Supplementary Material of LSOTB-TIR

Qiao Liu
Xin Li
Harbin Institute of Technology, Shenzhen
liuqiao.hit@gmail.com

Zhenyu He*
Harbin Institute of Technology, Shenzhen
Peng Cheng Laboratory
zhenyuhe@hit.edu.cn

Chenglong Li
Anhui University
chenglongli@ahu.edu.cn

Jun Li
Zikun Zhou
Di Yuan
Harbin Institute of Technology, Shenzhen

Jing Li
Kai Yang
Nana Fan
Harbin Institute of Technology, Shenzhen

Feng Zheng
Southern University of Science and Technology
zfeng02@gmail.com

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1 PROPOSED LSOTB-TIR BENCHMARK

Comparison with more tracking benchmarks. Table 1 compares the proposed LSOTB-TIR with the existing TIR and RGB tracking benchmarks. It shows that our benchmark is not only the largest and the most diverse in all TIR tracking benchmarks but also larger and more diverse than most RGB tracking benchmarks.

Statistic information of LSOTB-TIR. Table 2 shows some statistic data, such as the object class, number of instances of each class, and number of bounding boxes of each class, of the proposed LSOTB-TIR benchmark.

The designed label tool. Fig. 1 shows the proposed semi-automatic label tool (Codes are available in 'Codes' folder). We just need to adjust the bounding box position at current frame and then run the ECO-HC tracker to automatic obtain the annotations of next ten frames. We suggest that the label tool makes the annotation more accurate, smoother, and faster than the annotation in each frame manually.

Training dataset examples. As shown in Fig. 2, we show some annotated frames of all the 47 object classes of the proposed TIR training dataset. We also show some annotated sequences in a video, i.e., 'video-demo.mp4'.

*Corresponding author.

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2 EXPERIMENTS

Evaluated trackers. We choose publicly available 33 TIR tracking methods and RGB tracking methods for evaluation on LSOTB-TIR. These methods includes hand-crated feature based sparse representation trackers, such as L1APG [2] and ASLA [48]; hand-crafted feature based correlation filter trackers, such as KCF [17], DSST [8], SRDCF [9], BACF [20], Staple [4], ECO-HC [7], and MCCT [43]; other hand-crafted feature based trackers, such as MIL [1], TGPR [14], LCT [33], Struck [16], and RPT [28]; deep feature based correlation filter trackers, such as HDT [38], ECO [7], HCF [32], DeepSTRCF [25], MCFTS [31], CREST [39], and ECO-stir [49]; matching based deep trackers, such as SiamFC [5], CFNet [41], DSiam [15], SiamFC-tri [11], TADT [27], SiamRPN++ [23], SiamMask [44], UDT [42], HSSNet [26], and MLSSNet [30]; classification based deep trackers, such as MDNet [36], VITAL [40], and ATOM [6]. We do not change the parameters of these trackers provided by the authors in the experiment. Furthermore, we re-train several deep trackers on the proposed training dataset for evaluation, such as ECO-TIR, SiamFC-TIR, CFNet-TIR. We use the backbone network of SiamFC-TIR as the feature extractor in the ECO-TIR tracker.

Attribute-based evaluated results. Fig. 3 shows the evaluated results of all the trackers on the 4 scenario subsets. Figs. 4, 5, and 6 show the success plots, precision plots, and normalized precision plots of all the trackers on the 12 challenge subsets, respectively.

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Table 1: Comparison of the proposed LSOTB-TIR benchmark with existing TIR and RGB tracking benchmarks. The first eight rows are TIR tracking benchmarks and last nine rows are RGB tracking benchmarks.

Benchmarks	Num. of sequences	Max frames	Min frames	Mean frames	Total frames	Frame rates	Object classes	Num. of challenges	Scenario attribute	Training dataset
OSU [10]	6	2,031	601	1,424	8K	30 fps	1	n/a	✗	✗
PDT-ATV [37]	8	775	77	486	4K	20 fps	3	n/a	✗	✗
BU-TIV [47]	16	26,760	150	3,750	60K	30 fps	5	n/a	✗	✗
LTIR [3]	20	1,451	71	563	11K	30 fps	6	6	✗	✗
VOT-TIR2016 [13]	25	1,451	71	555	14K	30 fps	8	6	✗	✗
PTB-TIR [29]	60	1,451	50	502	30K	30 fps	1	9	✗	✗
RGB-T [24]	234	4,000	45	500	117K	30 fps	6	12	✗	✗
LSOTB-TIR (Ours)	1,400	3,056	47	428	600K	30 fps	47	12	✓	✓
OTB13 [45]	51	3,872	71	578	29K	30 fps	10	11	✗	✗
OTB15 [46]	100	3,872	71	590	59K	30 fps	16	11	✗	✗
VOT14 [22]	25	1,210	164	409	10K	30 fps	11	n/a	✗	✗
VOT17 [21]	60	1,500	41	356	21K	30 fps	24	n/a	✗	✗
UAV123 [34]	123	3,085	109	915	113K	30 fps	9	12	✗	✗
Nfs [19]	100	20,665	169	3,830	383K	240 fps	17	9	✗	✗
TrackingNet [35]	30,643	-	-	498	14.43M	30 fps	21	15	✗	✓
LaSOT [12]	1,400	11,397	1,000	2,506	3.52M	30 fps	70	14	✗	✓
GOT-10K [18]	10,000	-	-	150	1.5M	30 fps	563	6	✗	✓

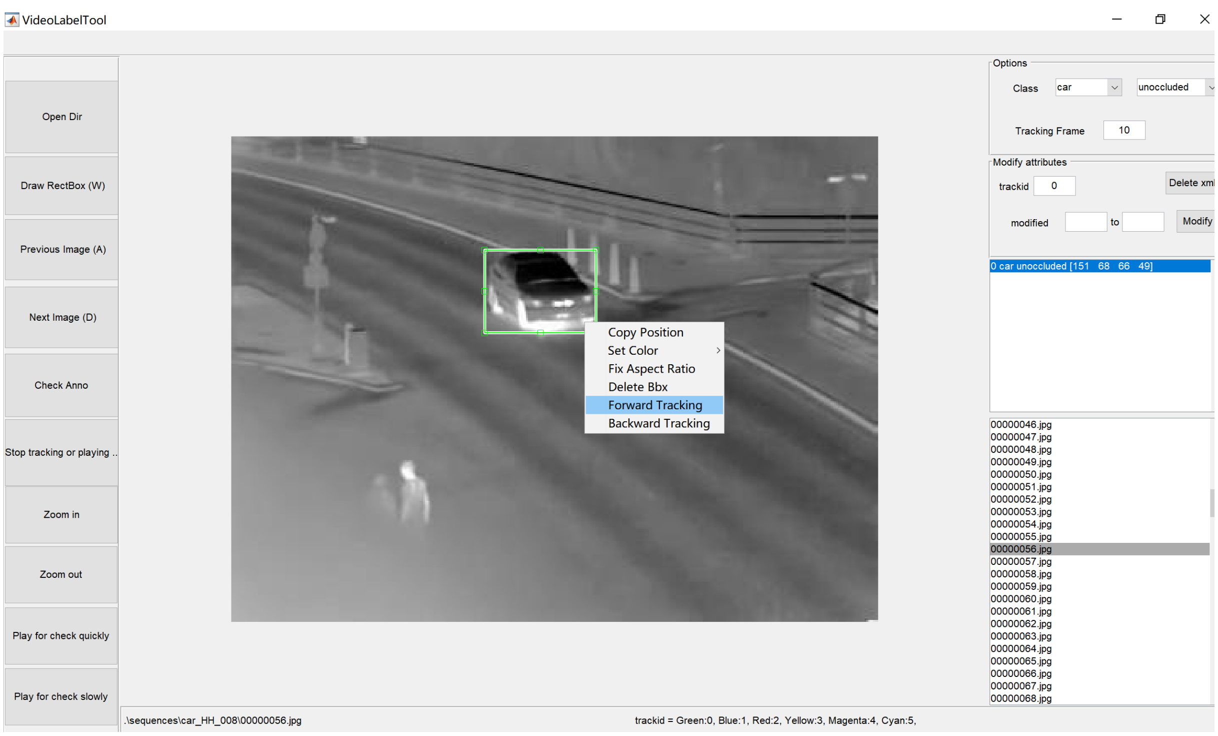

Figure 1: The main window of our designed semi-automatic label tool.

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Table 2: Statistic information of the proposed LSOTB-TIR, which includes object class, number of instances (Num. of ins.) of each class, and number of bounding boxes (Num. of BBs) of each class.

Category	Training dataset			Evaluation dataset		
	Object class	Num. of ins.	Num. of BBs	Object class	Num. of ins.	Num. of BBs
Aircraft	airplane	31	16,871	airplane	2	1,782
	drone	2	996	drone	1	559
	helicopter	49	23,211	helicopter	3	1,800
Vehicle	bus	13	1,741	bus	6	7,124
	car	116	36,954	car	20	19,835
	motobike	16	6,512	motobike	2	1,760
	tricycle	8	1,361	-	-	-
	truck	9	2,616	truck	1	450
	tank	6	475	-	-	-
Animal	bird	40	12,514	bird	3	1,335
	bat	20	4,305	bat	1	270
	bear	13	2,956	-	-	-
	badger	32	20,224	badger	1	600
	buffalo	48	6,295	-	-	-
	cat	57	17,024	cat	3	1,480
	coyote	85	23,762	coyote	1	475
	cow	51	15,354	cow	1	340
	chicken	26	5,527	-	-	-
	crocodile	4	566	-	-	-
	deer	75	43,244	deer	1	330
	dog	56	23,093	dog	3	1,585
	duck	7	3,243	-	-	-
	elephant	44	17,692	-	-	-
	ericius	8	1,481	-	-	-
	fox	46	36,477	fox	1	620
	goose	10	1,842	-	-	-
	giraffe	31	5,641	-	-	-
	hog	44	15,685	hog	6	3,572
	horse	50	21,023	-	-	-
	hedgehog	4	2,416	-	-	-
	hippo	10	3,754	-	-	-
	hyenas	11	2,060	-	-	-
	lion	69	16,056	-	-	-
	leopard	40	9,645	leopard	1	208
	rat	32	13,886	-	-	-
	monkey	6	1,310	-	-	-
	penguin	4	2,822	-	-	-
	rabbit	24	11,812	-	-	-
	raccoon	31	9,322	-	-	-
	roo	13	6,995	-	-	-
	rhino	21	6,775	-	-	-
	sheep	55	16,543	-	-	-
	squirrel	5	894	-	-	-
	snake	5	2,049	-	-	-
	seal	3	1,049	-	-	-
Boat	boat	63	20,908	boat	2	865
Person	person	362	157,348	person	62	37,348
	-	-	-	head	2	1,135
	-	-	-	face	2	1,740
	Total classes	Total ins.	Total BBs.	Total classes	Total ins.	Total BBs
	47	1,755	654,330	22	120	82,133

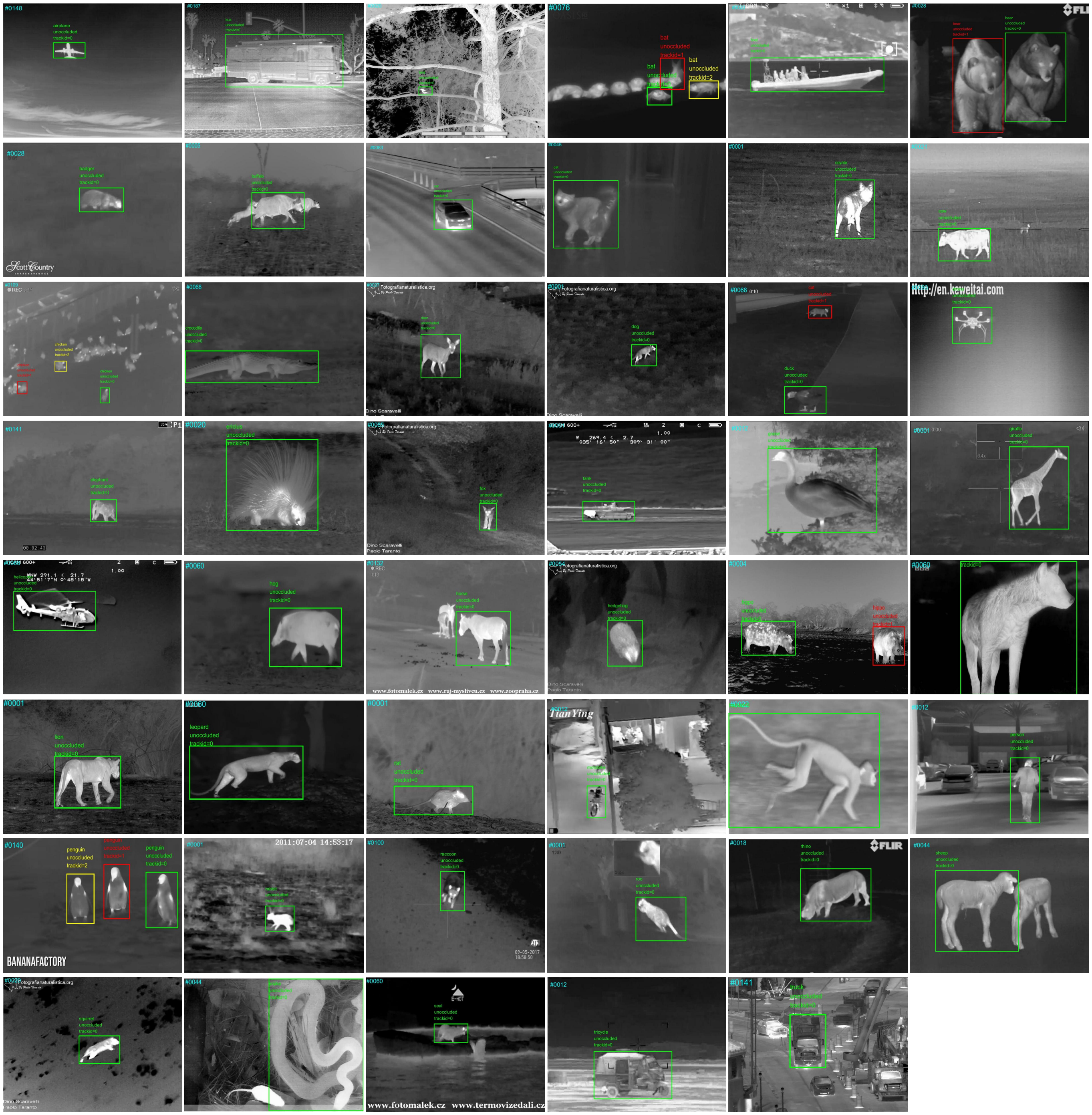

Figure 2: Some samples of the proposed TIR training dataset which consists of 47 classes and 1,280 image sequences. We annotate the classname and bounding box of objects in every frame of each sequence.

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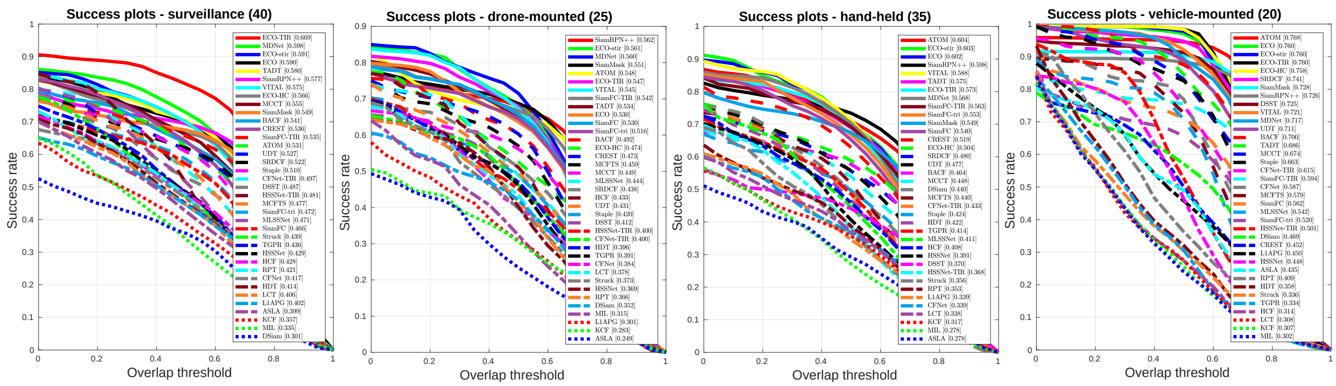
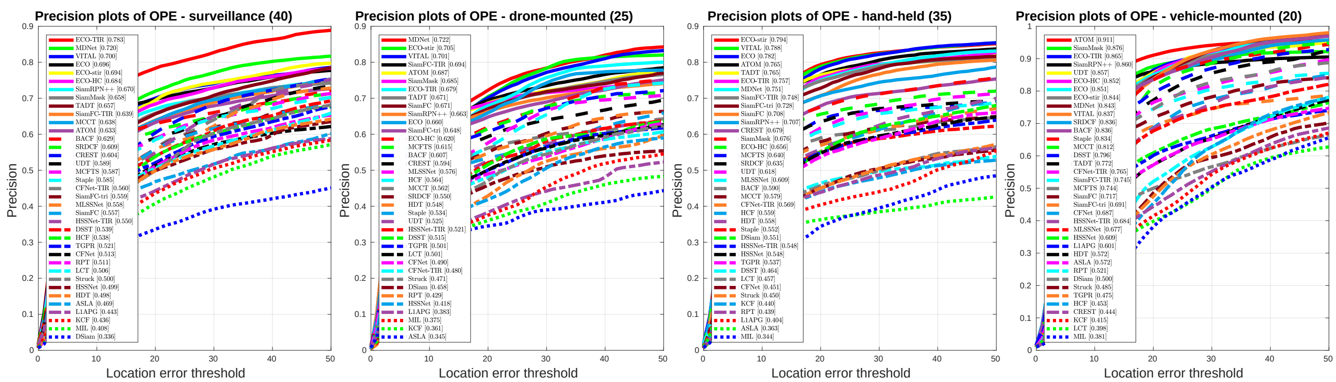
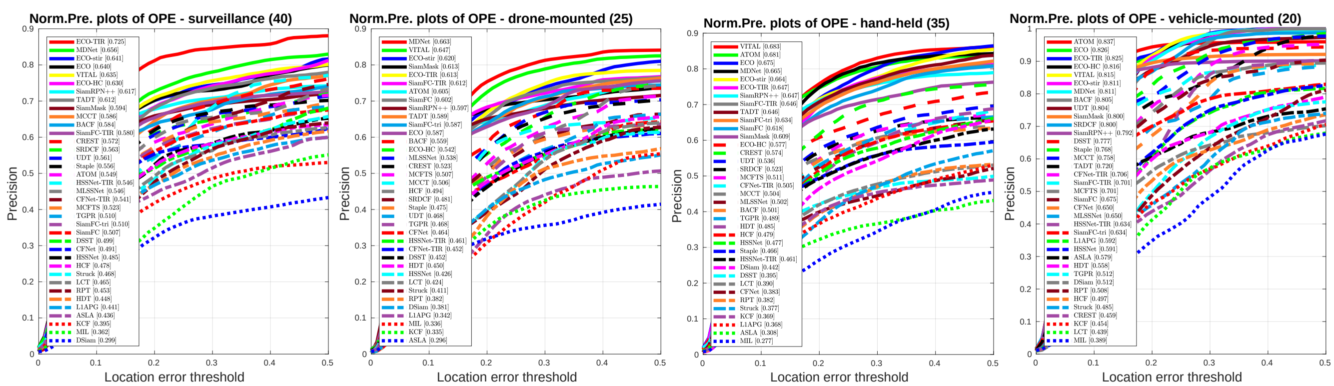


(a) Success plots.



(b) Precision plots.



(c) Normalized precision plots.

Figure 3: Evaluation results of all the evaluated trackers on the 4 scenario attribute subsets.

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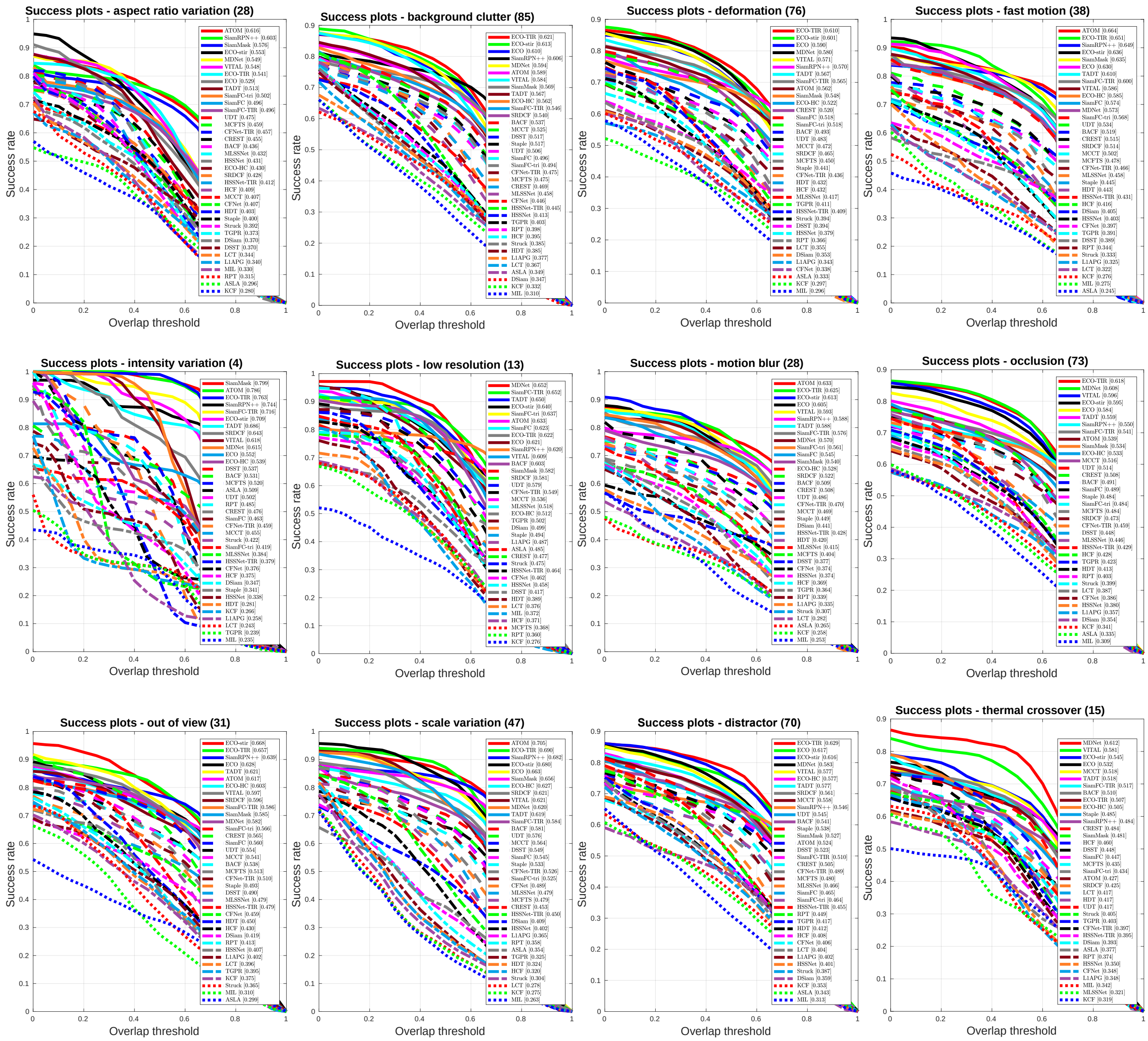

Figure 4: Success plots of all the evaluated trackers on the 12 challenge attribute subsets.

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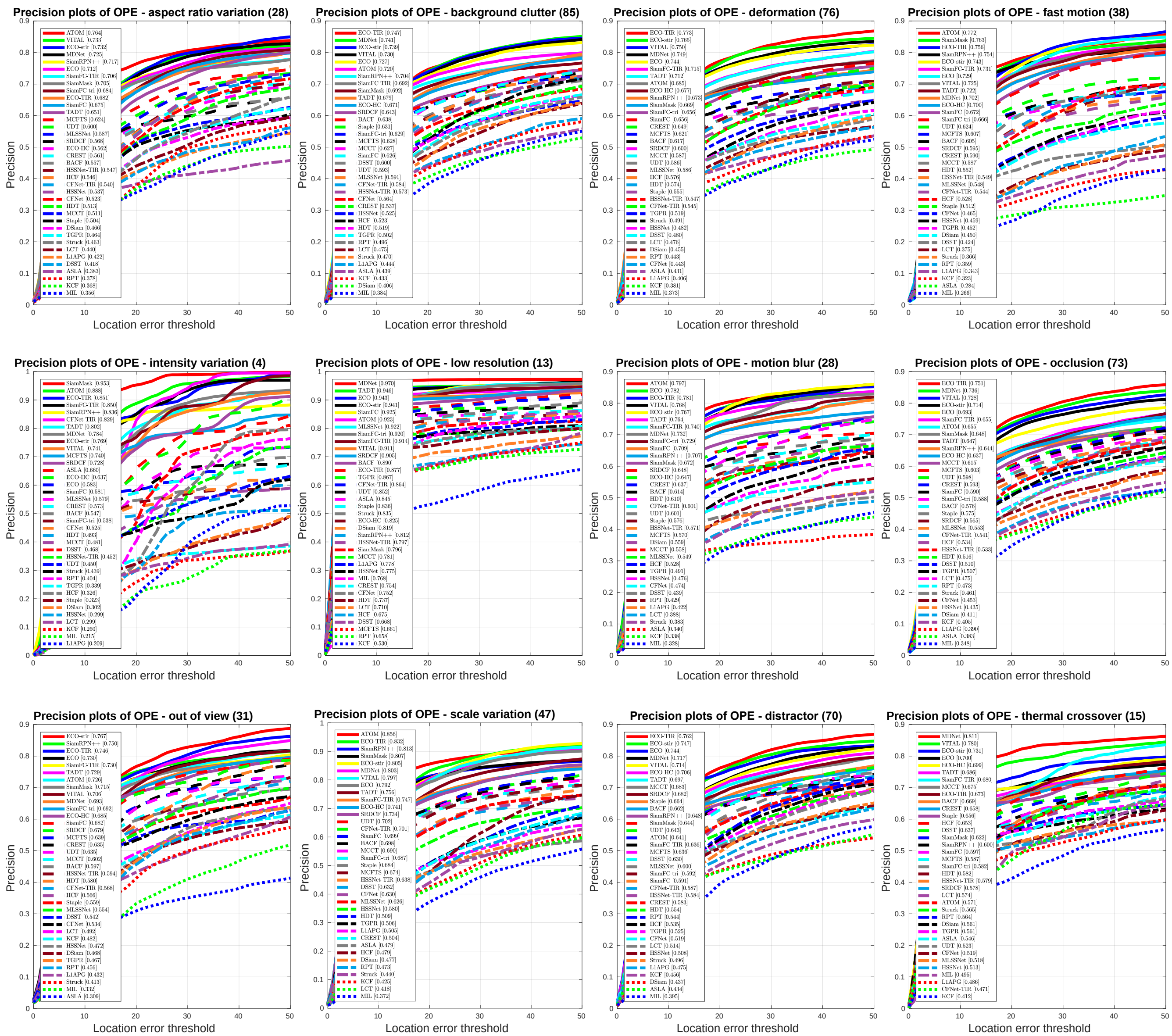

Figure 5: Precision plots of all the evaluated trackers on the 12 challenge attribute subsets.

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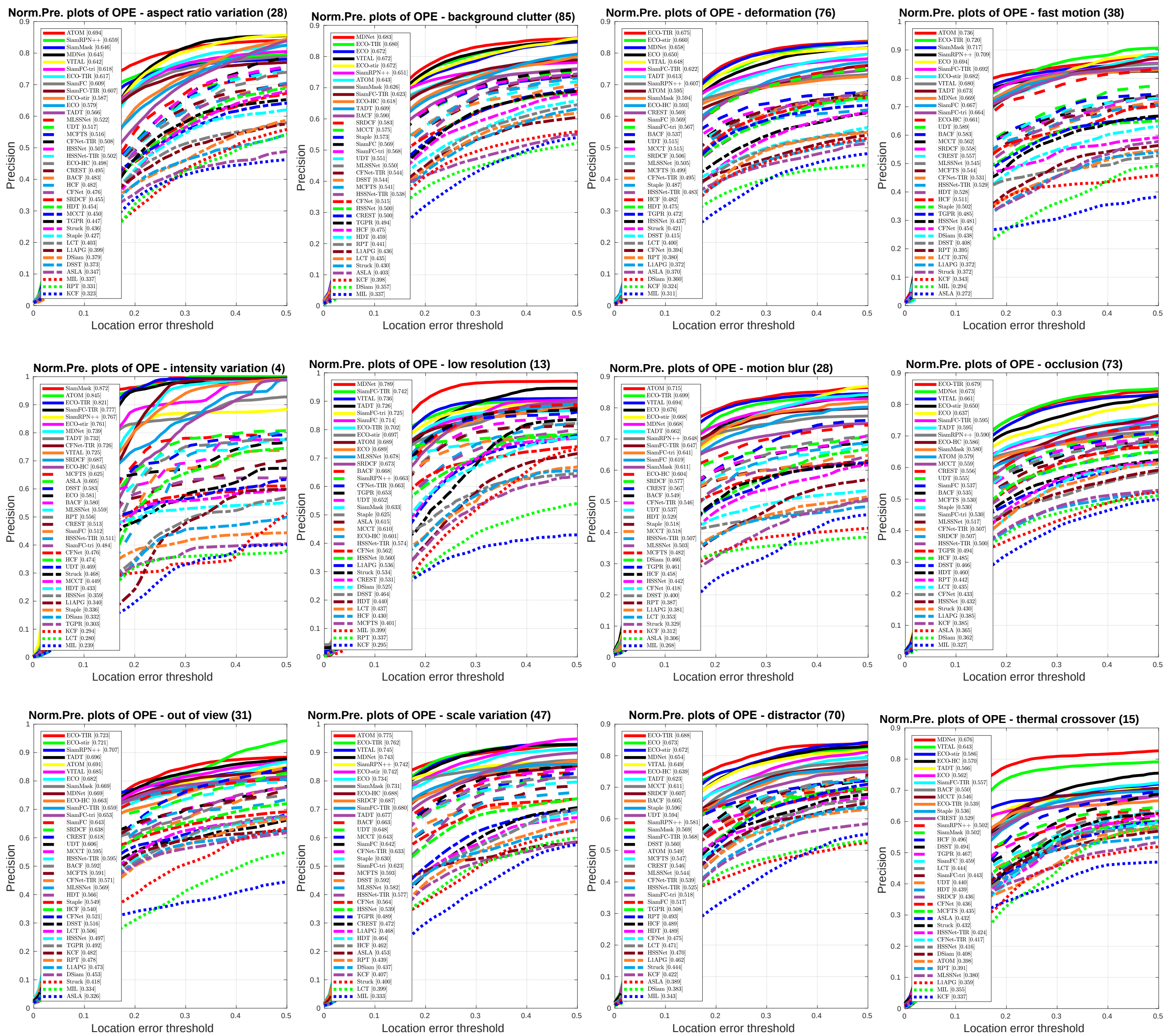

Figure 6: Normalized precision plots of all the evaluated trackers on the 12 challenge attribute subsets.

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