0.650	0.813	0.231	0.838	0.506	0.138	0.838	0.556	0.819	0.294	0.694	0.713
skater2	0.834	0.154	0.621	0.138	0.720	0.425	0.009	0.030	0.772	0.356	0.262	0.867	0.418
skating2-1	0.469	0.047	0.279	0.036	0.186	0.068	0.144	0.218	0.061	0.116	0.032	0.093	0.296
skating2-2	0.252	0.144	0.279	0.023	0.330	0.438	0.209	0.304	0.228	0.078	0.027	0.197	0.317
surfer	0.436	0.521	0.399	0.037	0.157	0.407	0.003	0.027	0.005	0.088	0.899	0.386	0.513
toy	0.410	0.125	0.432	0.048	0.491	0.221	0.044	0.358	0.332	0.210	0.734	0.362	0.292
trans	0.435	0.323	0.476	0.218	0.403	0.323	0.452	0.403	0.540	0.202	0.395	0.435	0.339
twinnings	0.625	0.864	0.542	0.358	0.646	0.644	0.322	0.377	0.434	0.434	0.343	0.614	0.636
vase	0.162	0.122	0.162	0.100	0.140	0.107	0.166	0.129	0.166	0.166	0.550	0.144	0.181
Average	**0.655**	**0.430**	**0.548**	**0.314**	**0.516**	**0.512**	**0.278**	**0.388**	**0.413**	**0.331**	**0.497**	**0.622**	**0.535**

2.2. Center Location Error

We show tracking results on eight sample frames with equal temporal intervals and compare the center location error frame-by-frame on the entire 100 sequences in Figure 1-25. To avoid cluttered plots, we compare only four other representative trackers: (1) MEEM [11]; (2) KCF [6]; (3) DLT [8]; (4) Struck [3].

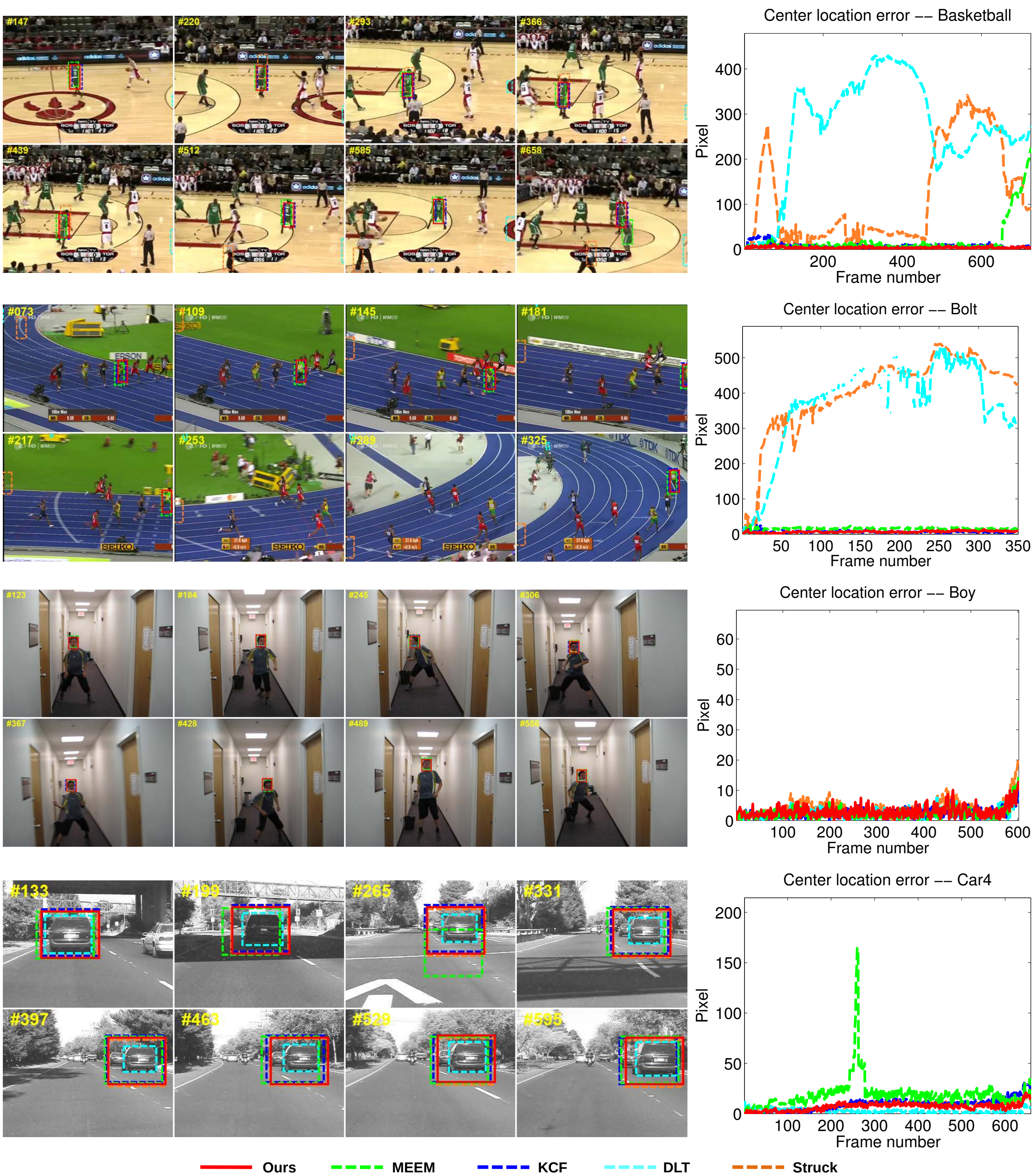

Figure 1. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Basketball*, *Bolt*, *Boy*, *Car4* sequences.

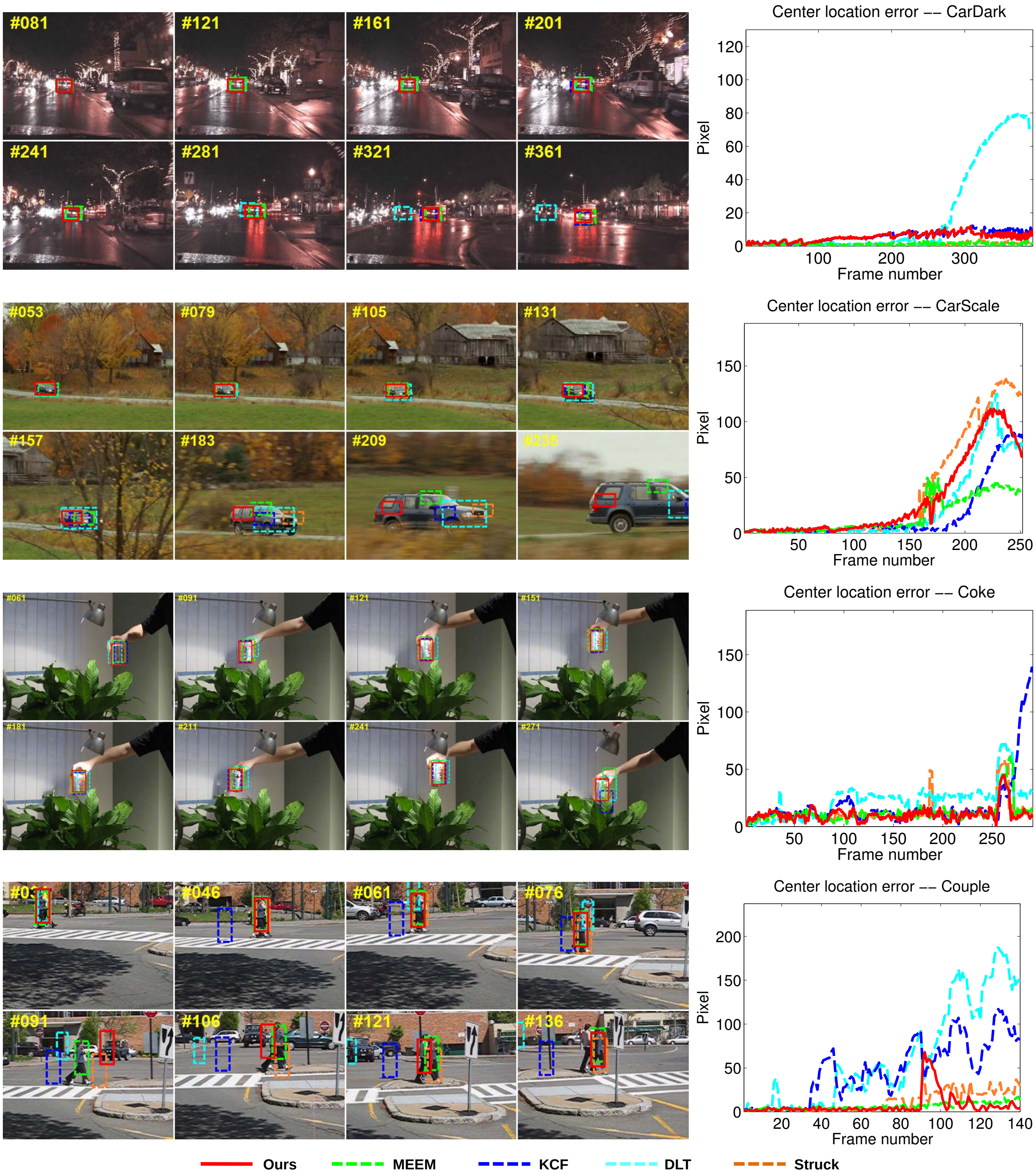

Figure 2. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *CarDark*, *CarScale*, *Coke*, *Couple* sequences.

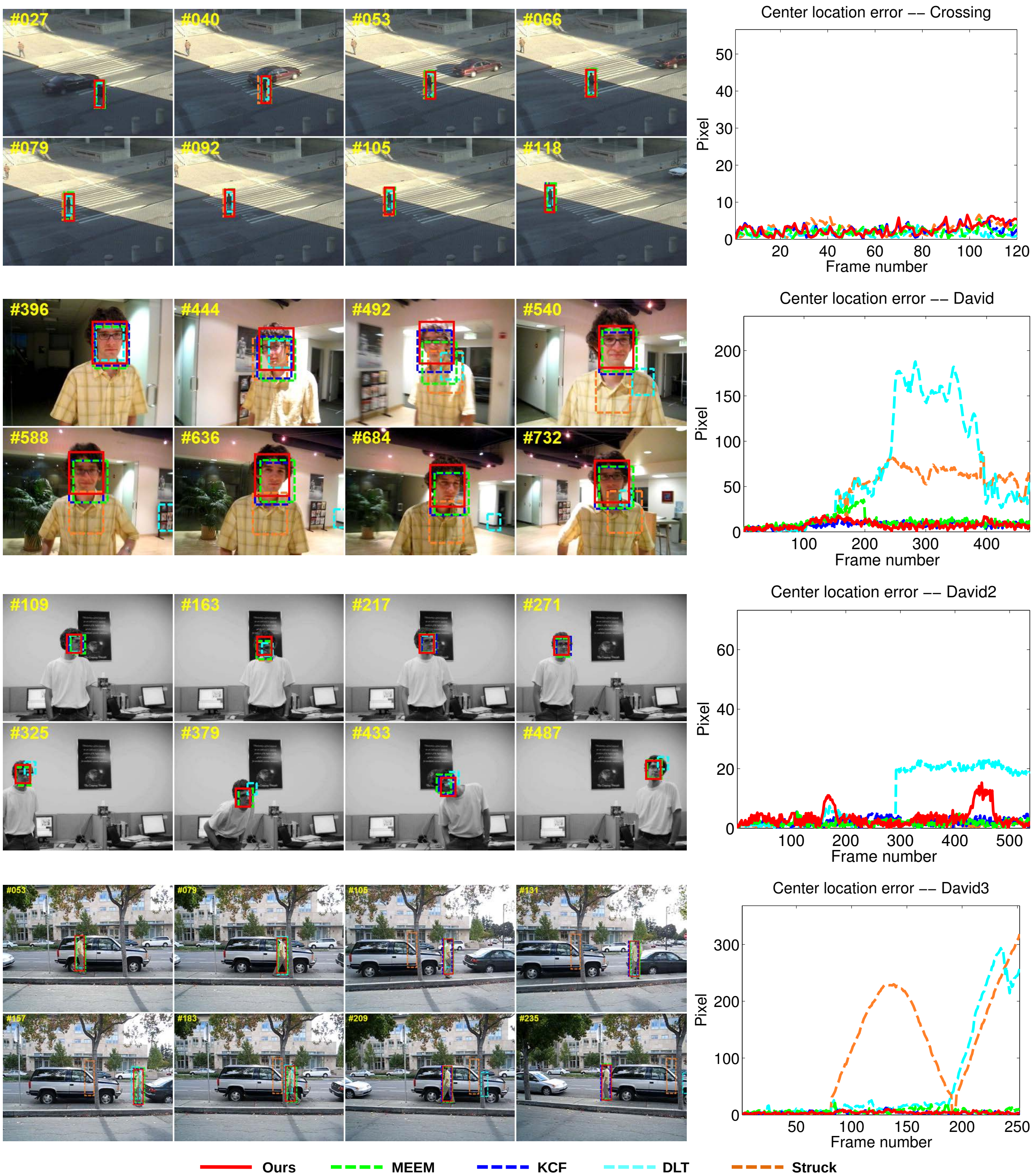

Figure 3. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Crossing*, *David*, *David2*, *David3* sequences.

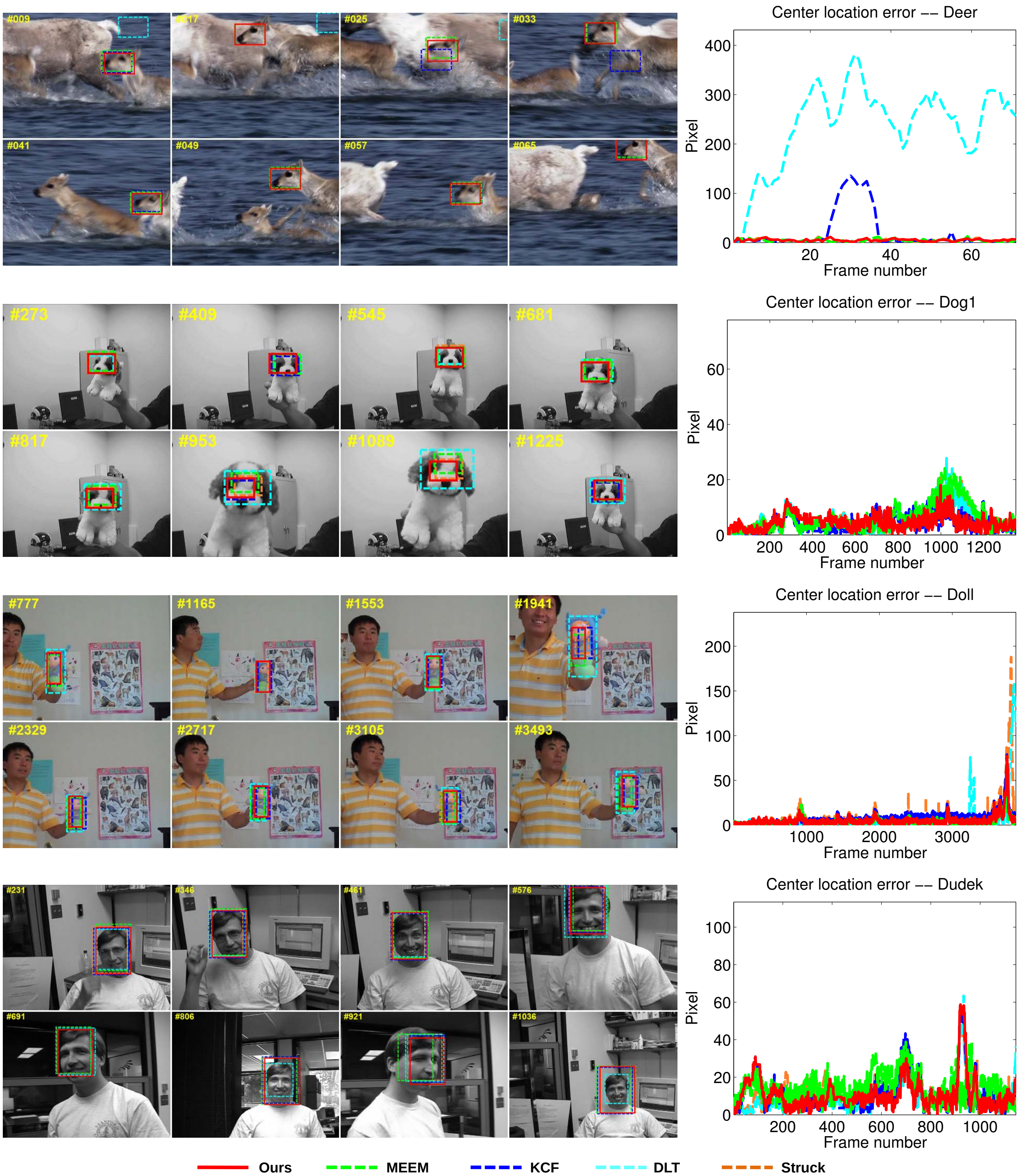

Figure 4. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Deer*, *Dog1*, *Doll*, *Dudek* sequences.

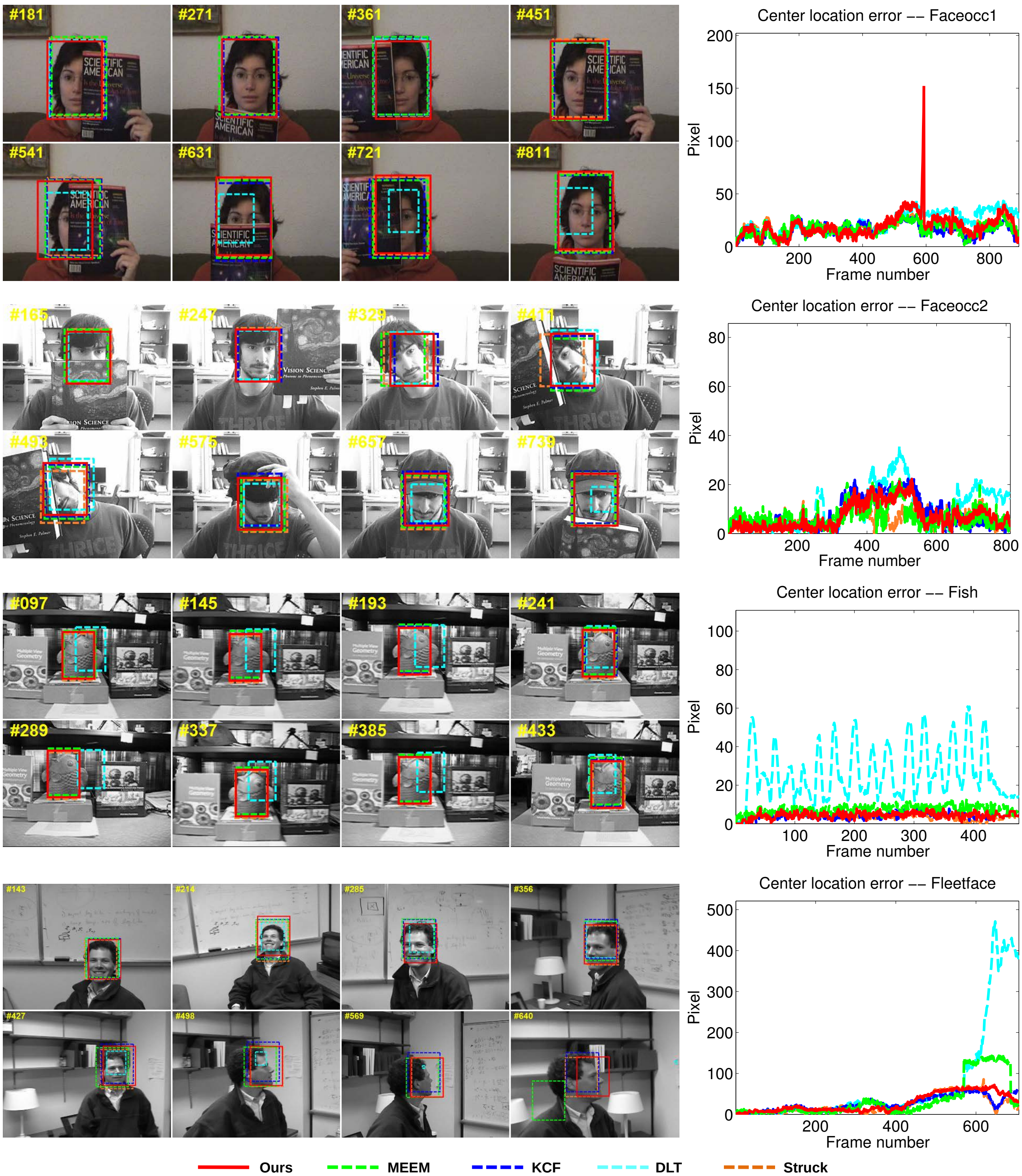

Figure 5. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Faceocc1*, *Faceocc2*, *Fish*, *Fleetface* sequences.

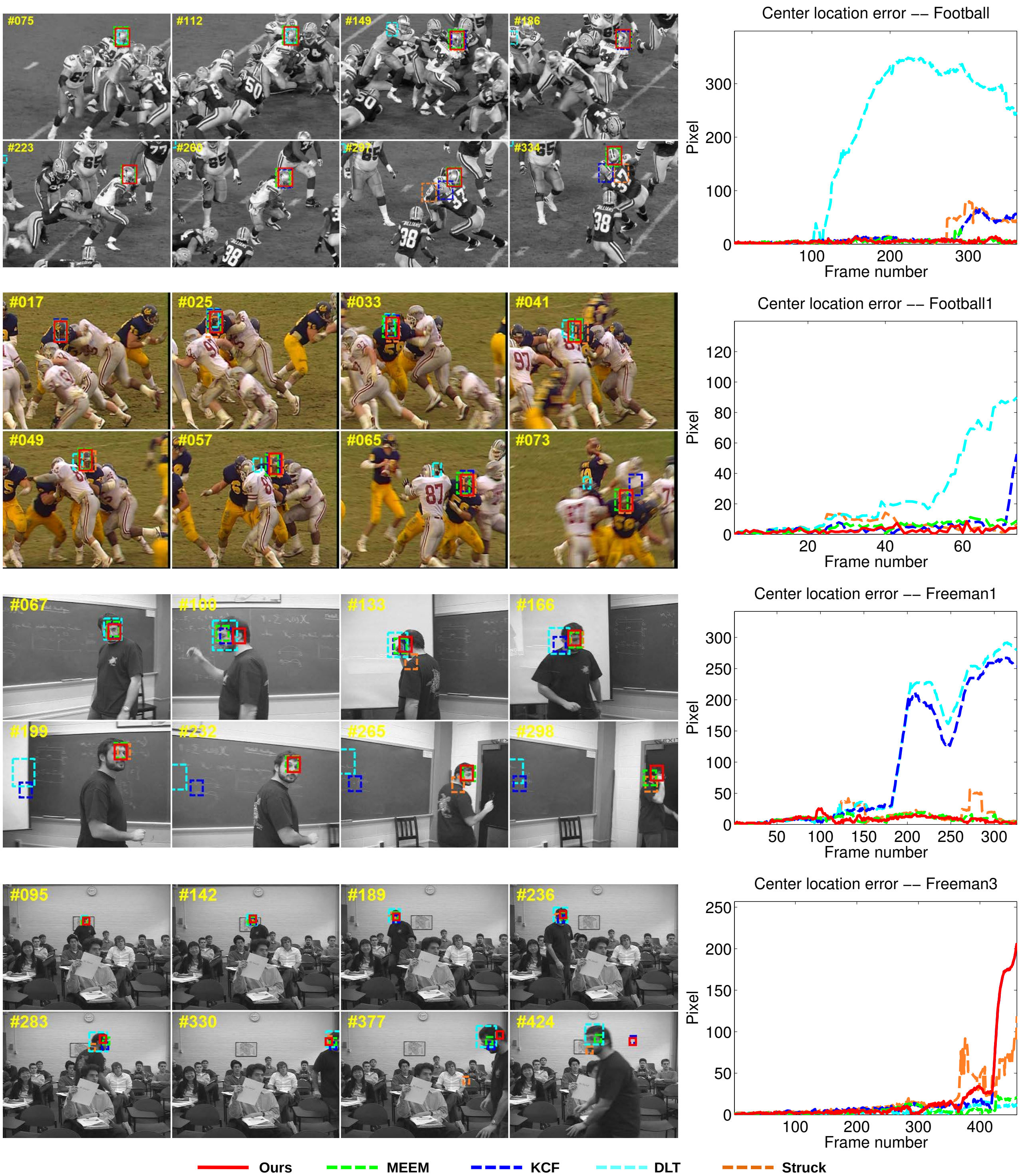

Figure 6. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Football*, *Football1*, *Freeman1*, *Freeman3* sequences.

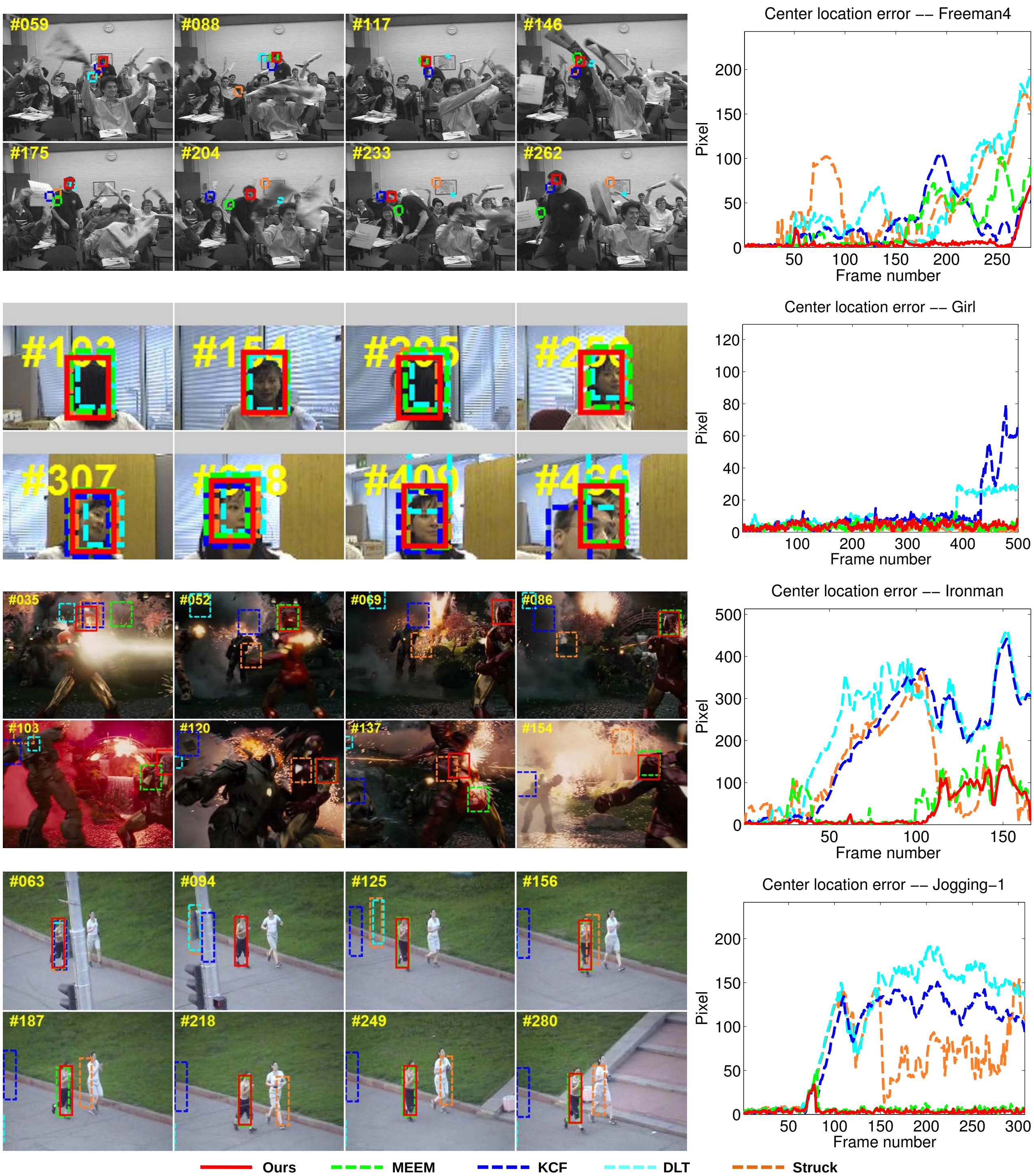

Figure 7. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Freeman4*, *Girl*, *Ironman*, *Jogging-1* sequences.

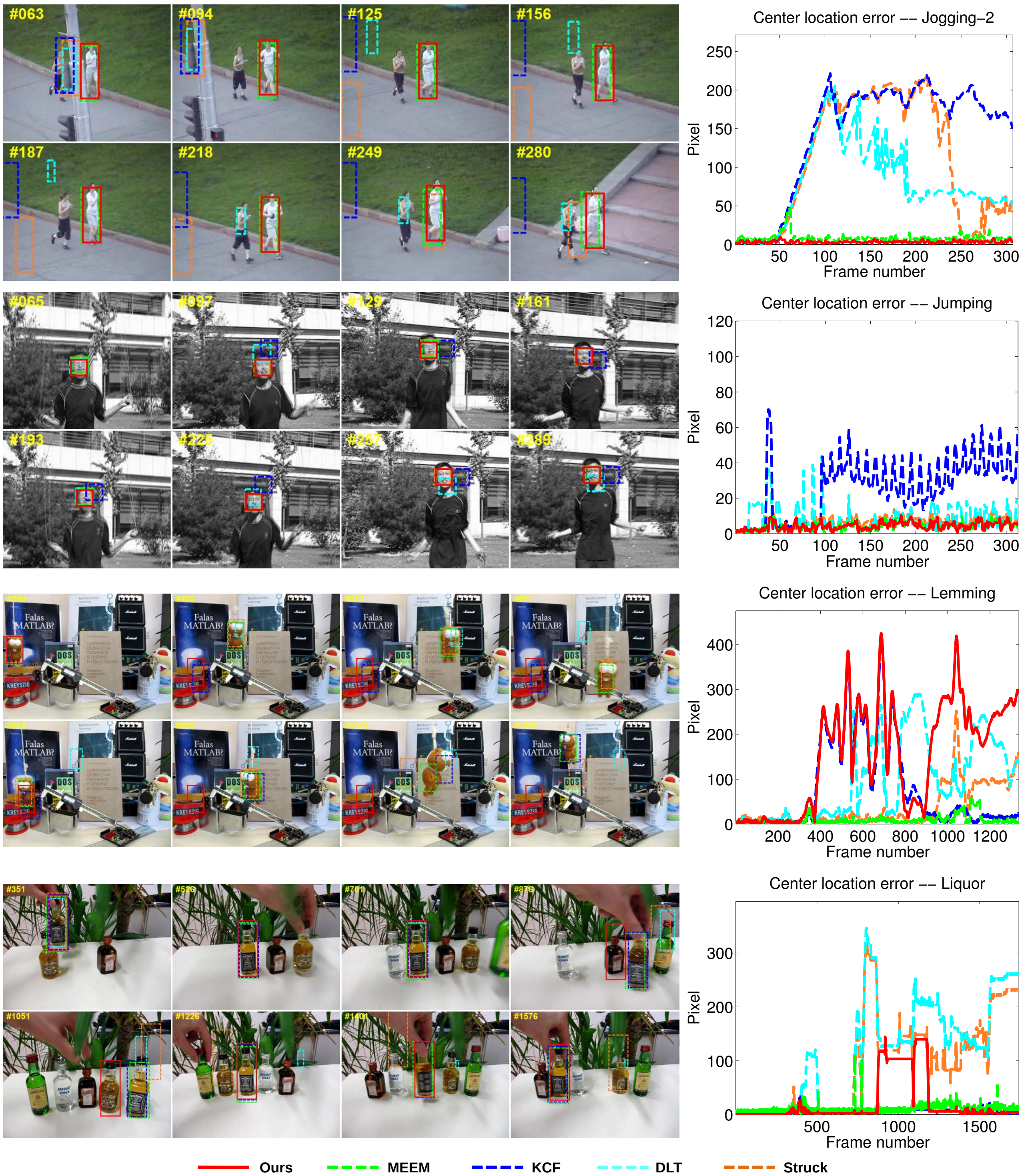

Figure 8. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Jogging-2*, *Jumping*, *Lemming*, *Liquor* sequences.

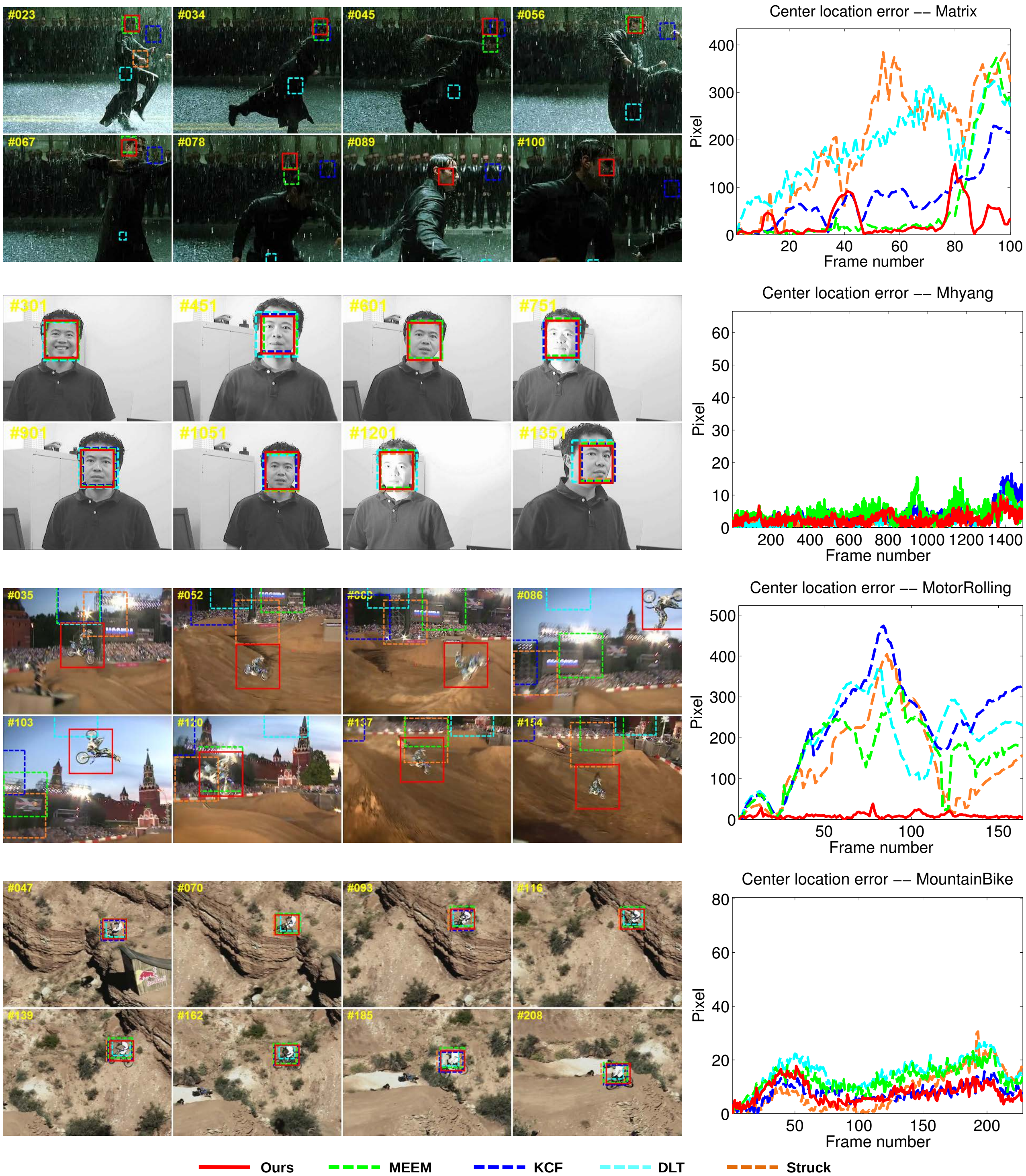

Figure 9. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Matrix*, *Mhyang*, *MotorRolling*, *MountainBike* sequences.

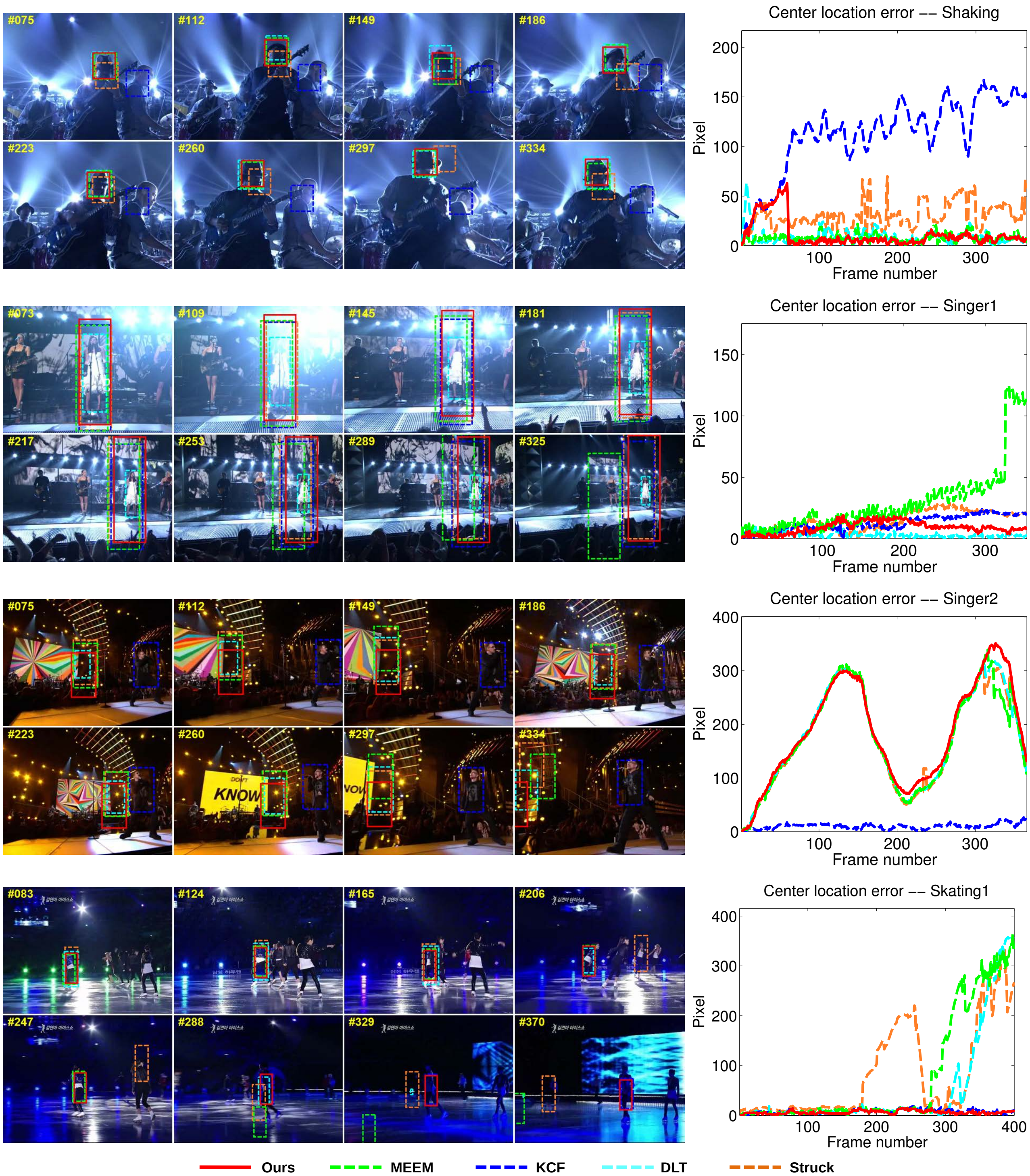

Figure 10. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Shaking*, *Singer1*, *Singer2*, *Skating1* sequences.

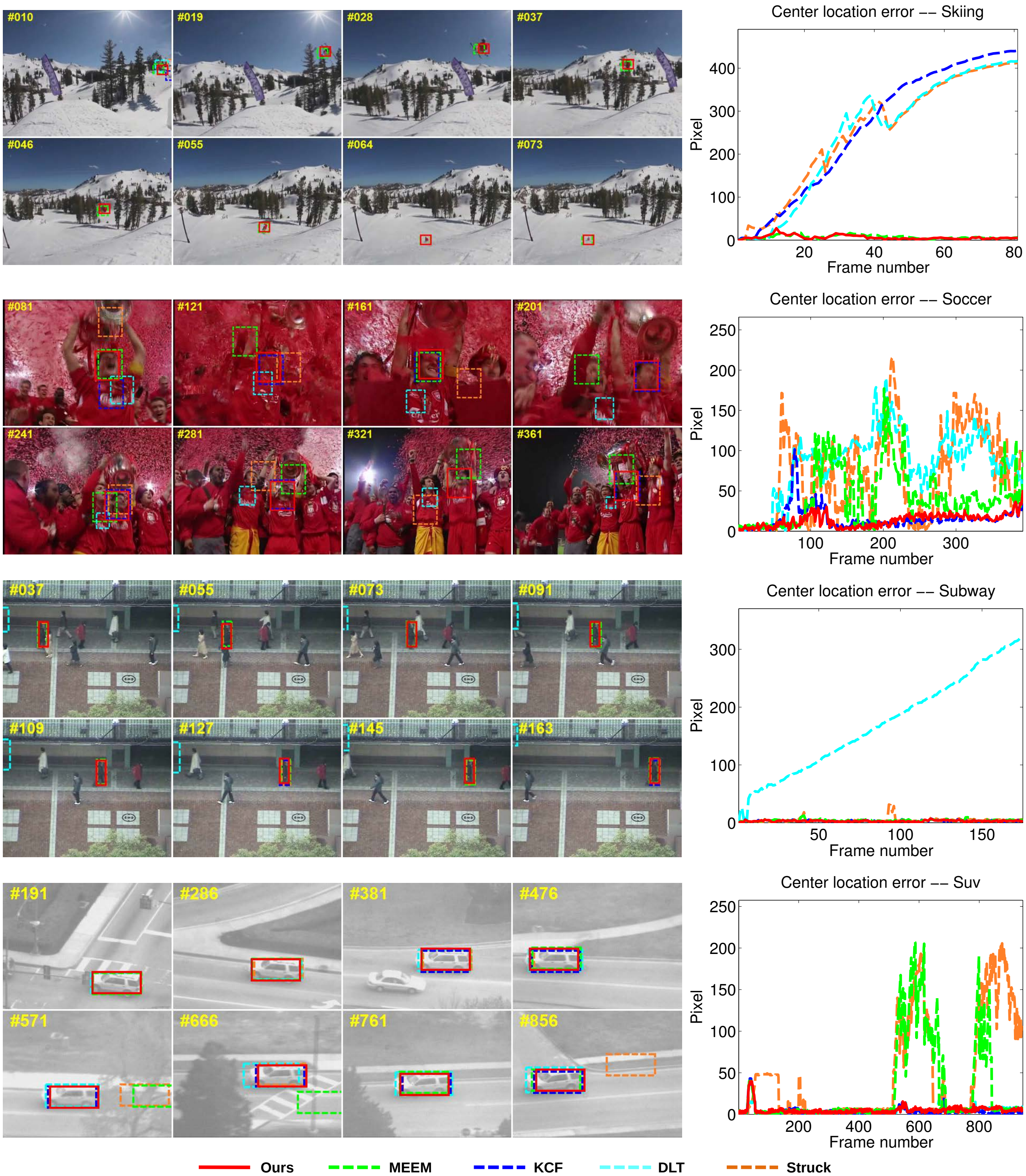

Figure 11. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Skiing*, *Soccer*, *Subway*, *Suv* sequences.

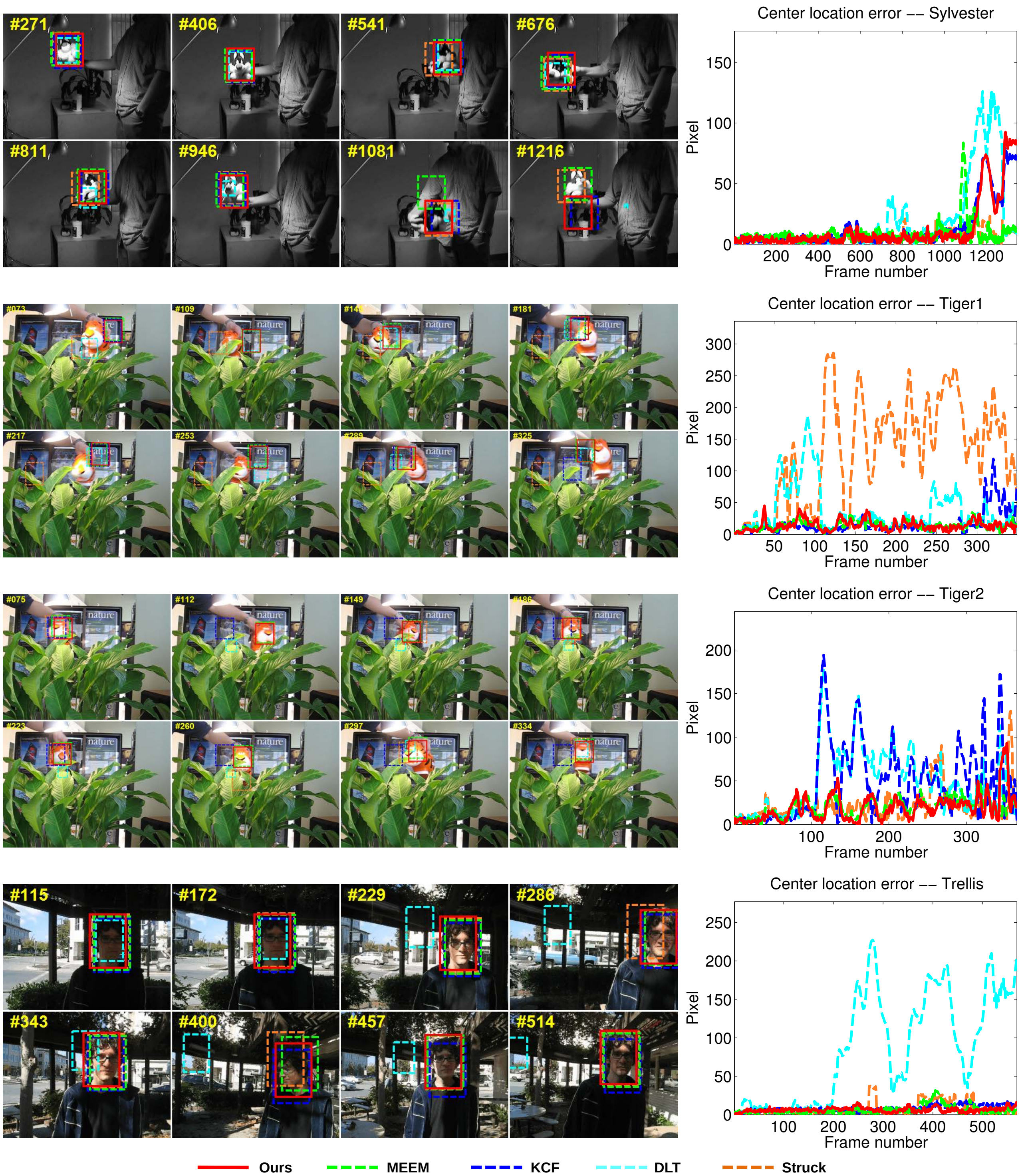

Figure 12. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Sylvester*, *Tiger1*, *Tiger2*, *Trellis* sequences.

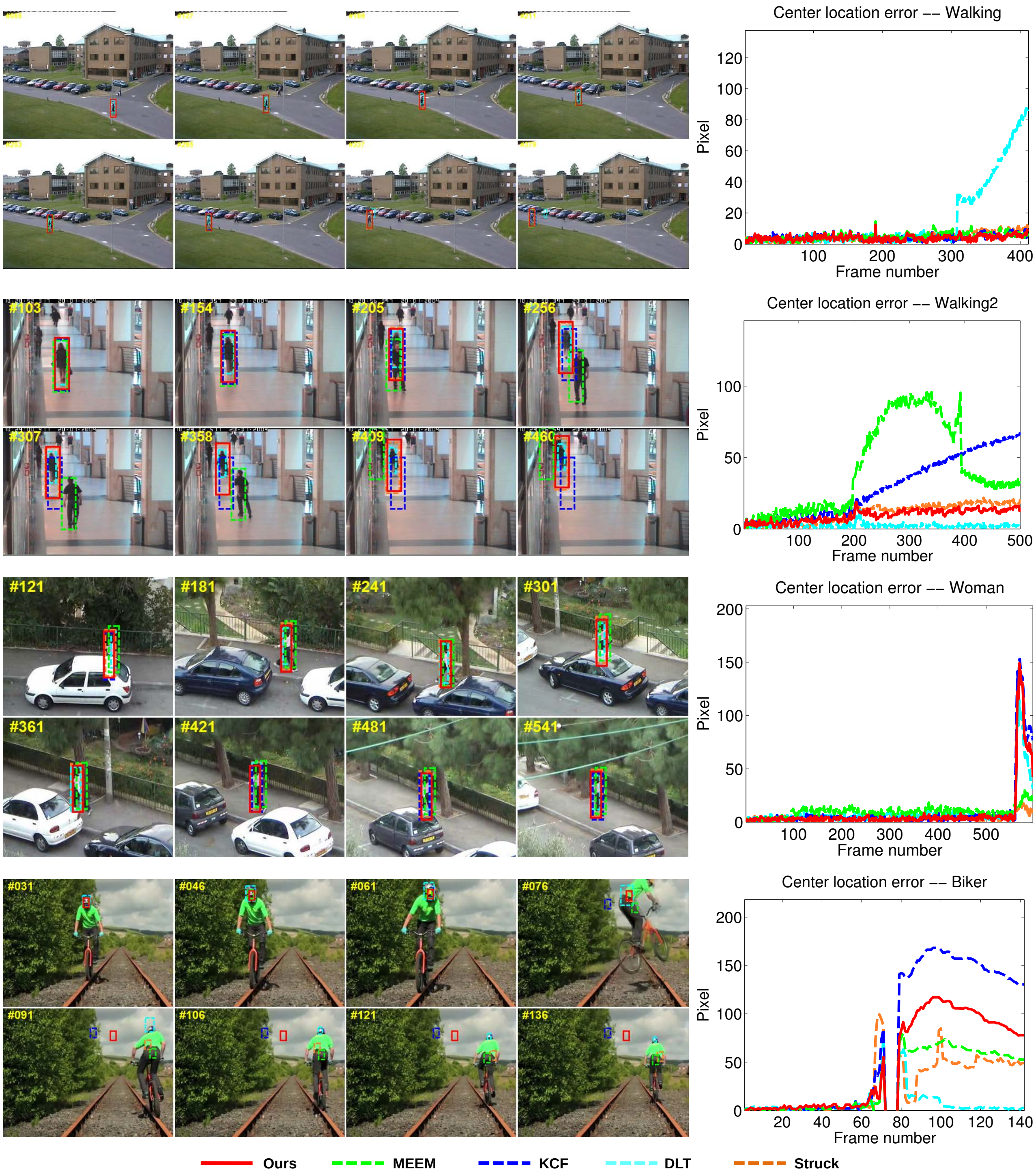

Figure 13. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Walking*, *Walking2*, *Woman*, *Biker* sequences.

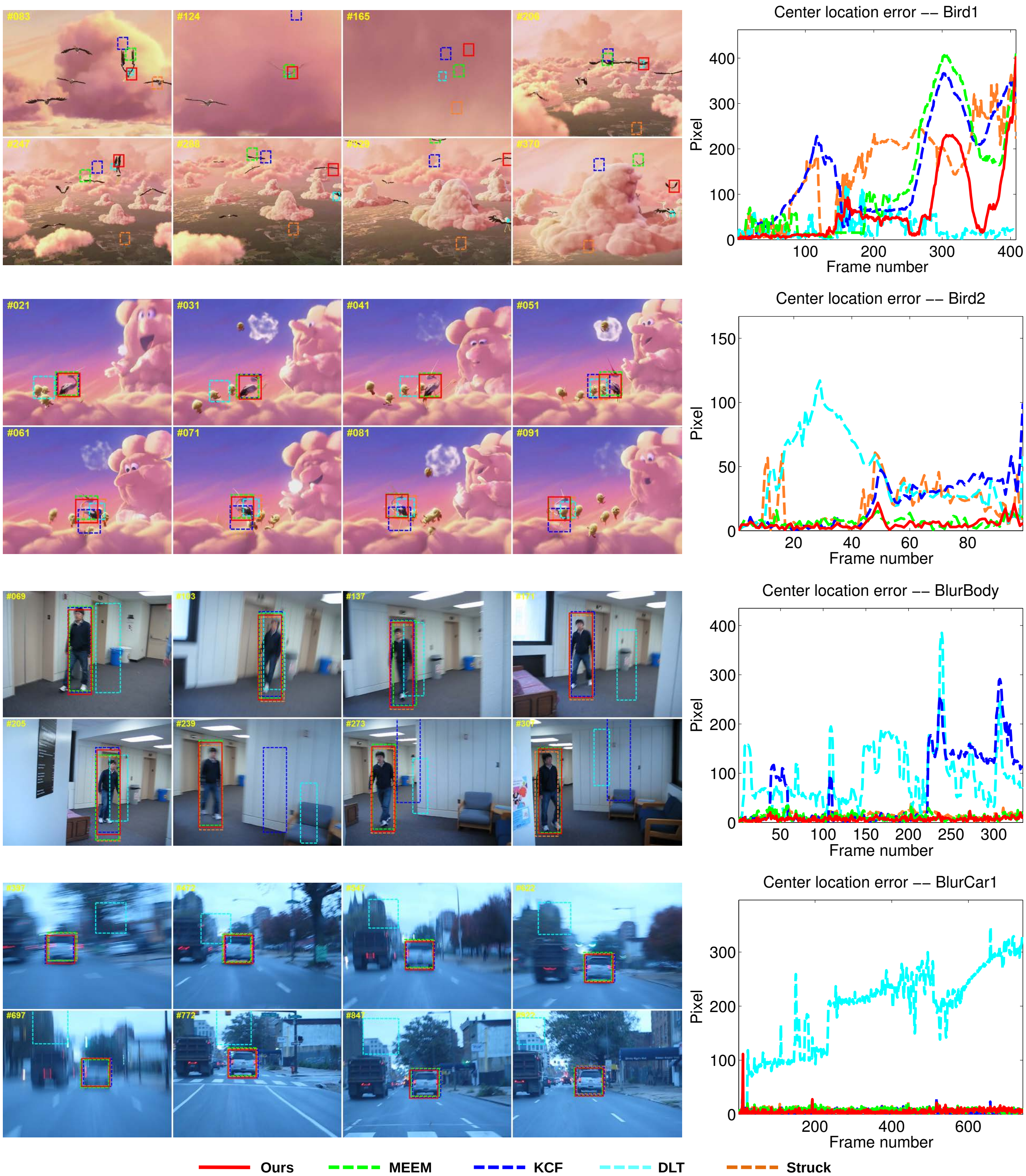

Figure 14. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Bird1*, *Bird2*, *BlurBody*, *BlurCar1* sequences.

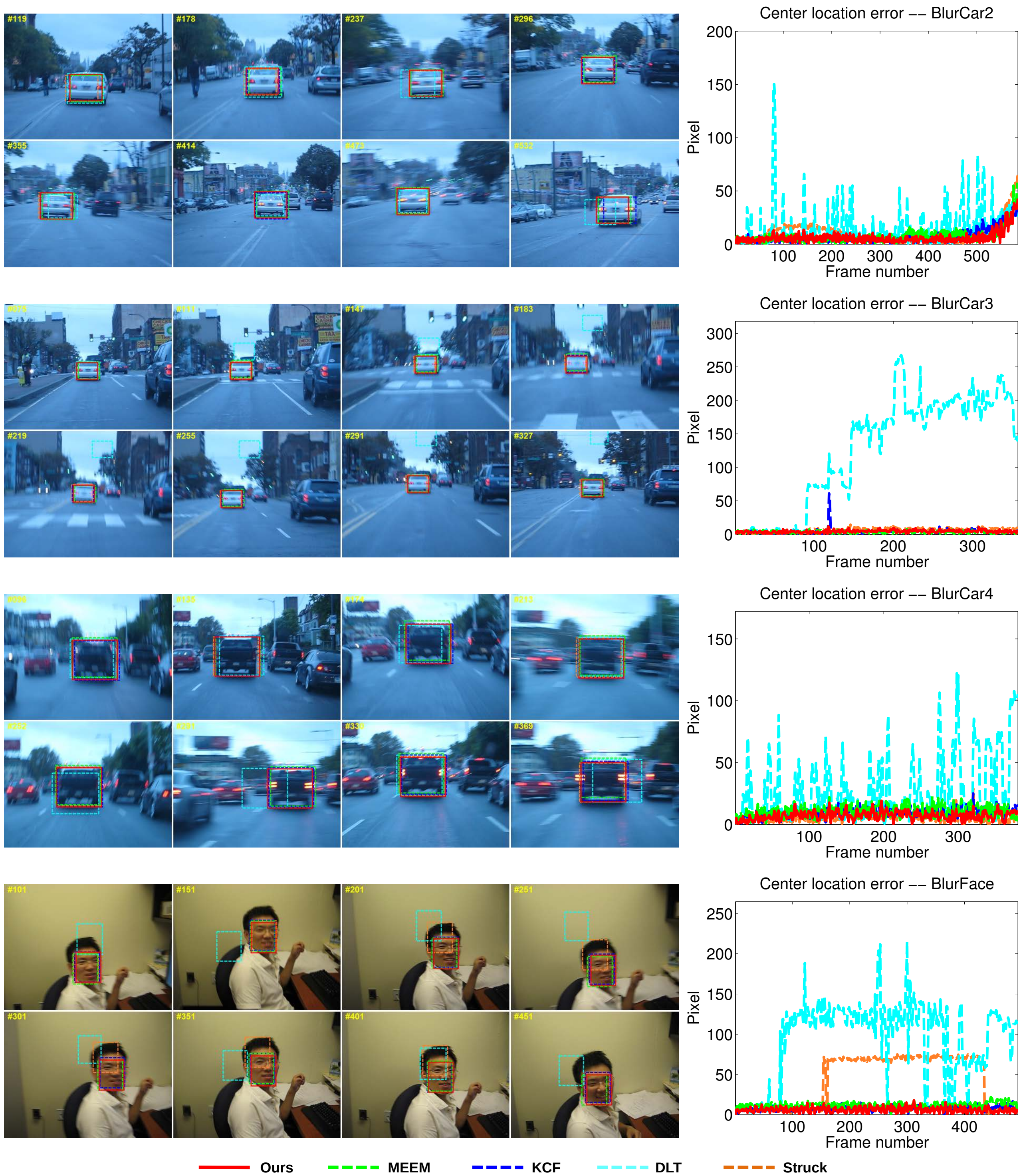

Figure 15. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *BlurCar2*, *BlurCar3*, *BlurCar4*, *BlurFace* sequences.

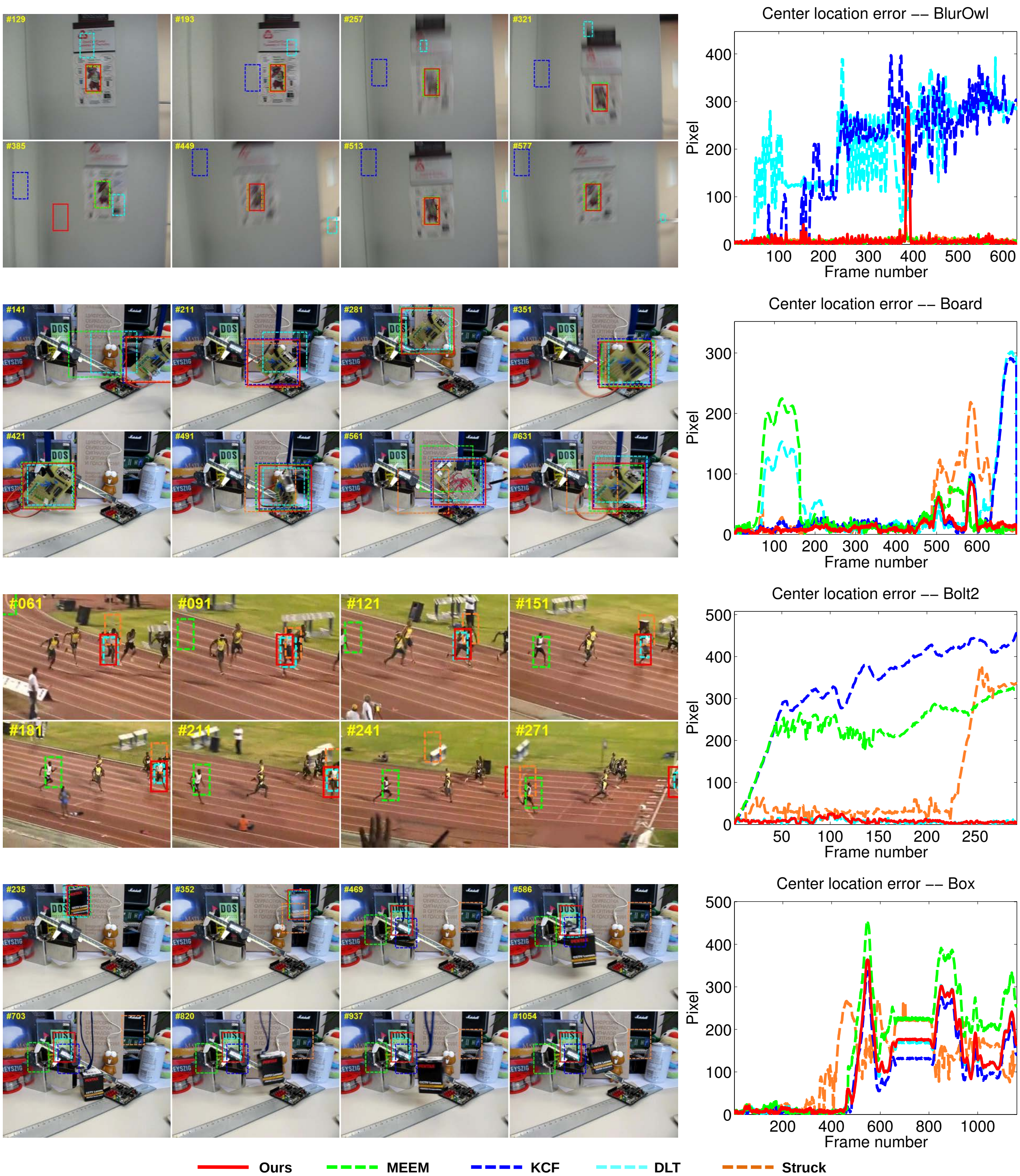

Figure 16. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *BlurOwl*, *Board*, *Bolt2*, *Box* sequences.

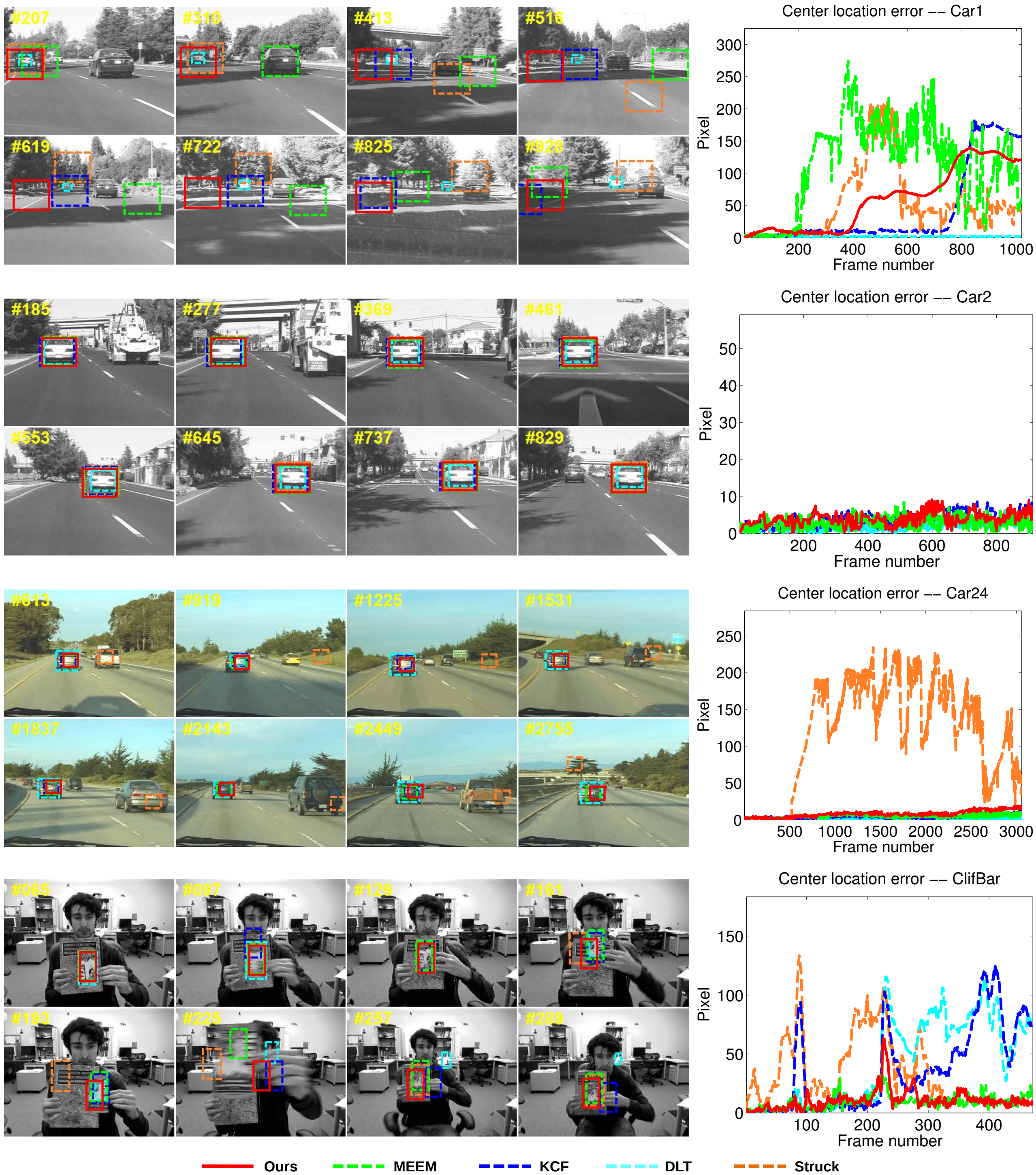

Figure 17. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Car1*, *Car2*, *Car24*, *ClifBar* sequences.

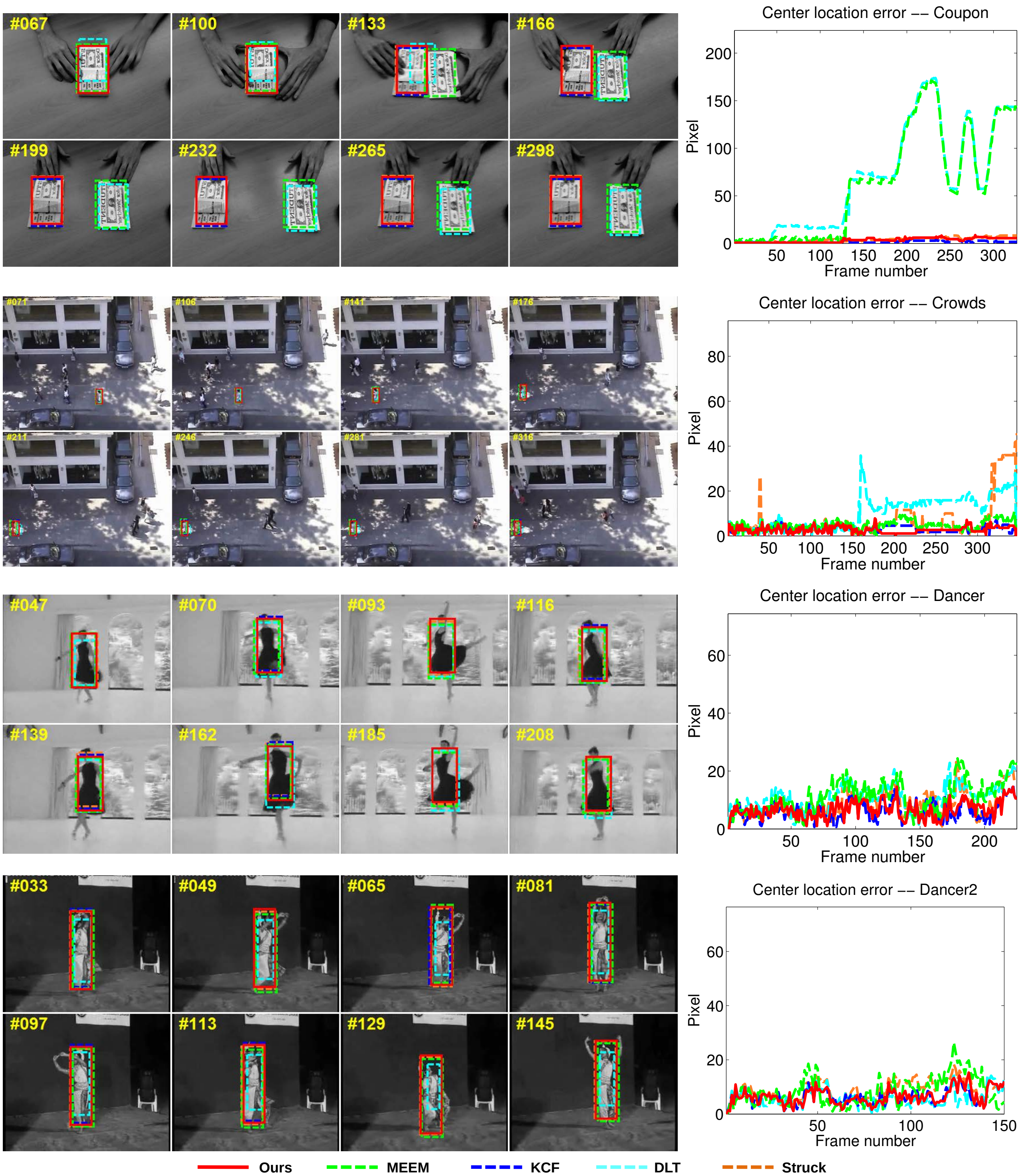

Figure 18. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Coupon*, *Crowds*, *Dancer*, *Dancer2* sequences.

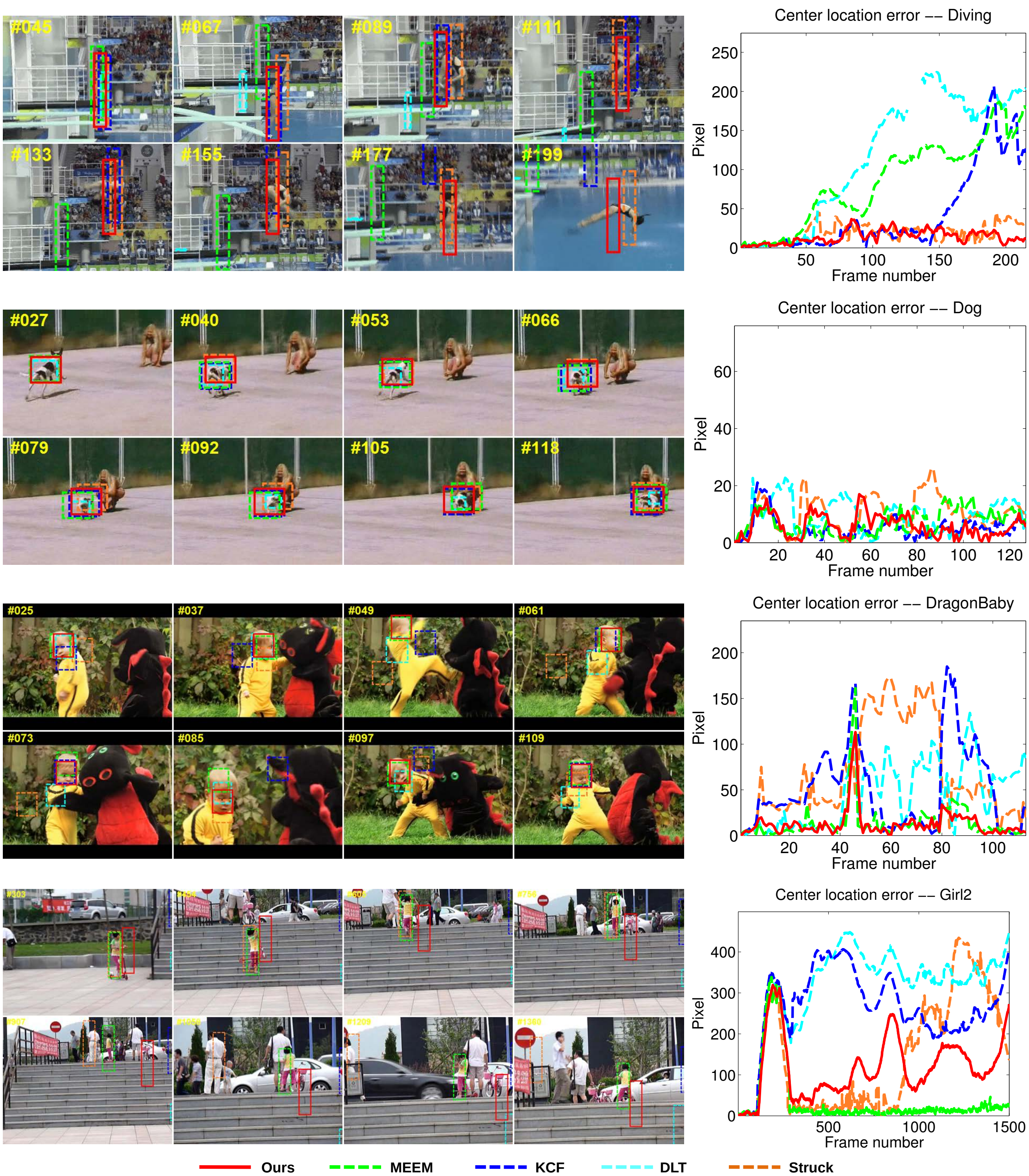

Figure 19. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Diving*, *Dog*, *DragonBaby*, *Girl2* sequences.

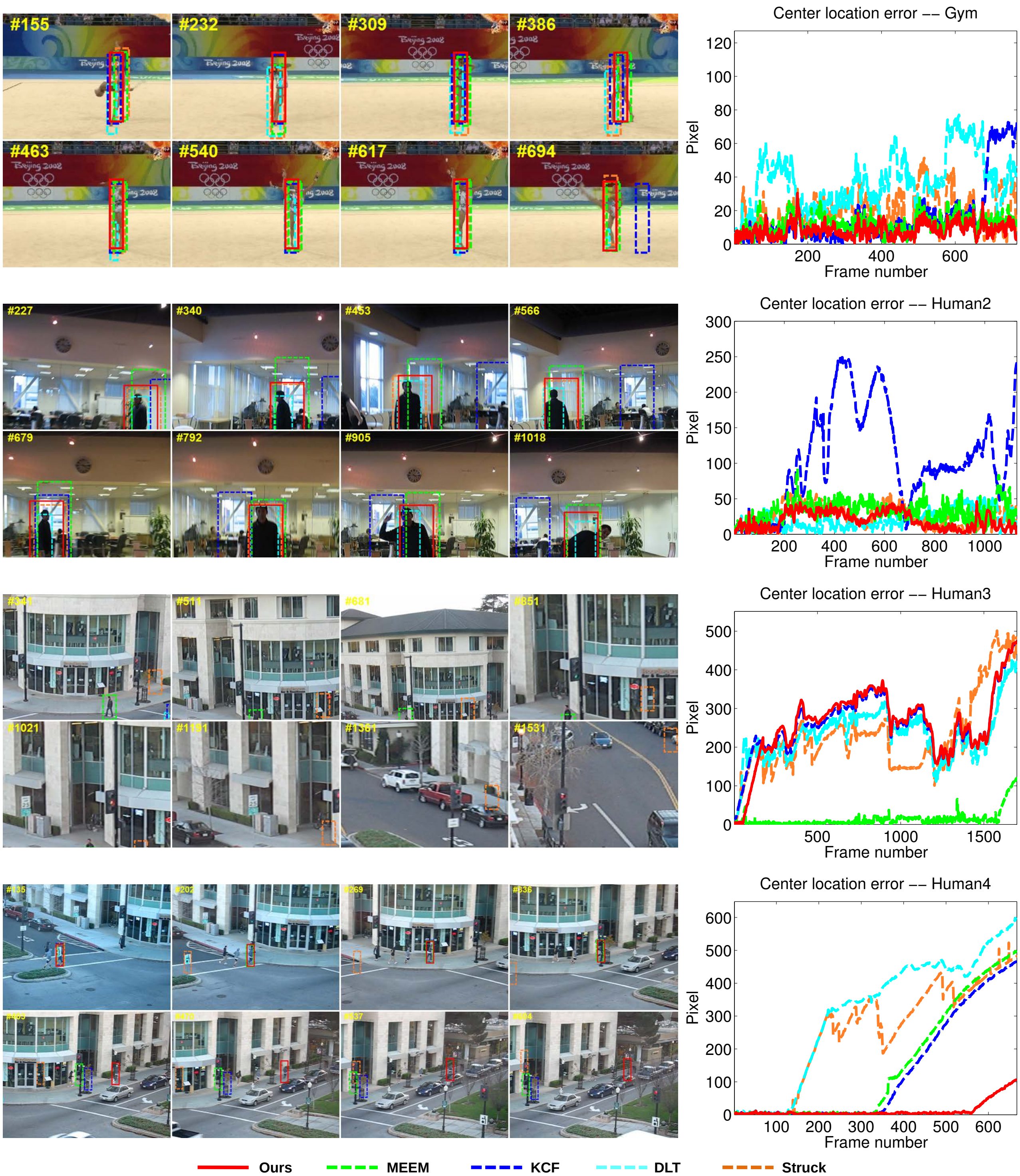

Figure 20. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Gym*, *Human2*, *Human3*, *Human4* sequences.

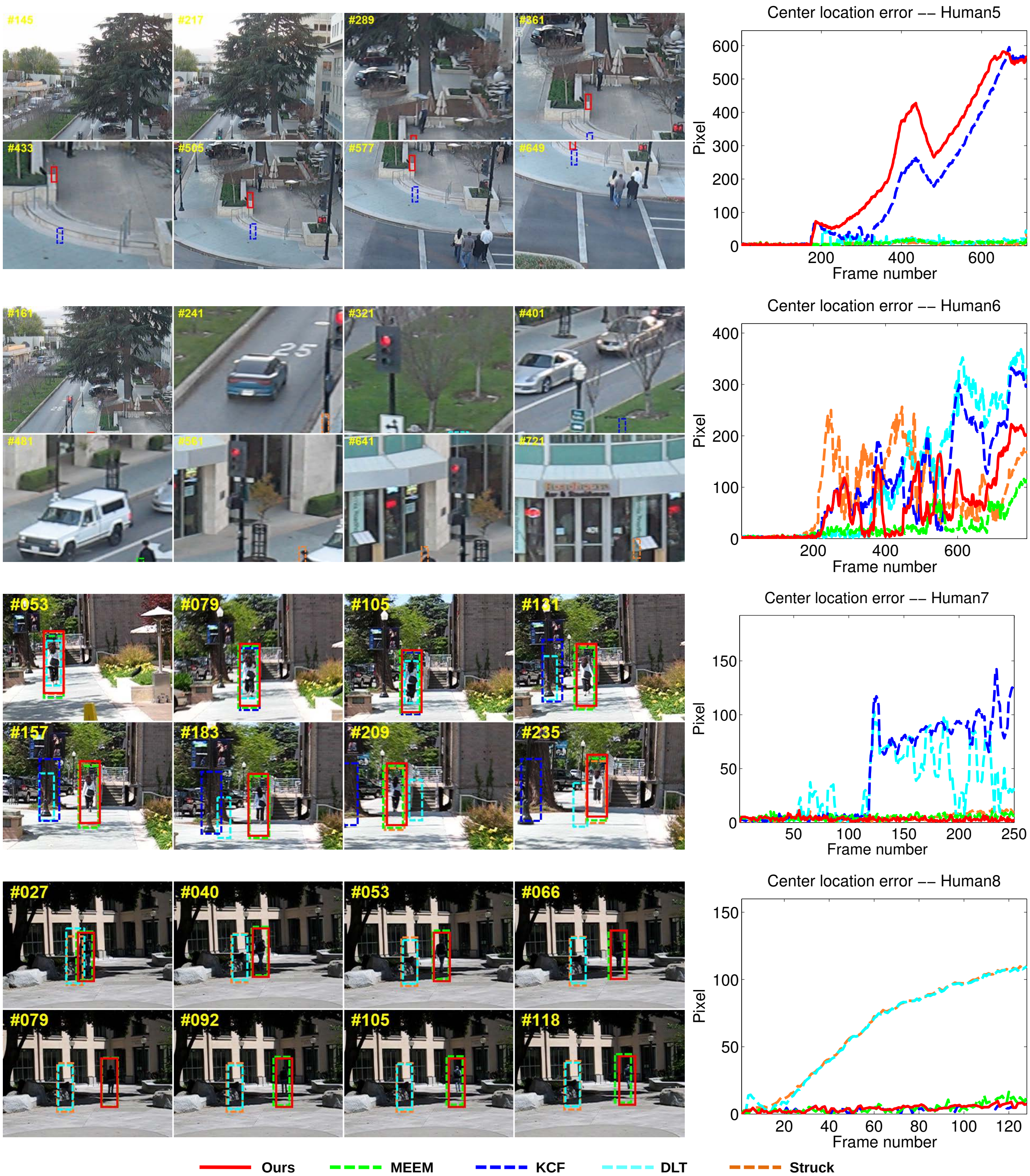

Figure 21. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Human5*, *Human6*, *Human7*, *Human8* sequences.

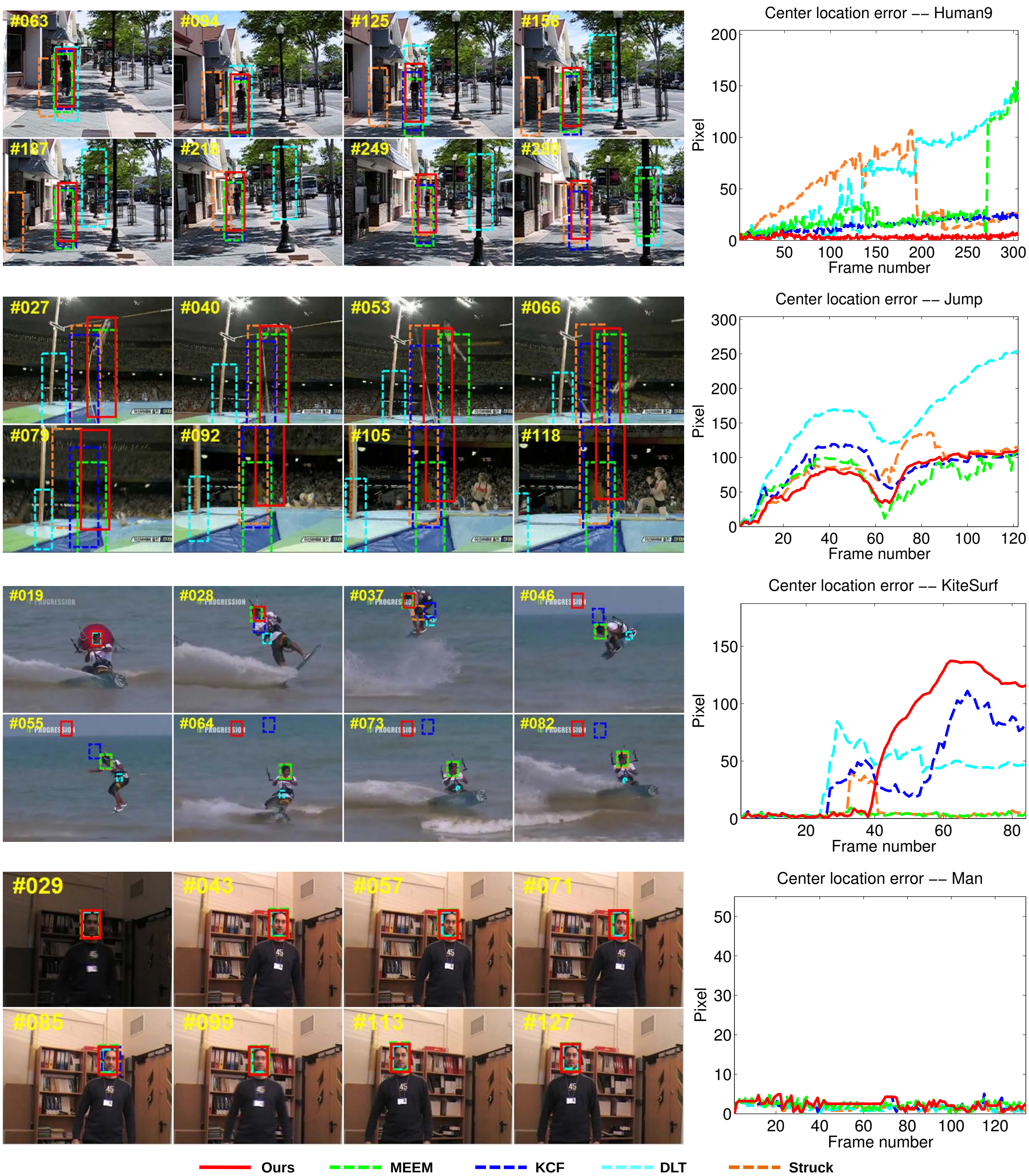

Figure 22. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Human9*, *Jump*, *KiteSurf*, *Man* sequences.

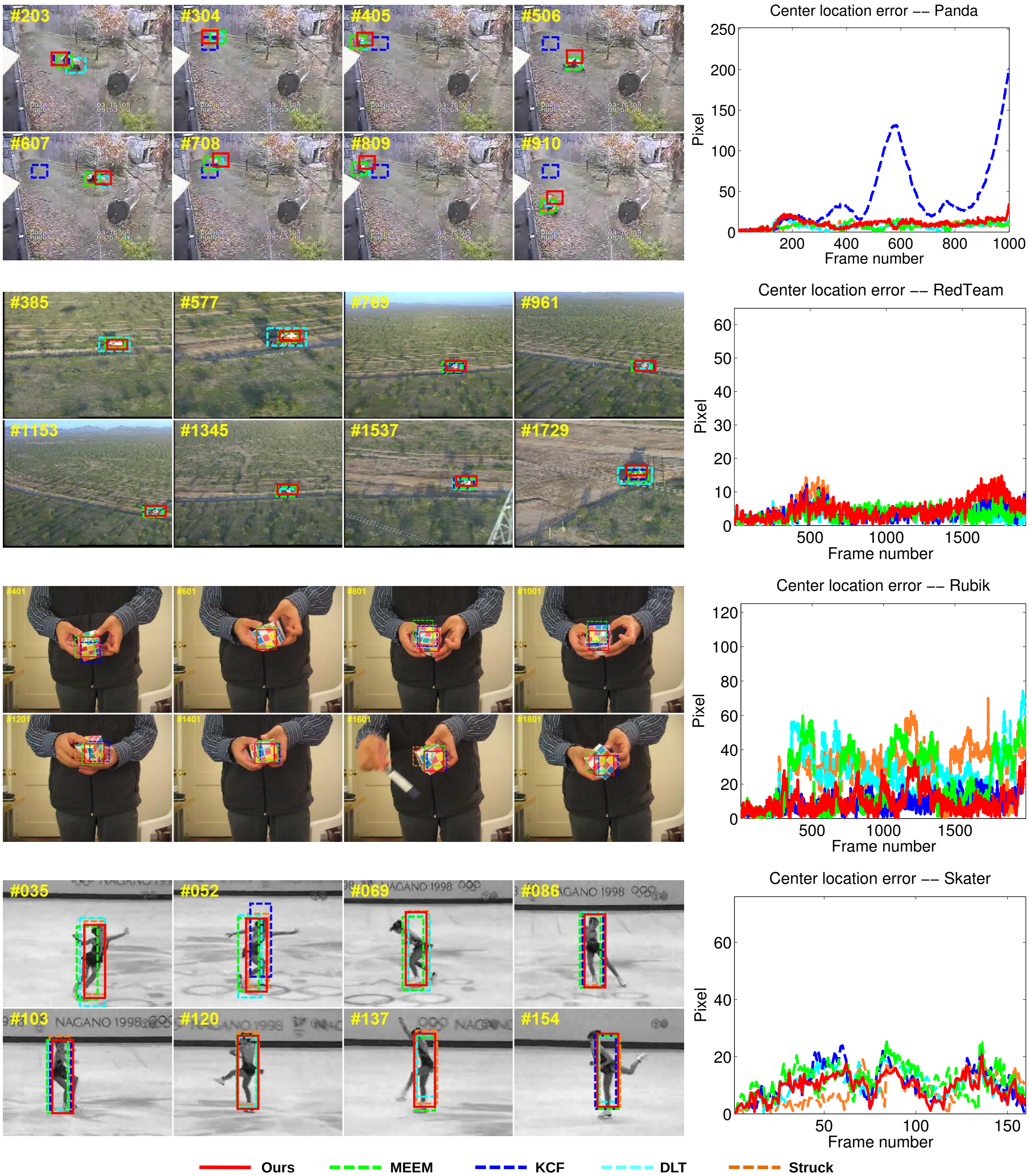

Figure 23. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Panda*, *RedTeam*, *Rubik*, *Skater* sequences.

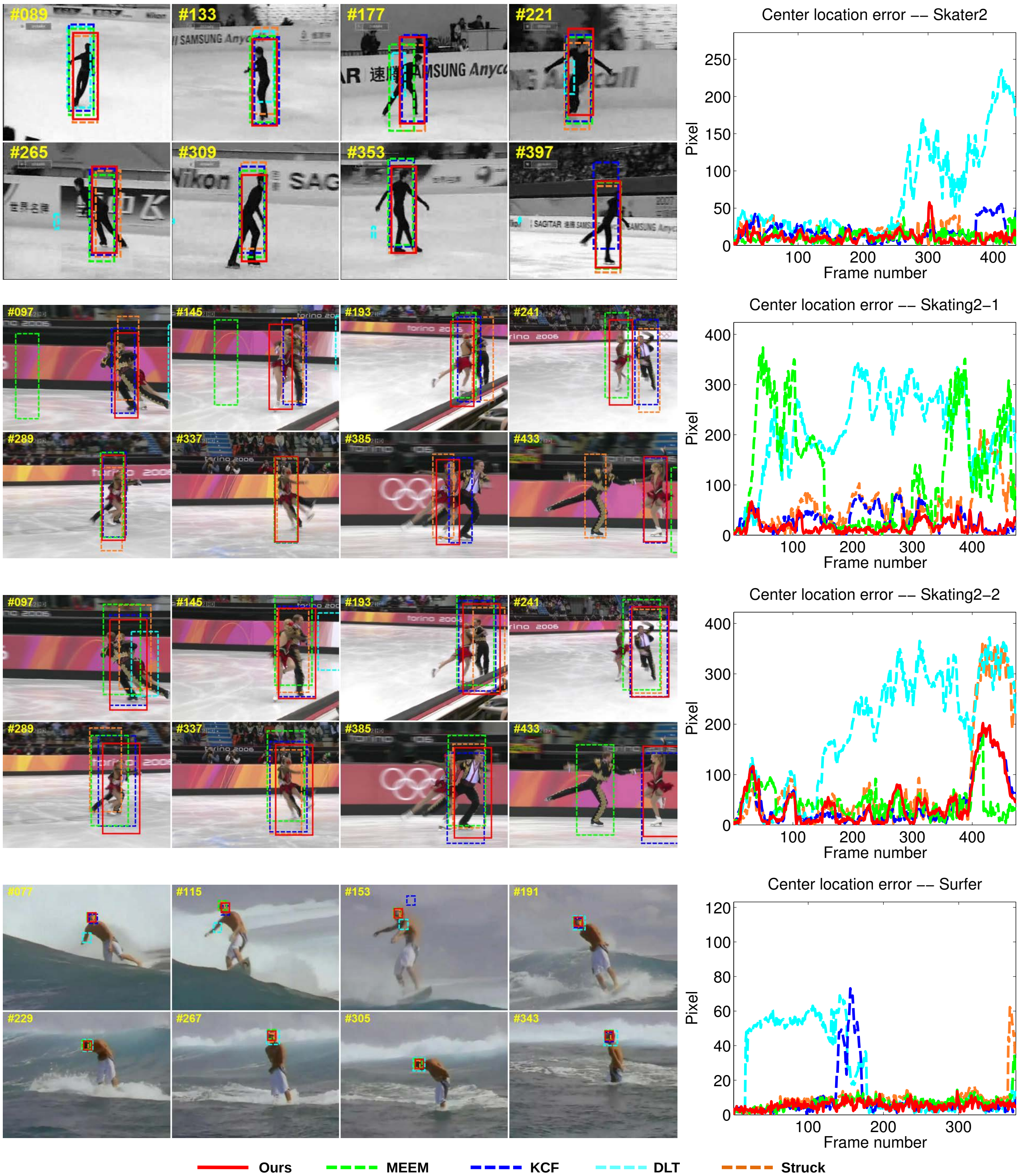

Figure 24. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Skater2*, *Skating2-1*, *Skating2-2*, *Surfer* sequences.

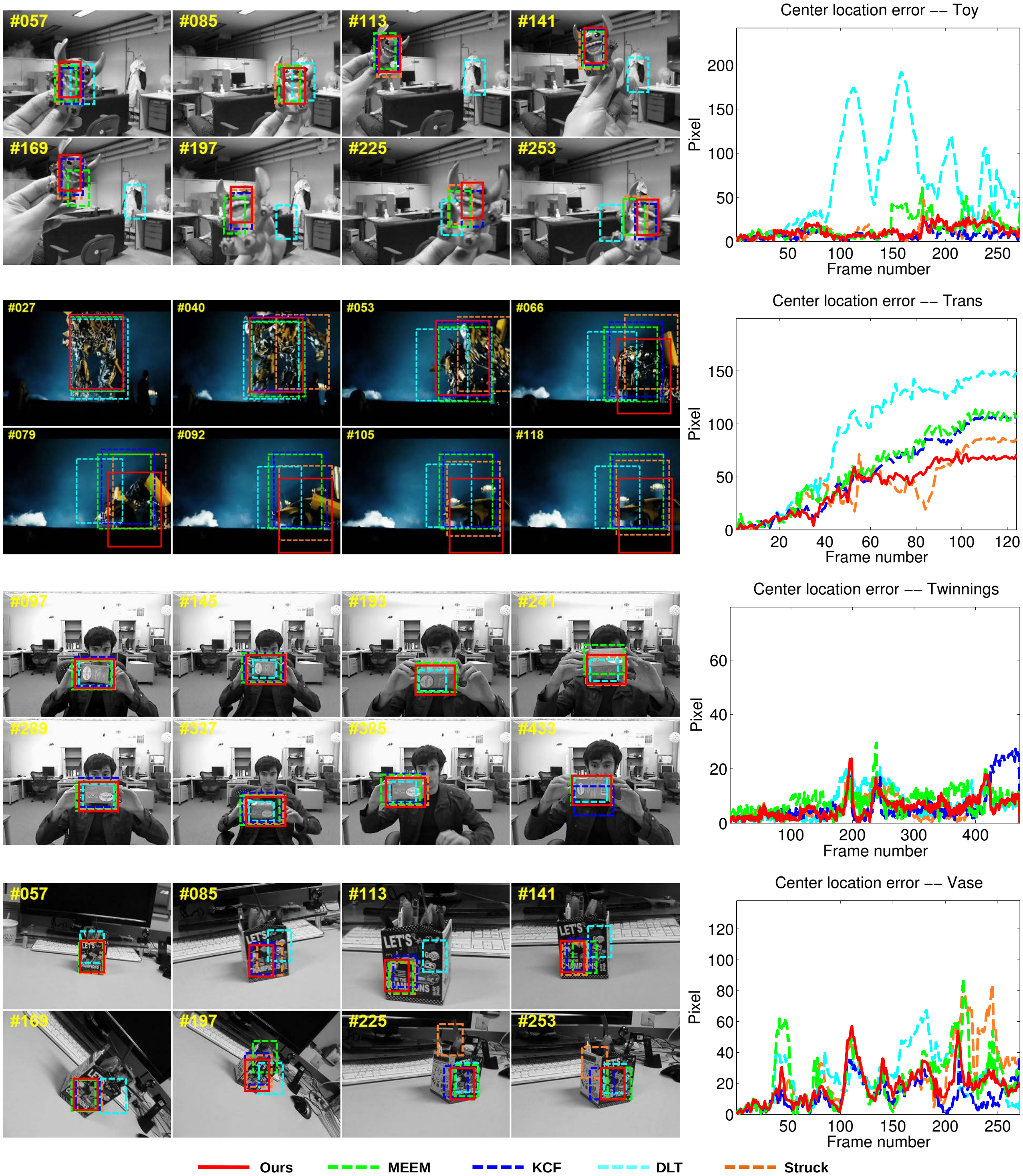

Figure 25. Tracking results and fame-by-frame comparison of center location errors (in pixels) on *Toy*, *Trans*, *Twinnings*, *Vase* sequences.

2.3. Robustness Evaluation

Here we evaluate the robustness of trackers using the one-pass evaluation (OPE), temporal robustness evaluation (TRE) and spatial robustness evaluation (SRE) as described in [9]. Figure 26 shows the distance precision and overlap success plots using OPE, TRE and SRE. In Figure 27 to 38, we further report the robustness evaluation results for each video attribute: fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. Each tracker is color coded.

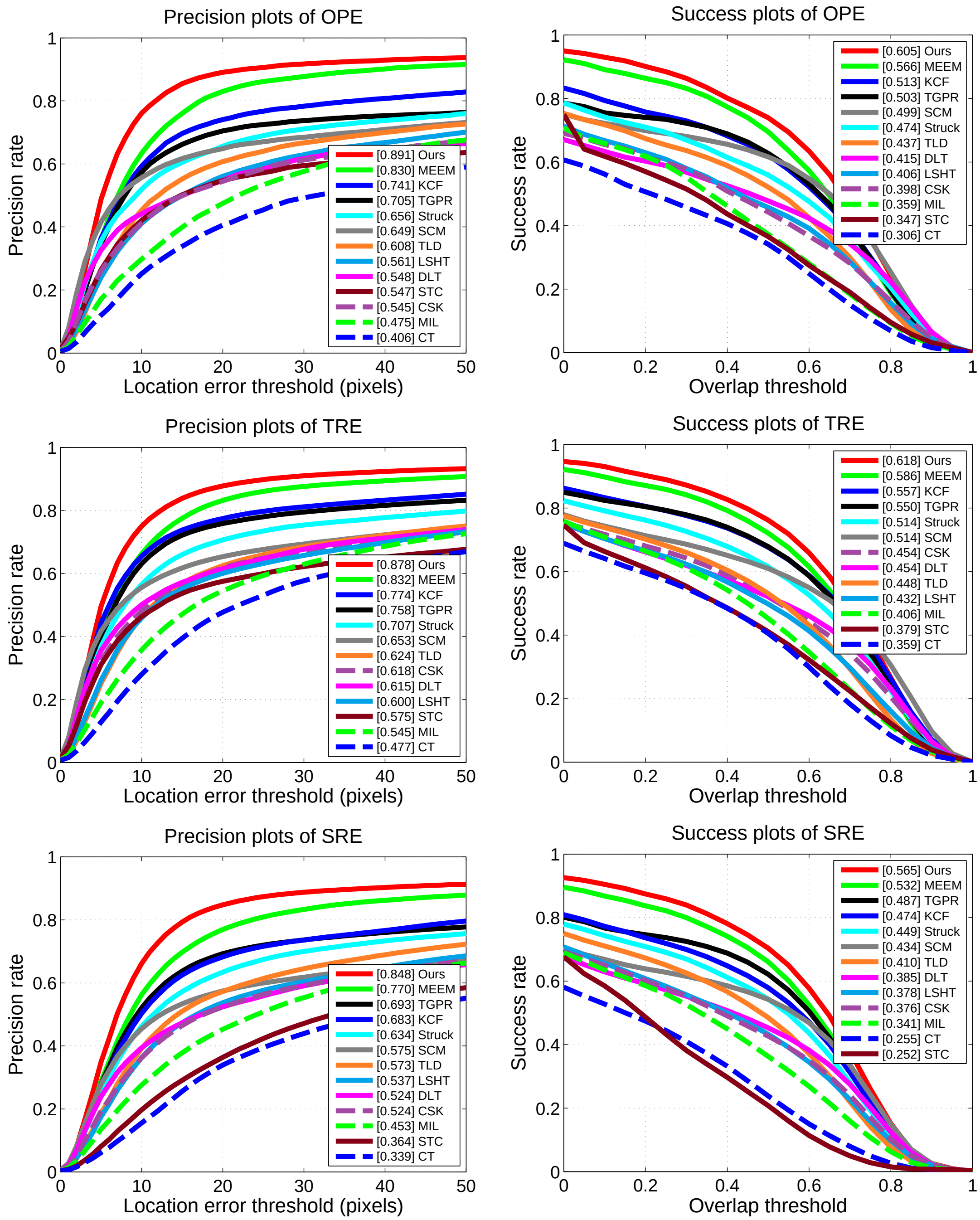

Figure 26. Distance precision and overlap success plots over first 50 benchmark sequences [9] using one-pass evaluation (OPE), temporal robustness evaluation (TRE) and spatial robustness evaluation (SRE). The legends in the distance precision plots contain the average distance precision rate (DPR) using a threshold at 20 pixels. The legends in the overlap success plots contain the area-under-the-curve (AUC) scores. The proposed algorithm performs favorably against the state-of-the-art trackers.

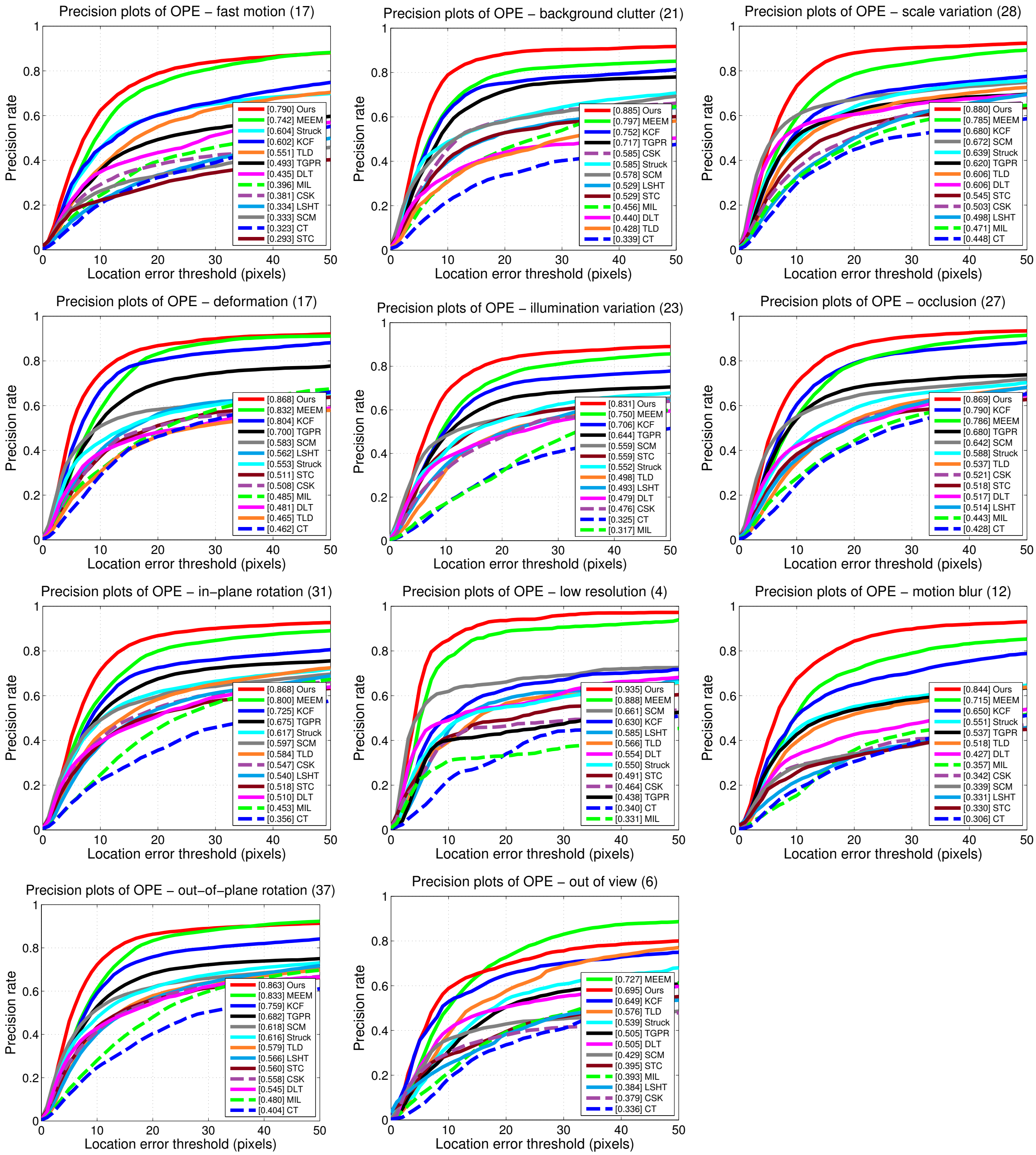

Figure 27. Distance precision plots on the 50 benchmark sequences [9] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the average distance precision rate (DPR) using a threshold at 20 pixels. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

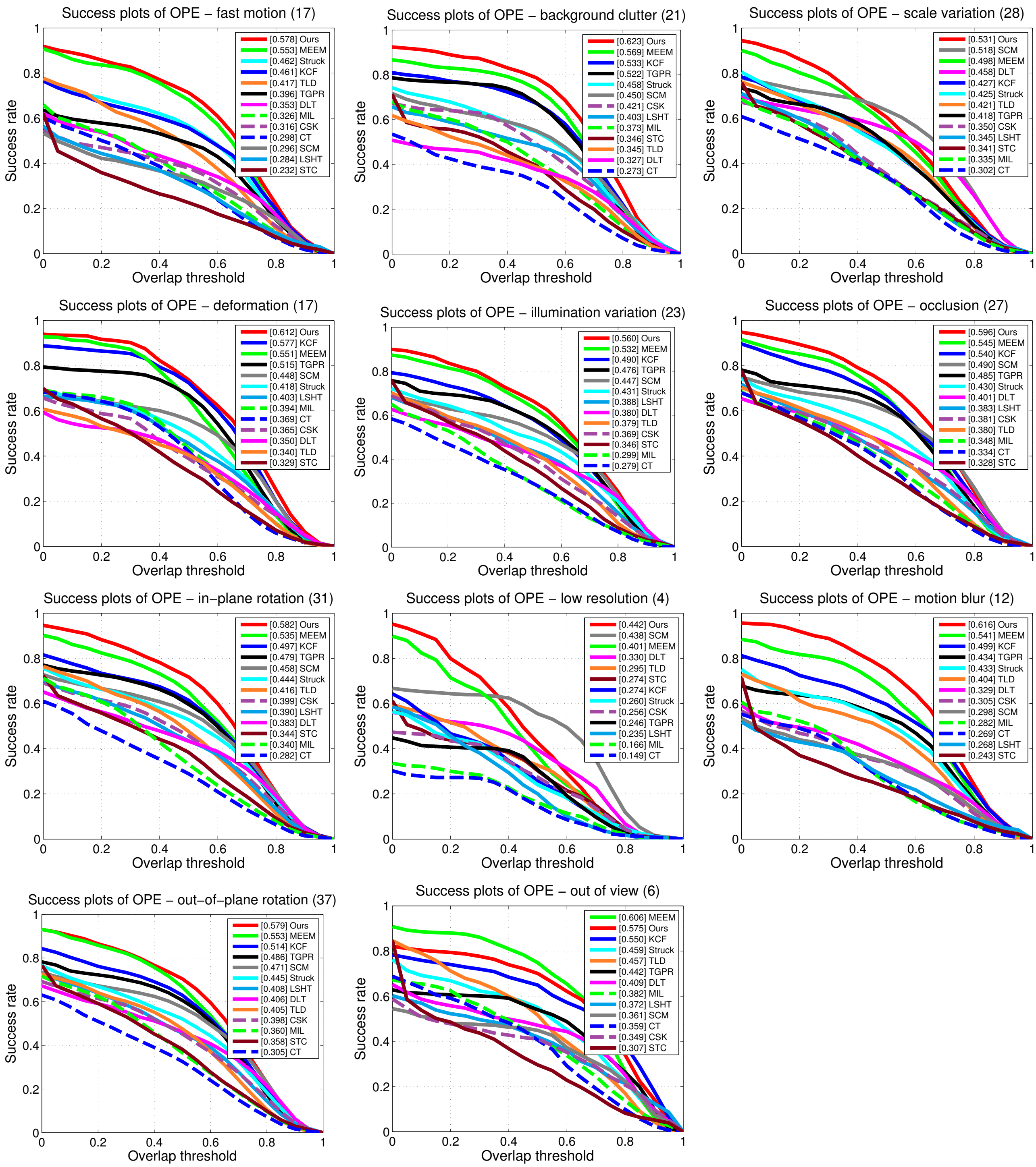

Figure 28. Overlap success plots on the 50 benchmark sequences [9] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

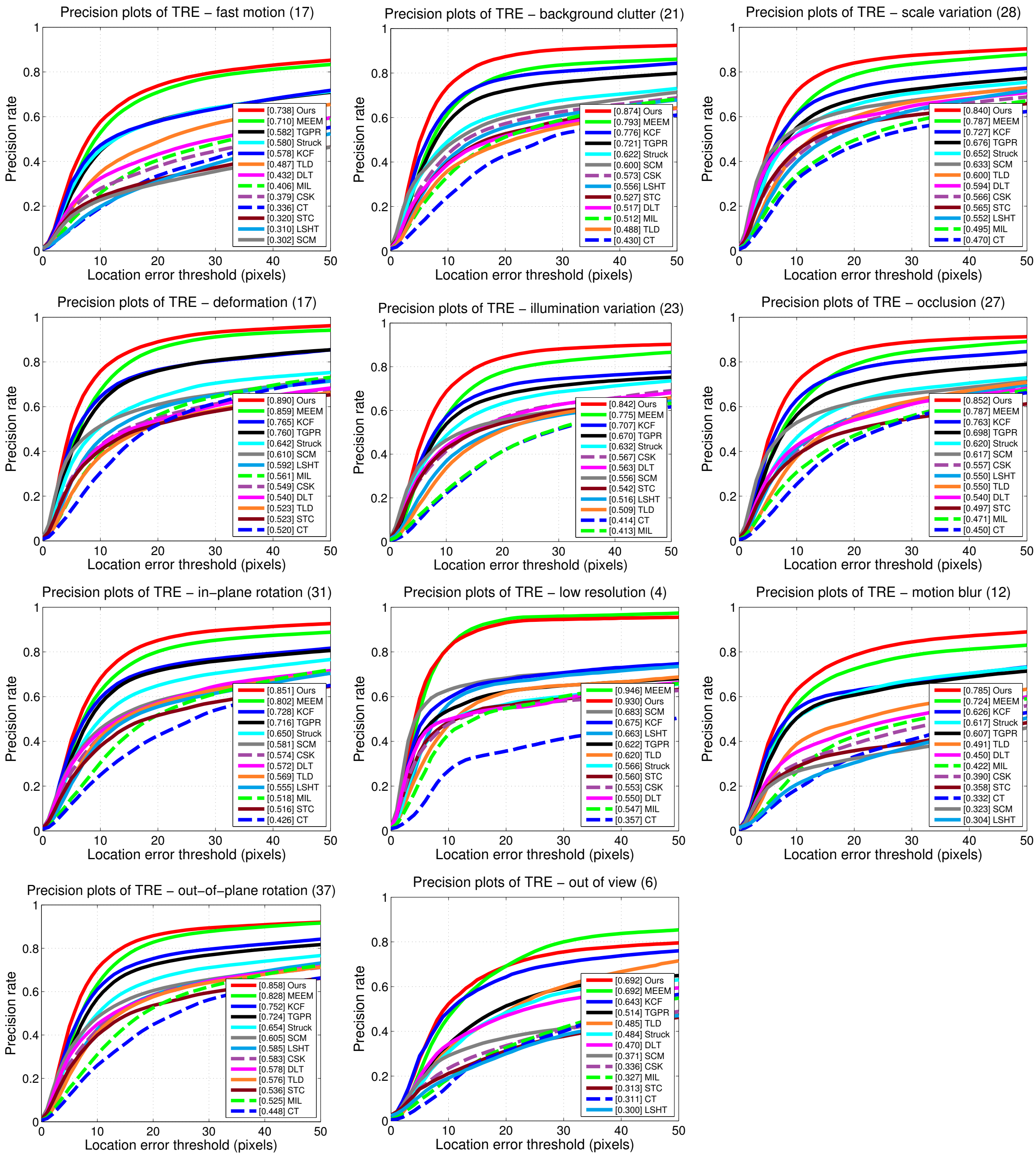

Figure 29. Distance precision plots on the 50 benchmark sequences [9] using temporal robustness evaluation (TRE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the distance precision rate (DPR) at a threshold of 20 pixels for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

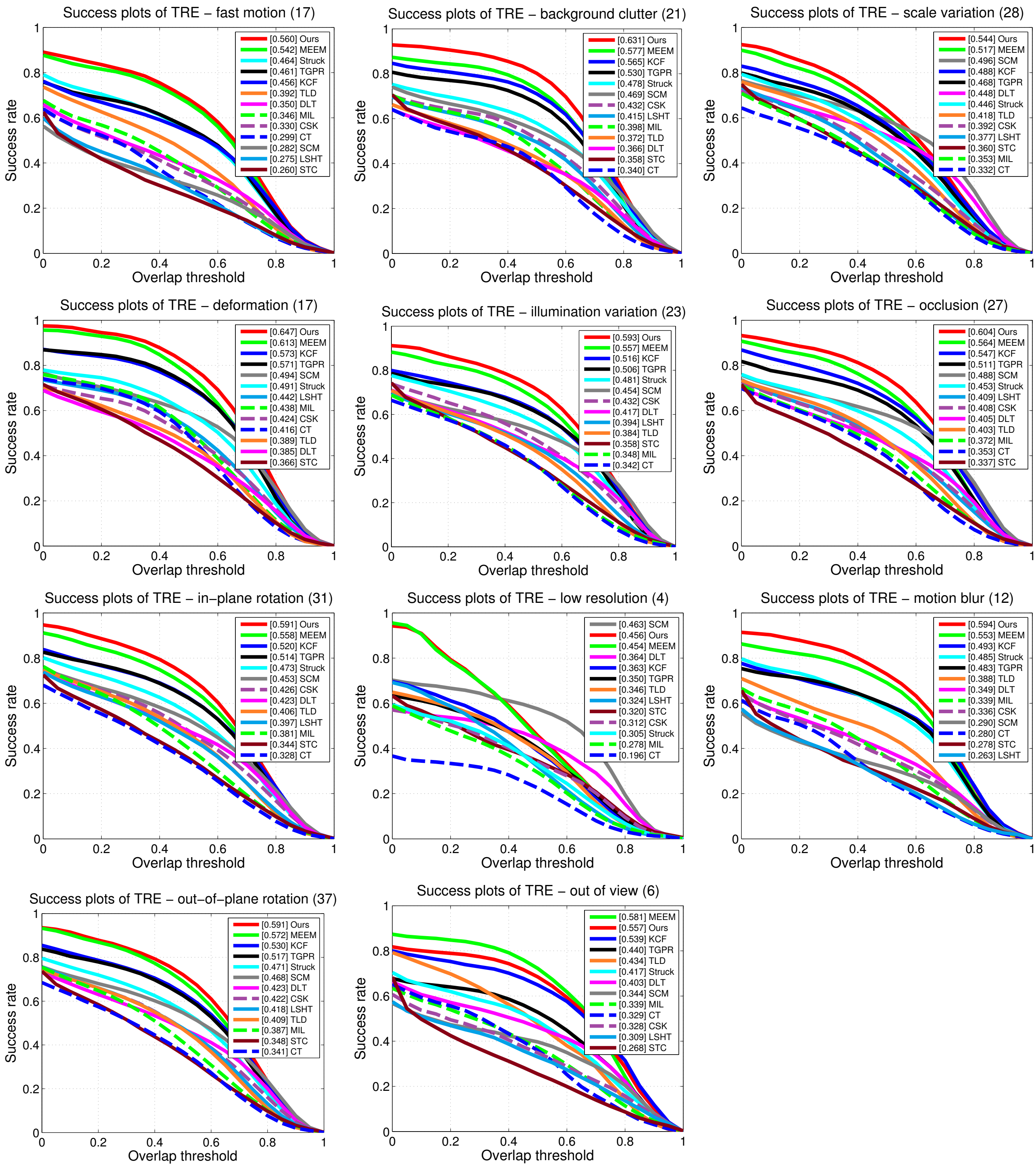

Figure 30. Overlap success plots on the 50 benchmark sequences [9] using temporal robustness evaluation (TRE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

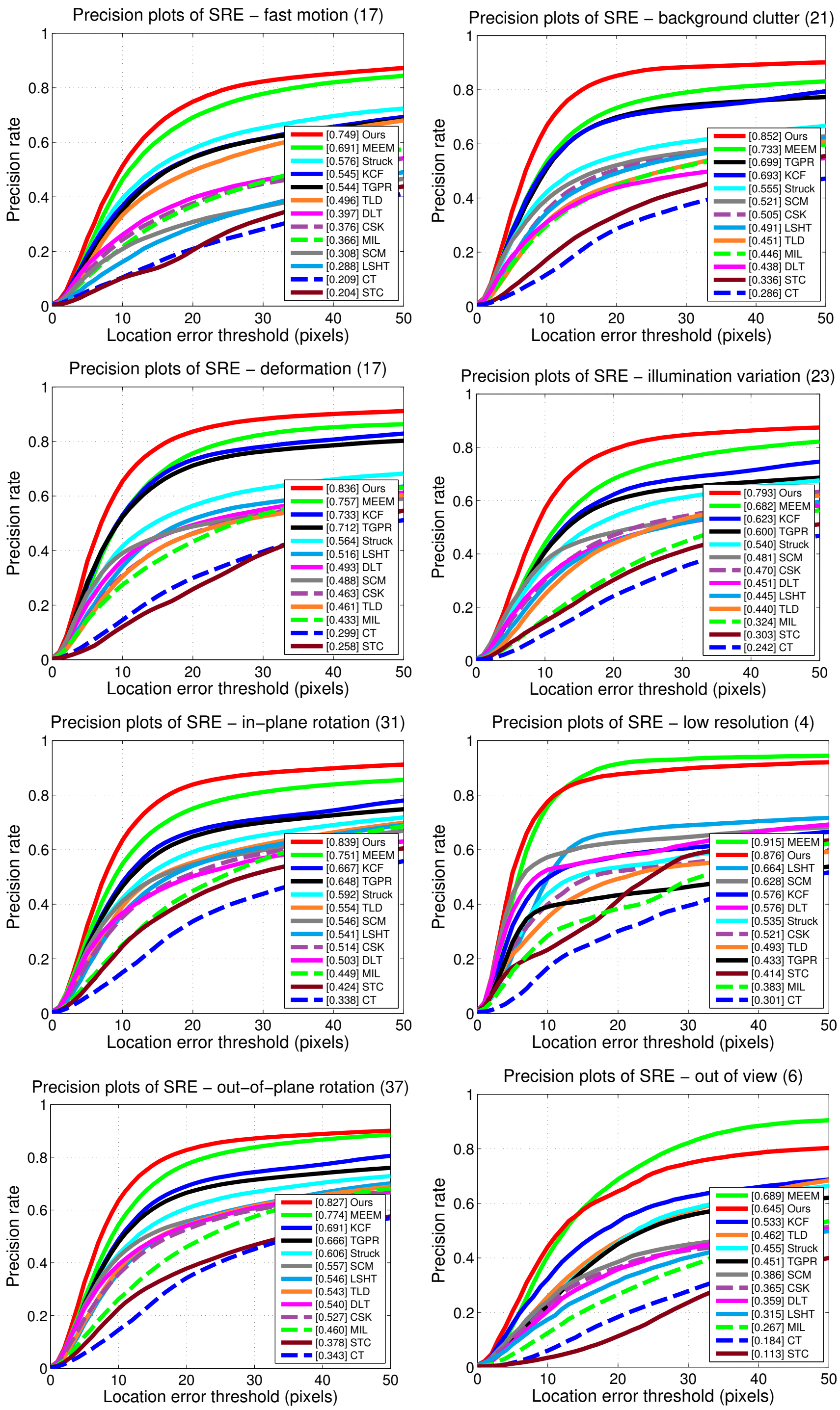

Figure 31. Distance precision plots on the 50 benchmark sequences [9] using spatial robustness evaluation (SRE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the distance precision rate (DPR) at a threshold of 20 pixels for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

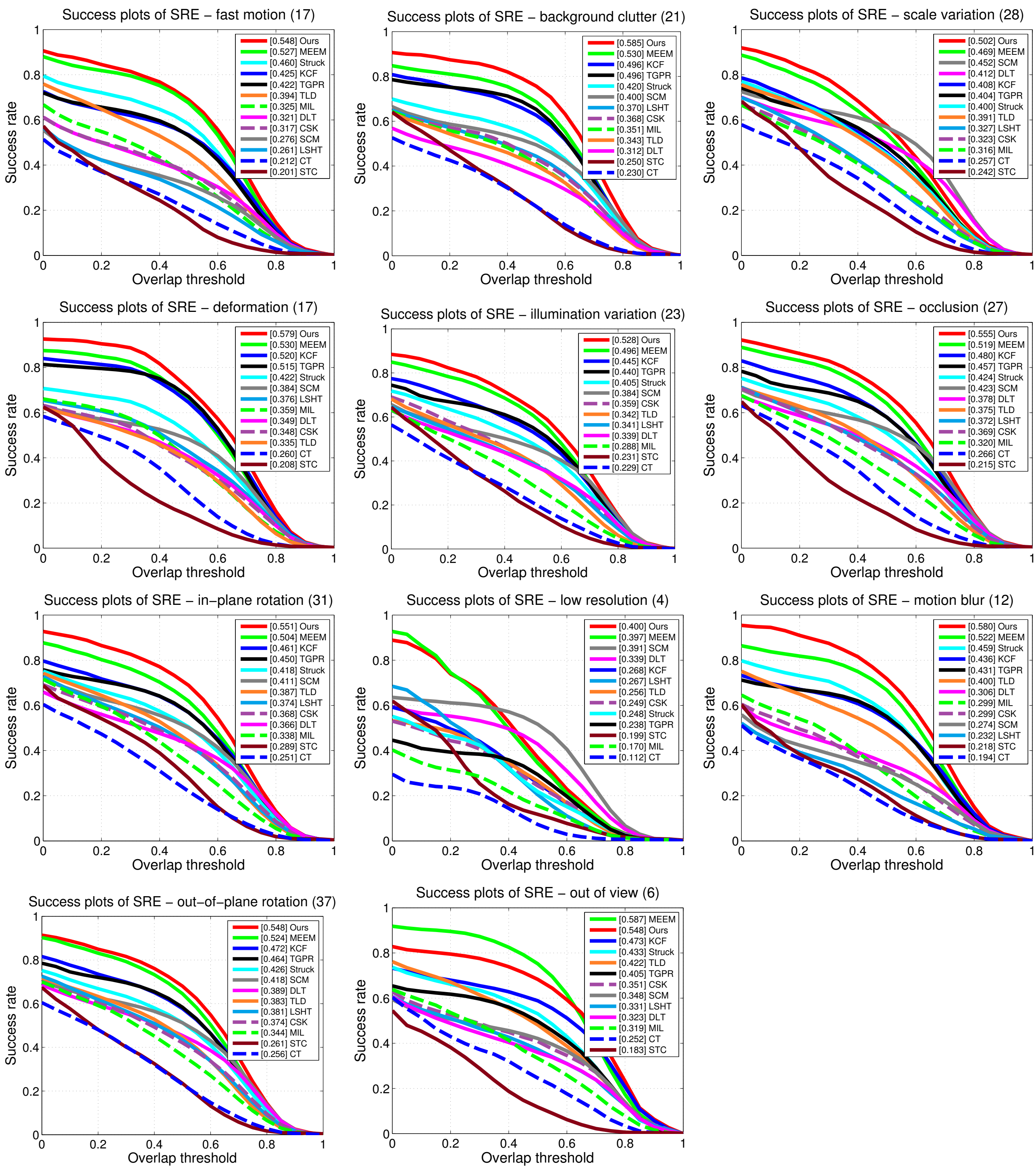

Figure 32. Overlap success plots on the 50 benchmark sequences [9] using spatial robustness evaluation (SRE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

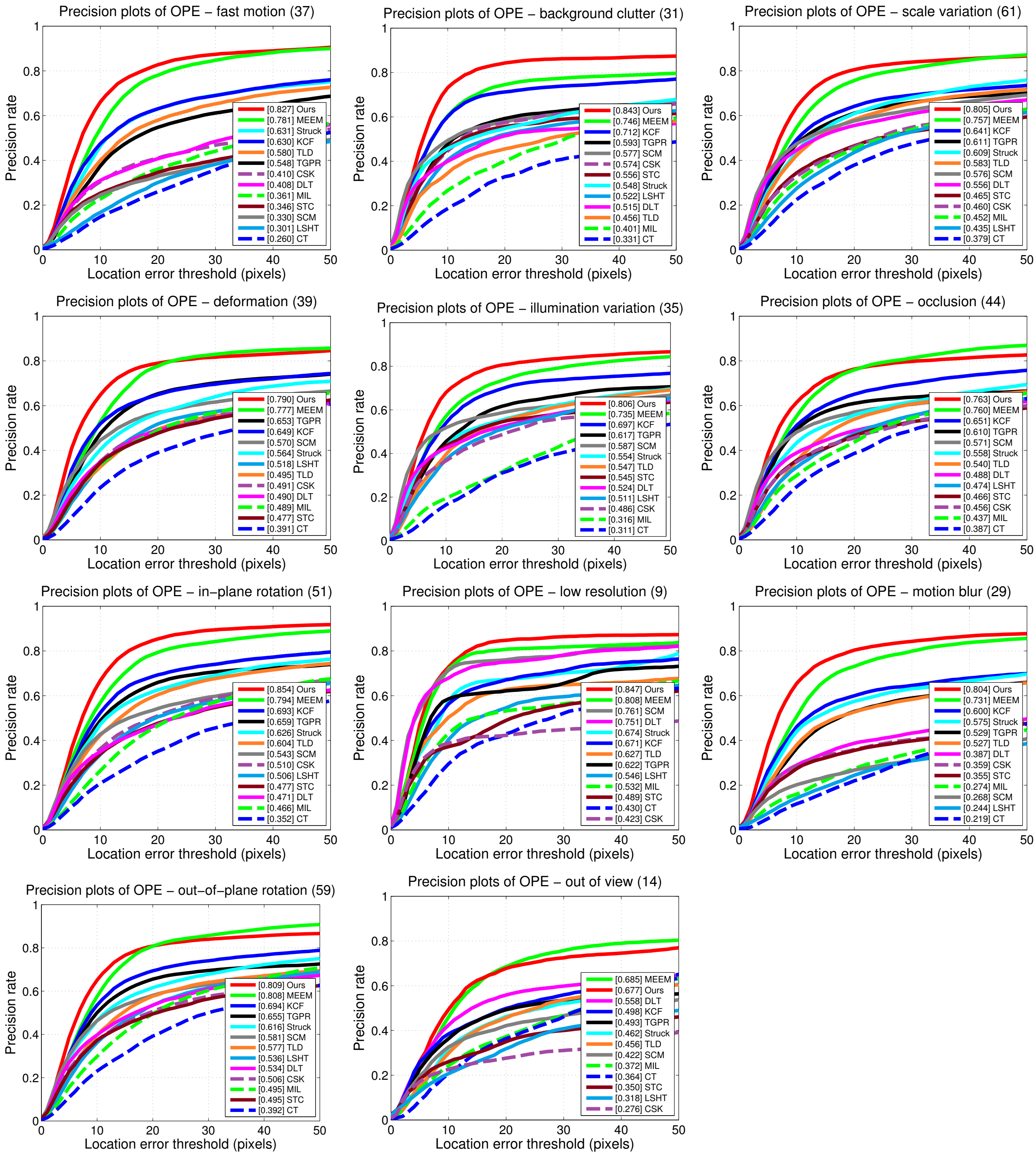

Figure 33. Distance precision plots on the 100 benchmark sequences [10] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the distance precision rate at a threshold of 20 pixels for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

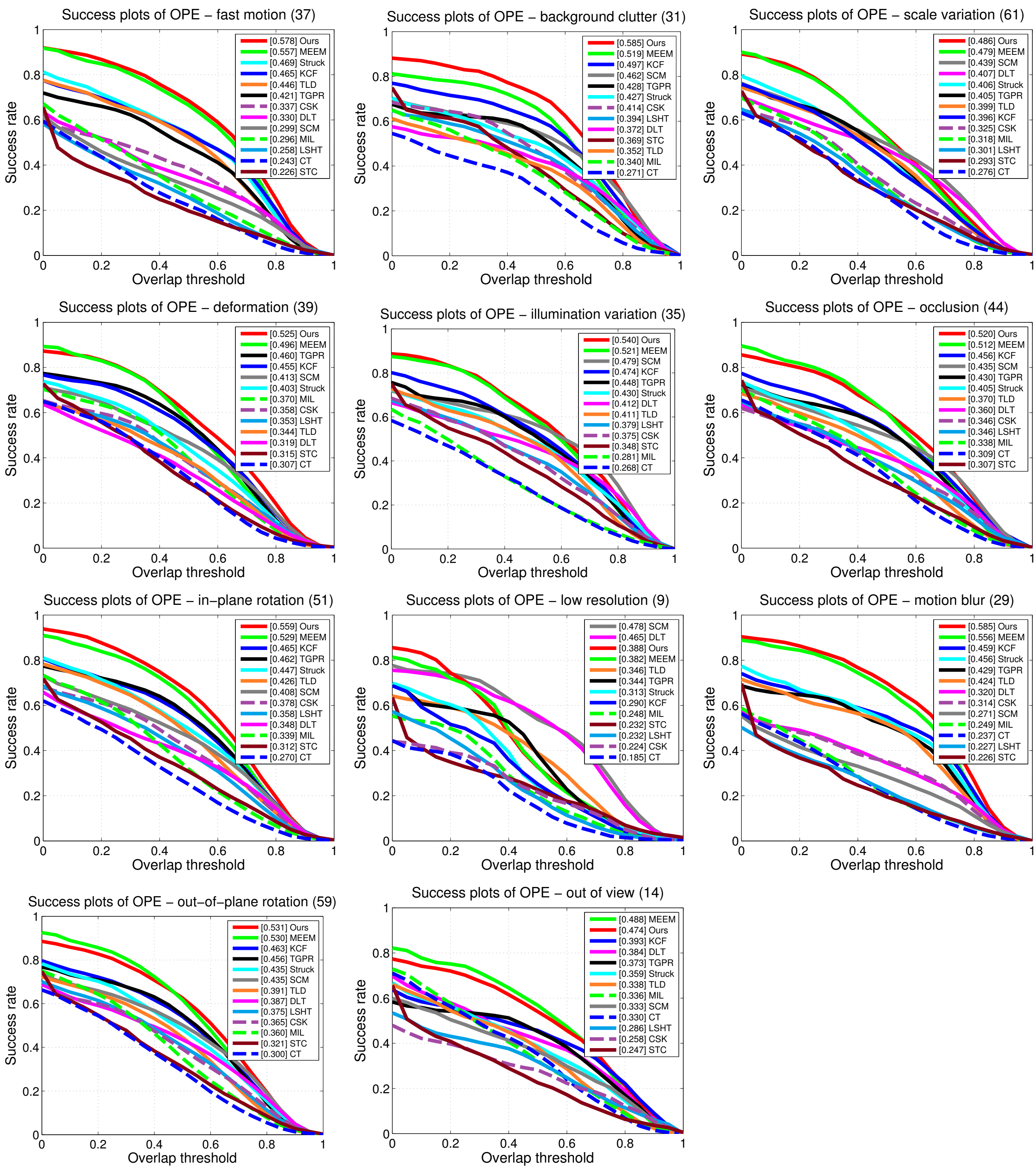

Figure 34. Overlap success plots on the 100 benchmark sequences [10] using one-pass evaluation (OPE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legend contains the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

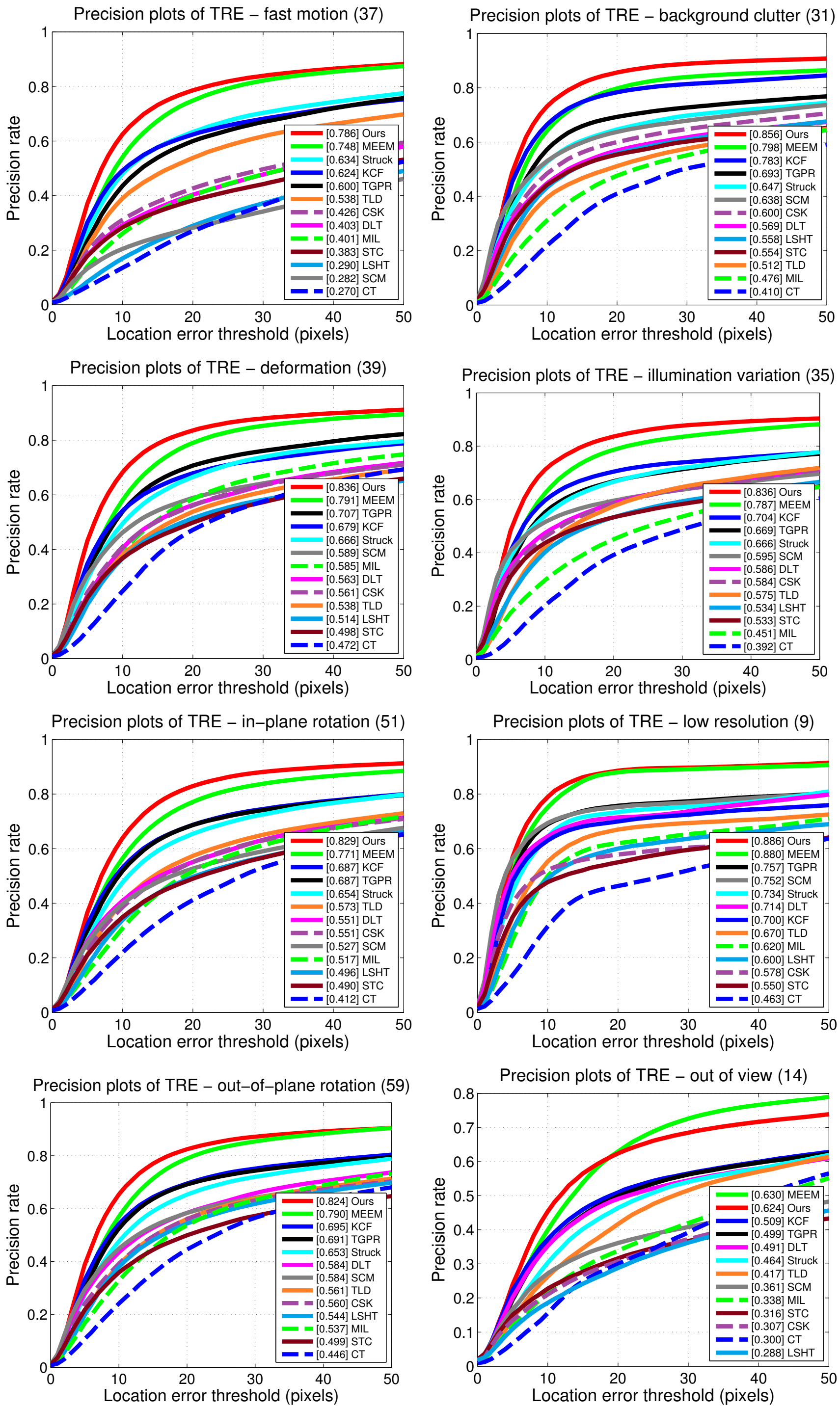

Figure 35. Distance precision plots on the 100 benchmark sequences [10] using TRE validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, blur, out-of-plane rotation and out-of-view. The legends contain the distance precision rate (DPR) at a threshold of 20 pixels for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

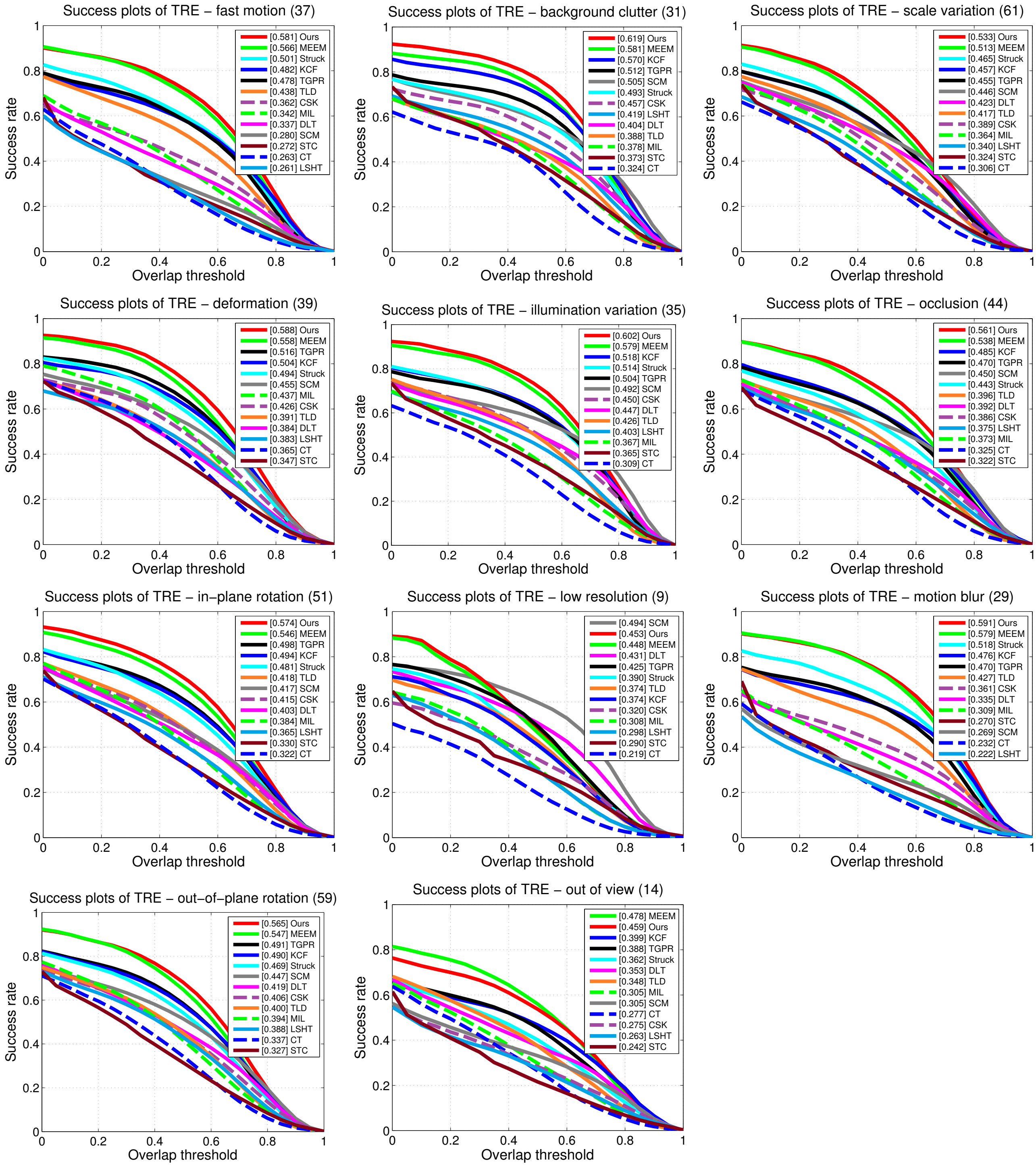

Figure 36. Overlap success plots on 100 benchmark sequences [10] using temporal robustness evaluation (TRE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

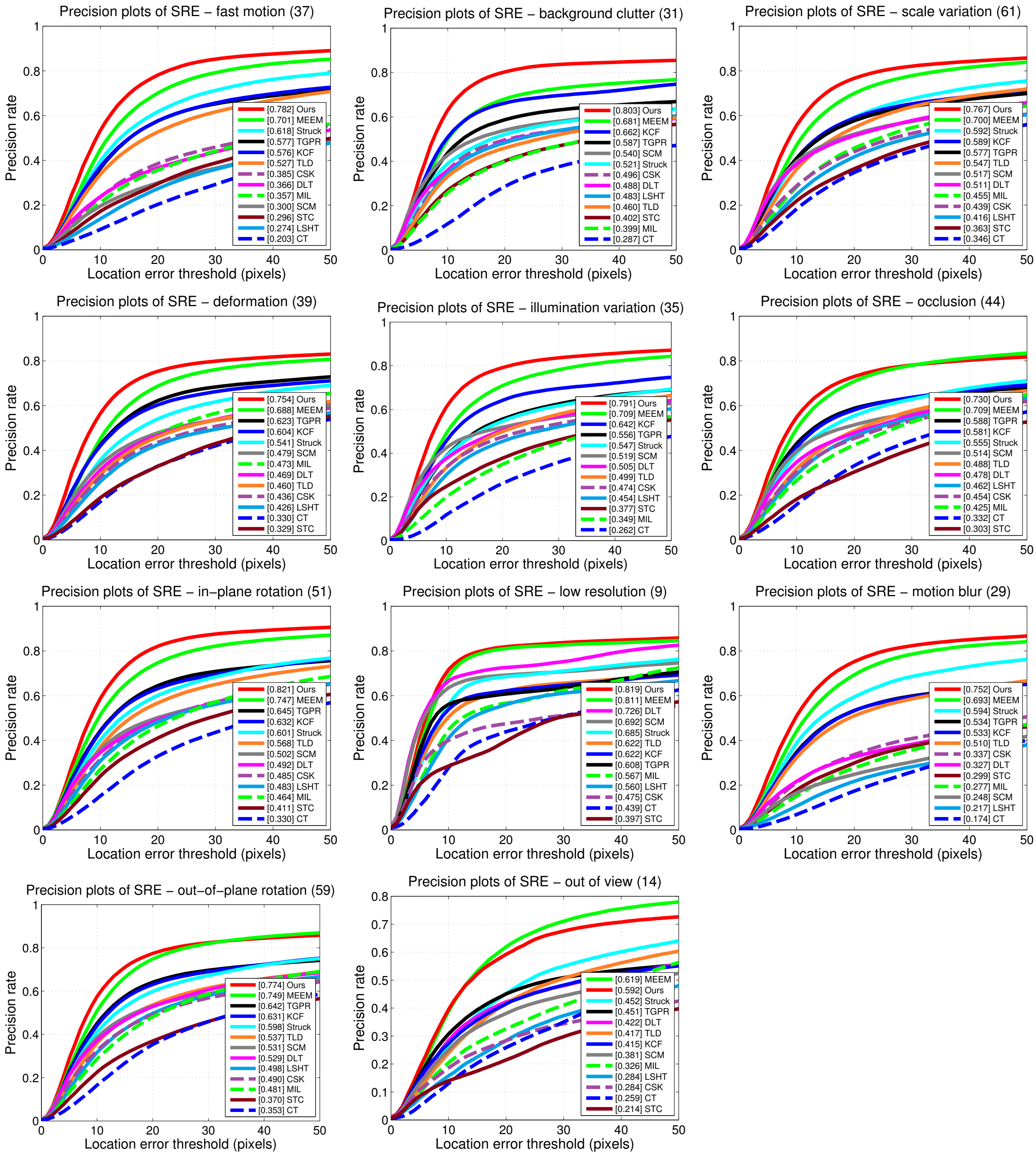

Figure 37. Distance precision plots on 100 benchmark sequences [10] using spatial robustness evaluation (SRE) validation over eleven tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the distance precision rate (DPR) at a threshold of 20 pixels for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

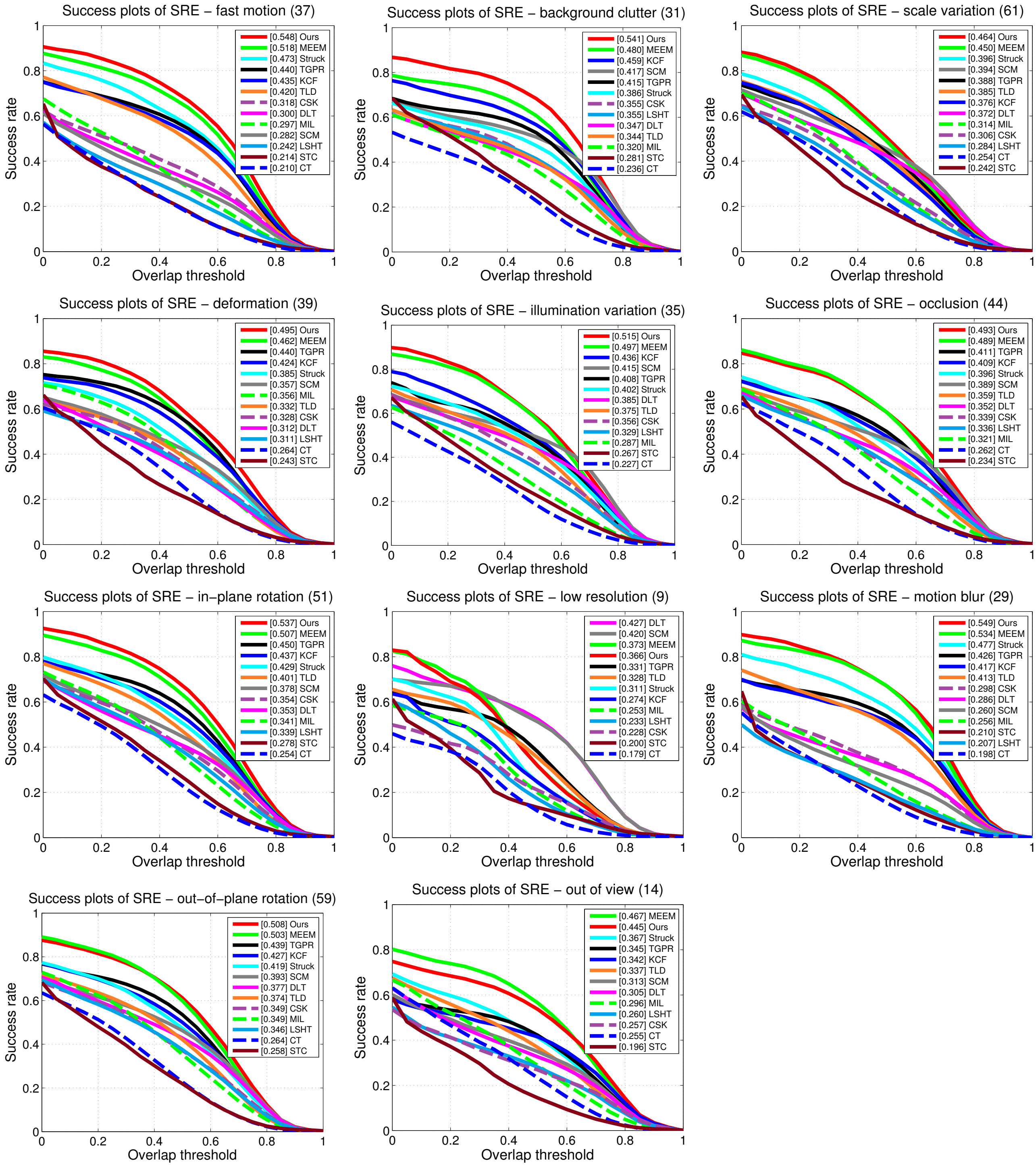

Figure 38. Overlap success plots on 100 benchmark sequences [10] using spatial robustness evaluation (SRE) validation over 11 tracking challenges of fast motion, background clutter, scale variation, deformation, illumination variation, occlusion, in-plane rotation, low resolution, motion blur, out-of-plane rotation and out-of-view. The legends contain the scores of the area under the curve (AUC) for each tracker. The proposed algorithm performs favorably against the state-of-the-art trackers with these challenging attributes.

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