AVSS2017
Advance Traffic Monitoring Challenge

in conjunction with

International Workshop on Traffic & Street Surveillance
for Safety & Security (T4S)

and sponsored by

Nvidia Inc.

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motivation

The goal of this challenge is ***to provide a comprehensive performance evaluation to the state-of-the-art detection and tracking algorithms in the context of traffic monitoring.***

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people

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challenge supporting team

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L. Wen, D. Du, Z. Cai, Z. Lei, M. Chang, H. Qi, J. Lim, M. Yang, and S. Lyu. UA-DETRAC: A new benchmark and protocol for multi-object tracking. CoRR, abs/1511.04136, 2015.

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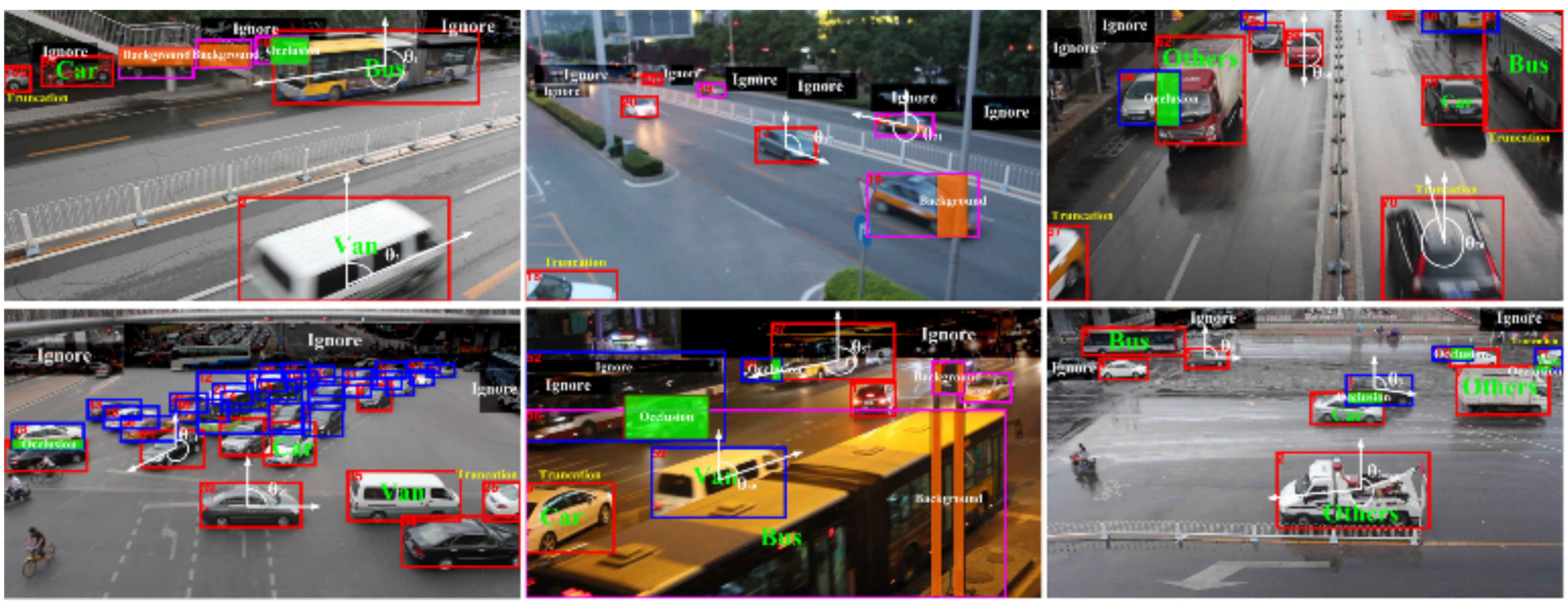
dataset

- **University** at **Albany** **DEtection** and **TRACking** dataset and benchmark
  - 100 video sequence of traffic surveillance videos
  - 140K frames of over 8K vehicles and 1.2M annotated bounding boxes



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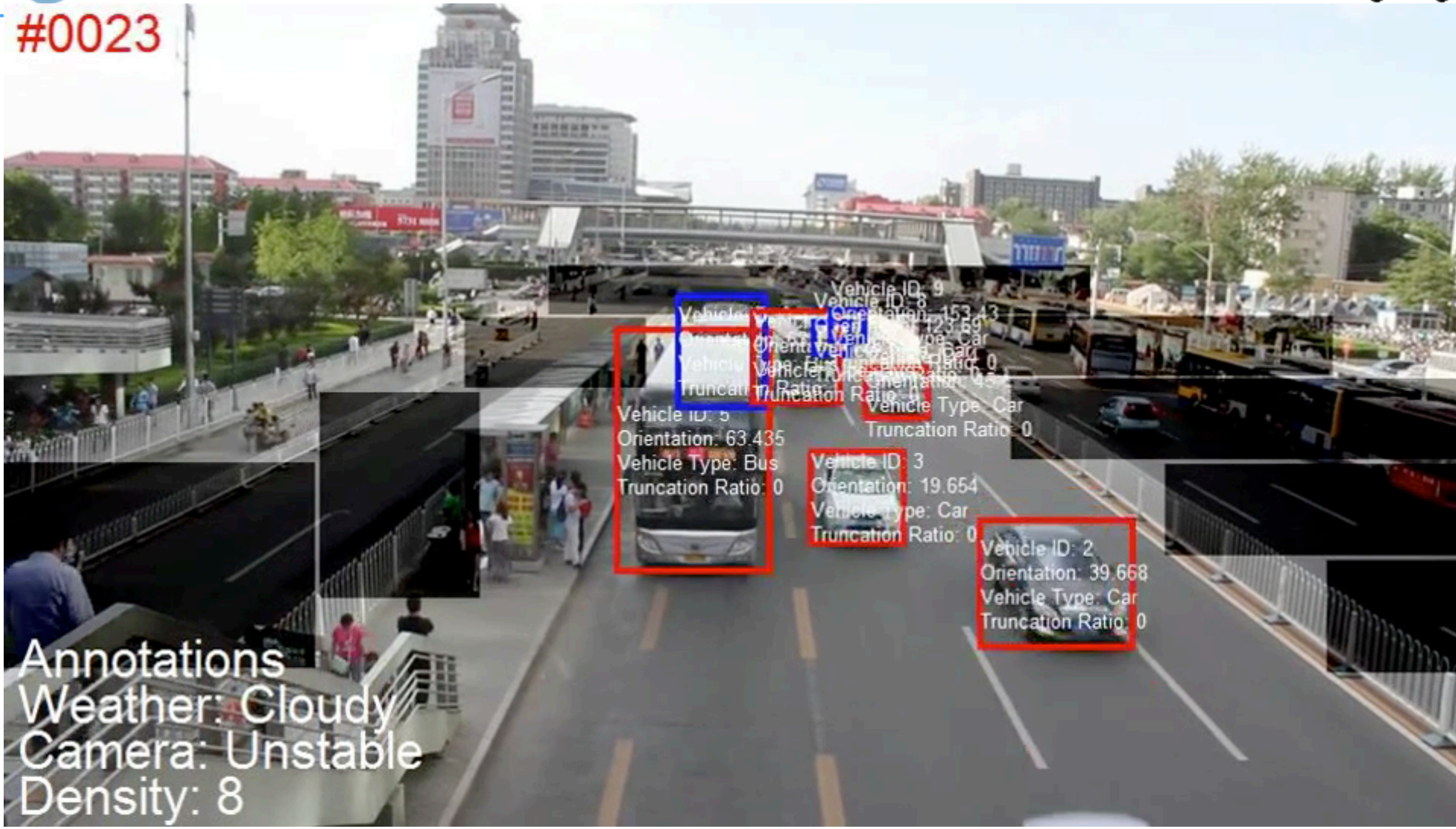
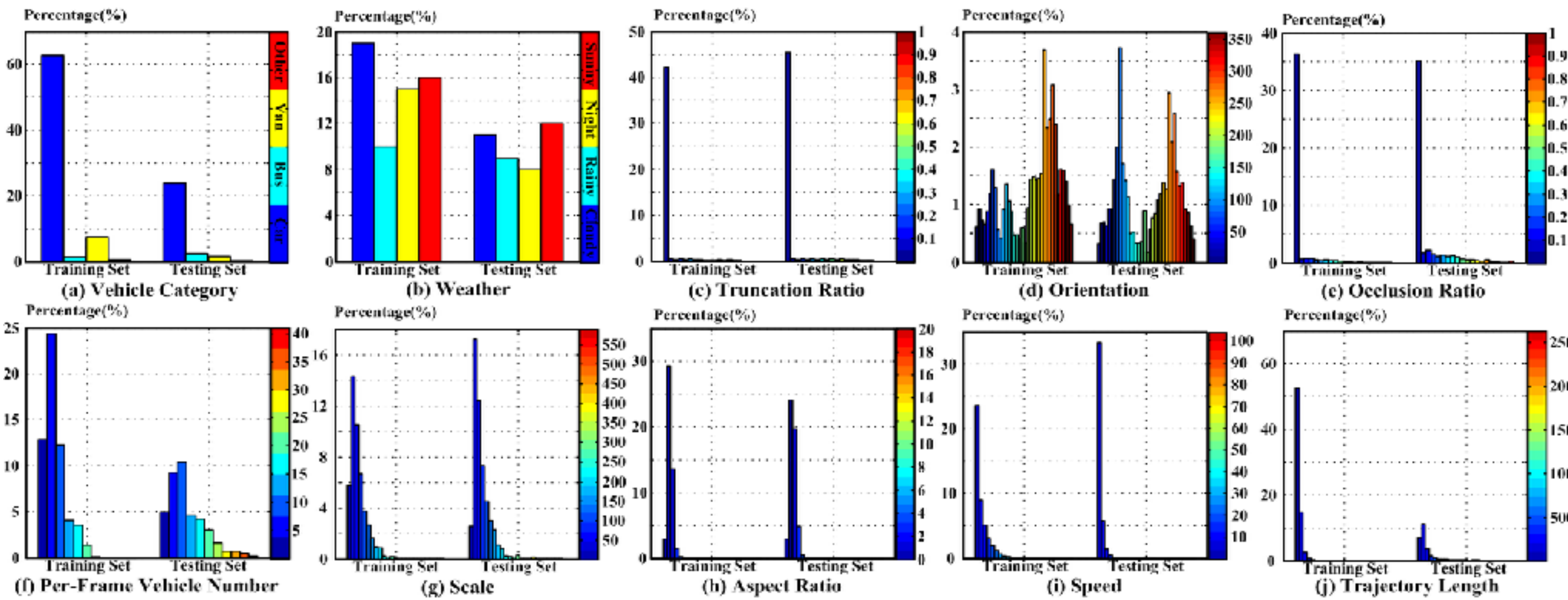
UA-DETRAC dataset



UA-DETRAC dataset

- attributes: weather, vehicle category, orientation, speed, and occlusion ratio



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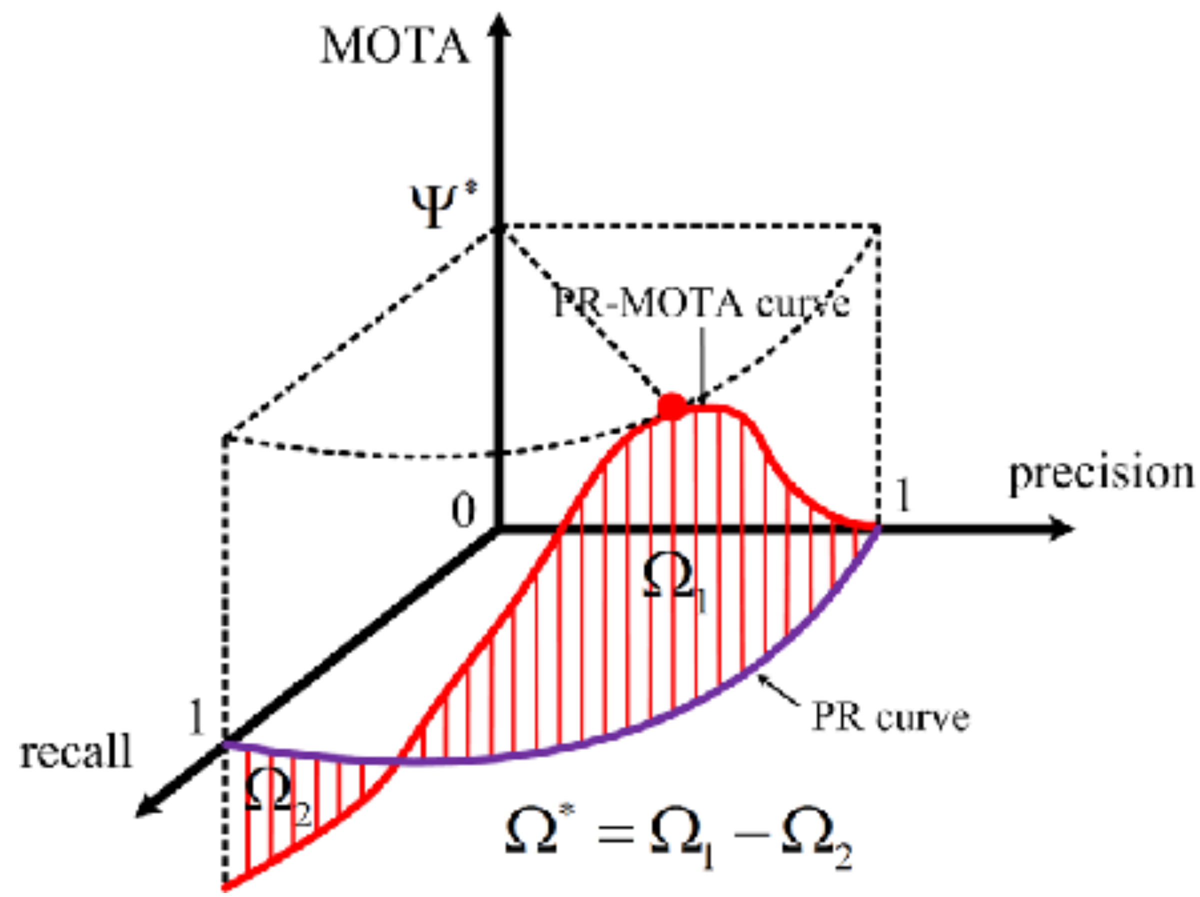
evaluation metric

- detection: average precision (AP)
- tracking: DETRAC PR-MOTA



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UA-DETRAC: A new benchmark and protocol for multi-object tracking.
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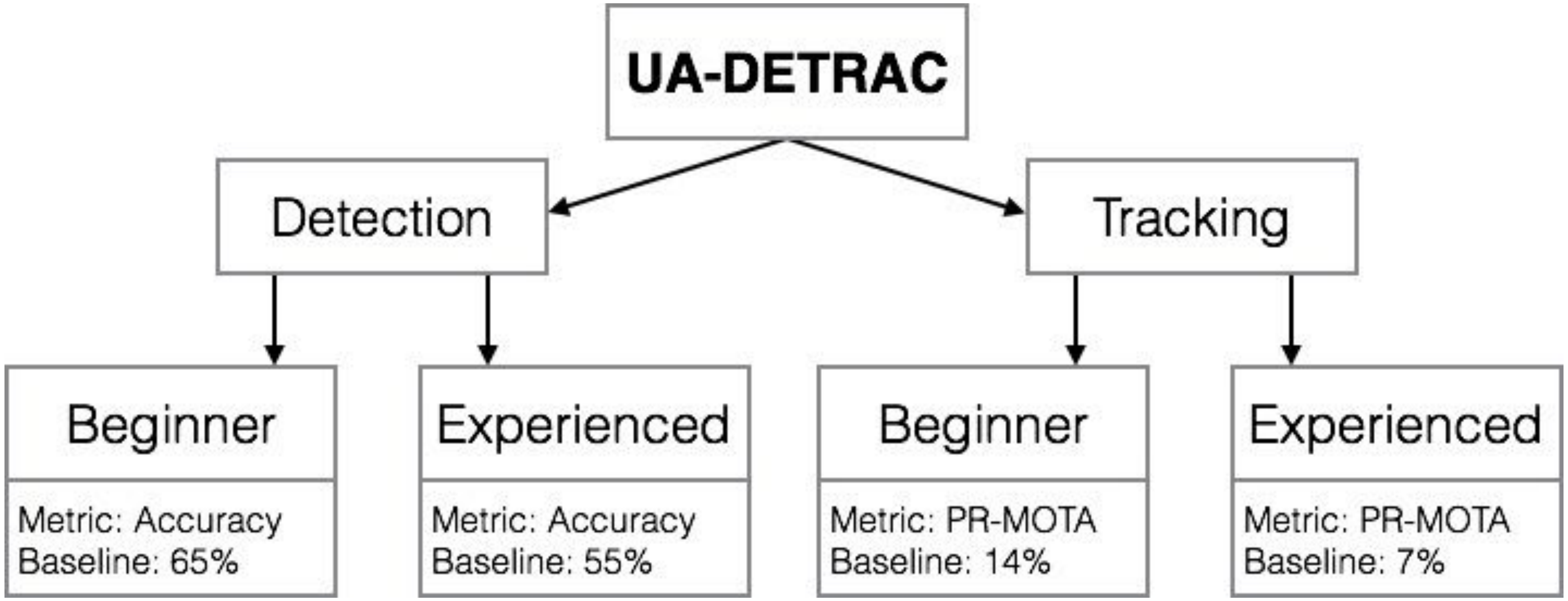
challenge rules



detection: submissions

1. 🇩🇪 Geometric proposals for faster R-CNN (GPFRCNN): OSRAM GmbH, Munich, Germany
2. 🇺🇸 Evolving boxes for fast vehicle detection (EB): University of Washington, Seattle, USA
3. 🇷🇺 Lightweight SSD based on ResNet10 with dilations (SSDR): Intel, Nizhny Novgorod, Russia
4. 🇹🇭 R-CNN with Sub-Classes (RCNNSC): National Electronics and Computer Technology Center, Bangkok, Thailand
5. 🇺🇸 Faster R-CNN with ResNet101 (FRCNN-Res): University at Albany, Albany, USA
6. 🇺🇸 Region-based Deformable Fully Convolutional Network (DFCN): Iowa State University, Des Monies, Iowa, USA
7. 🇬🇷 CERTH Single Shot multibox Detector (SSD) for vehicle detection (CERTH-SSD): Information Technologies Institute (ITI), Thessaloniki, Greece**

detection: winners

- beginner category (prize: free registration)
  R-CNN with Sub-Classes
  Nattachai Watcharapinchai and Sitapa Rujikietgumjorn
  National Electronics and Computer Technology Center, Bangkok, Thailand 🇹🇭
  mAP = 93.4%

- experienced category (prize: €350)
  Geometric proposals for faster R-CNN
  Sikandar Amin and Fabio Galasso
  OSRAM GmbH, Munich, Germany 🇩🇪
  mAP = 76.6%

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detection: observations & analyses

- vehicle detection performance is significantly improved by CNN-based methods, e.g., R-CNN, SSD, and resNet
- all detection algorithms benefit from the use of GPUs
- there are still much room for improvement
    - real time running efficiency (>30fps) is still not common (only the one team achieved this)
    - performance significantly affected by weather conditions (e.g., rainy) and occlusions
- for details, please refer to our report in the AVSS proceedings

tracking: submissions

1. 🇨🇳 Higher-order graph and flow network based tracker (HGFT): Nanjing University of Posts and Telecommunications, Nanjing, China
2. 🇩🇪 Real-time multi-human tracking using a probability hypothesis density filter and multiple detectors (GMPHD): Technische Universität Berlin, Berlin, Germany*
3. 🇺🇸 Online distance based and offline appearance based tracker with correlated color dissimilarity matrix (CCM): University of Missouri, Columbia, USA
4. 🇩🇪 Intersection-over-union tracker (IOU): Technische Universität Berlin, Berlin, Germany*
5. 🇩🇪 Joint tracking with event grouping and temporal constraints (JTEGTC): Karlsruhe Institute of Technology, Karlsruhe, Germany
6. 🇨🇳 Multi-task deep learning for fast online multiple object Tracking (MTT): Institute of Automation, Chinese Academy of Sciences, Beijing, China
7. 🇩🇪 Gaussian Mixture Probability Hypothesis Density Filter extended by Kernelized Correlation Filters (GMPHD-KCF): Technische Universität Berlin, Berlin, Germany*
8. 🇬🇷 CERTH Kernelized Correlation Filters (KCF) tracking algorithm for vehicle tracking (CERTH-KCF)**

tracking: winners

- beginner category (prize: free registration)
  R-CNN with Sub-Classes (RCNNSC)
  Intersection-over-union tracker
  Erik Bochinski, Volker Eiselein and Thomas Sikora
  Technische Universität Berlin, Berlin, Germany
  PR-MOTA = 29.3%

- experienced category (prize: Nvidia TX2 kit)
  Joint tracking with event grouping and temporal constraints
  Wei Tian and Martin Lauer
  Karlsruhe Institute of Technology, Karlsruhe, Germany
  PR-MOTA = 14.2%

tracking: observations & analyses

- unlike detection, tracking performance of state-of-the-art methods is still far from satisfactory
  - performance strongly depends on detection accuracy
  - but even with accurate detection results tracking still lags behind because complexity in the scenes (e.g., occlusion causes a lot of ID switches)
- best tracking algorithm + best detection algorithm achieves better performance (+5%)
- for details, please refer to our report in the AVSS proceedings

next steps

- enhance UA-DETRAC dataset
  - add annotations for more vehicle types
  - add annotations for bikes, motorcycles, pedestrians, traffic lights and signs
- implement more sophisticated baseline algorithms for detection and tracking
- evaluate algorithms considering both performance and running time
- include application challenges for applications more relevant to traffic surveillance and automatic driving
- provide a more convenient web-based interface for results submission and evaluation

AVSS 2017

acknowledgements

- IWT4S organizing committee and AVSS 2017
- all teams submitted results to the challenge
- UA-DETRAC dataset annotators
  Zhidan Wang, Fenfen Sheng, Yunteng Zhang, Yuxin Chen, Bin Liu, Lejie Chang, Yunxia Wang and Yuping Zhang
- University at Albany Information Technology Service for hosting the challenge web site
- generous support from NVIDIA
- UA-DETRAC project is supported by the US National Science Foundation under Grant No. CCF-1319800

NVIDIA

NSF

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Thank You!

detection: results

Methods	Overall	Easy	Medium	Hard	Cloudy	Night	Rainy	Sunny
GP-FRCNN (D.1)	91.90/**76.57**	91.90/**91.79**	–/**80.85**	–/**66.05**	92.77/**81.23**	**92.91**/**77.20**	82.77/**68.59**	93.96/**85.16**
EB (D.2)	89.57/67.99	89.57/87.77	–/73.03	–/54.74	94.68/75.13	90.26/71.80	71.34/52.99	90.57/82.04
SSDR (D.3)	79.47/59.07	79.47/77.84	–/64.41	–/45.98	88.86/62.79	75.27/60.88	70.26/48.55	86.36/74.32
RCNN-SC (D.4)	**93.43**/–	**93.43**/–	–/–	–/–	**96.69**/–	92.54/–	**87.30**/–	**94.47**/–
FRCNN-Res (D.5)	82.90/61.65	82.90/82.90	–/66.89	–/48.14	82.93/61.97	82.49/65.88	86.44/59.13	83.14/59.17
DFCN (D.6)	86.86/65.82	86.86/86.83	–/72.96	–/50.47	98.05/69.90	83.96/69.41	70.71/54.11	88.45/80.79
CERTH-SSD (D.7)	49.38/32.01	49.38/49.41	–/36.73	–/20.74	39.49/27.41	52.33/36.02	60.54/33.99	58.08/41.05
DPM	34.63/25.70	34.63/34.42	–/30.29	–/17.62	32.54/24.78	36.71/30.91	40.26/25.55	50.53/31.77
ACF	54.80/46.35	54.80/54.27	–/51.52	–/38.07	71.95/58.30	45.20/35.29	43.76/37.09	73.07/66.58
R-CNN	59.71/48.95	59.71/59.31	–/54.06	–/39.47	74.14/59.73	94.46/39.32	90.81/39.06	76.64/67.52
CompACT	65.50/53.23	65.50/64.84	–/58.70	–/43.16	77.27/63.23	61.98/46.37	57.68/44.21	77.35/71.16

Detectors	CPU	Frequency	GPU	RAM	Codes	Speed
GP-FRCNN (D.1)	12×Intel Xeon E5-2690v3	2.60GHz	Tesla K40	256GB	Python, C++	4.00
EB (D.2)	4×Intel Core i7-4770	3.40GHz	TitanX	16GB	C++	11.00
SSDR (D.3)	8×Intel Core i7-6700K	4.00GHz	GTX1080	32GB	C++	**34.00**
RCNN-SC (D.4)	2×Intel Xeon E5-2630v3	4.00GHz	2×Tesla K80	384GB	Python, Tensorflow	2.20
FRCNN-Res (D.5)	16×Intel Xeon X5570	2.93GHz	2×Titan X	96GB	Python, Tensorflow	1.00
DFCN (D.6)	11× Intel Xeon E5-1650v3	3.50GHz	Titan X	64GB	Python	11.00
CERTH-SSD (D.7)	16×Intel Xeon E5-2620v4	2.10GHz	Titan X	128GB	Python	9.60
DPM	4×Intel Core i7-6600U	2.60GHz	×	8GB	Matlab,C++	0.17
ACF	2×Intel Xeon E5-2470v2	2.40GHz	×	64GB	Matlab	0.67
R-CNN	2×Intel Xeon E5-2470v2	2.40GHz	Tesla K40	64GB	Matlab,C++	0.10
CompACT	2×Intel Xeon E5-2470v2	2.40GHz	Tesla K40	64GB	Matlab,C++	0.22

tracking: results

Methods	PR-MOTA↑	PR-MOTP↑	PR-MT↑	PR-ML↓	PR-IDS↓	PR-FM↓	PR-FP↓	PR-FN↓
GOG+CompACT	23.9/11.7	47.4/34.4	20.5/10.8	21.0/21.1	829.9/2571.2	776.2/2463.8	6276.5/25352.8	36738.3/145257.5
CEM+CompACT	8.1/4.5	44.2/33.2	3.8/2.6	40.9/34.5	73.7/**198.1**	**88.3/267.5**	3236.0/**9047.6**	60393.3/200703.1
DCT+R-CNN	23.2/8.5	45.8/36.5	18.5/6.5	18.1/27.1	183.3/541.8	176.3/532.4	8976.3/24204.6	36484.9/180873.7
IHTLS+CompACT	20.8/8.7	46.5/34.2	20.2/10.7	21.6/21.1	178.0/774.0	735.8/2835.9	10484.0/42814.2	37172.1/145188.5
H^2T+CompACT	21.8/10.1	44.0/33.6	21.7/11.5	21.7/20.3	162.9/687.8	191.7/922.2	10278.4/41193.8	36115.2/139703.2
CMOT+CompACT	22.5/10.3	45.9/33.4	23.3/12.6	20.0/19.7	**40.7/243.2**	254.1/1255.9	11424.4/45619.6	34134.9/134568.6
HGFT(T.1)+CompACT	−/12.1	−/33.5	−/10.4	−/21.5	−/1927.5	−/2141.0	−/24160.0	−/145262.2
GM-PHD(T.2)+EB(D.2)	−/14.4	−/26.5	−/12.3%	−/18.8%	−/994.3	−/1660.4	−/19627.3	−/139807.3
GM-PHD(T.2)+CompACT	21.8/10.9	**47.6/35.0**	16.2%/**15.1%**	20.4%/21.6%	641.8/556.4	2038.5/1674.9	37963.0/29687.1	186043.9/147257.0
CCM(T.3)+R-CNN/CompACT	25.2/10.7	45.8/33.8	23.8%/11.9%	**15.8%/20.0%**	179.9/514.7	590.6/1705.5	10155.4/35624.7	**32742.9/142110.0**
IOUT(T.4)+EB(D.2)	**34.0/16.4**	37.8/26.7	**27.9%/14.8%**	20.4%/**18.2%**	573.6/1743.2	603.7/1846.3	**1617.0/12627.0**	33760.8/136077.8
IOUT(T.4)+R-CNN	29.3/11.8	47.2/**36.5**	25.0%/8.9%	17.3%/25.0%	1112.5/3693.1	1261.0/4228.3	3457.6/16634.7	33394.1/168527.2
JTEGCTD(T.5)+CompACT	28.4/14.2	47.1/34.4	23.1%/13.5%	18.3%/18.7%	69.4/415.3	260.6/1345.7	5034.0/26221.8	33093.8/**133867.4**
MTT(T.6)+CompACT	−/12.0	−/35.7	−/7.7%	−/23.2%	−/814.7	−/3158.9	−/14016.8	−/156997.0
GMPHD-KCF(T.7)+EB(D.2)	−/14.1	−/25.9	−/12.5%	−/18.5%	−/909.9	−/1437.2	−/21863.7	−/139245.4
GMPHD-KCF(T.7)+CompACT	−/12.0	−/33.8	−/10.8%	−/19.5%	−/648.8	−/1300.2	−/30518.1	−/140669.4
CERTH-KCF(T.8)+CERTH-SSD(D.7)	−46.3/ − 11.3	27.5/18.2	8.4%/3.8%	21.2%/18.3%	325.8/625.2	403.7/717.7	81645.9/97626.1	41017.1/126198.2

Trackers	Codes	CPU	RAM	Frequency	GPU	Speed
HGFT	Matlab	-	32GB	-	×	3.97
GM-PHD	C++	Intel i7-4770	16GB	3.50GHz	×	947.24
CCM	Matlab	Intel i7-4720	16GB	2.60GHz	×	471.28
IOUT	Python	Intel i7-6700	32GB	3.40GHz	×	**6902.07**
JTEGCTD	Matlab	Intel i7-3720QM	8GB	2.70GHz	×	60.38
MTT	Python, C++	Intel E5-2650	128GB	2.00GHz	Titan X	24.30
GMPHD-KCF	C++	Intel i7-4770	32GB	3.50GHz	×	24.60
CERTH-KCF	Python	Intel E5-2620v4	128GB	2.10GHz	×	0.63
CEM	Matlab	Intel i7-3520M	16GB	2.90GHz	×	4.62
GOG	Matlab	Intel i7-3520M	16GB	2.90GHz	×	389.51
DCT	Matlab,C++	Intel i7-3520M	16GB	2.90GHz	×	0.71
IHTLS	Matlab	Intel i7-3520M	16GB	2.90GHz	×	19.79
H^2T	C++	Intel i7-3520M	16GB	2.90GHz	×	3.02
CMOT	Matlab	Intel i7-3520M	16GB	2.90GHz	×	3.79