



EAGLE: Large-scale Vehicle Detection Dataset in Real-World Scenarios using Aerial Imagery

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Knowledge for Tomorrow

Robust Vehicle Detection for the Real-World Applications

Disaster Management, Traffic Monitoring, Search & Rescue Missions, etc



Source: DLR



Source: DLR

An algorithm suitable for such scenarios should be very accurate with high accuracy and robust to

- ***Weather conditions: clouds, fog, haze, shadow, ...***
- ***Minor and major occlusions, different backgrounds, tiny object size, different scales, etc***



Large-scale Vehicle Detection Datasets in Remote Sensing are Scarce!

Datasets	# Vehicle Instances	# Vehicle Categories	# All Categories	# Images	# All Instances	Image Width (px)	Annotation Approach	Year
TAS	1,319	1	1	30	1,310	792	HBB	2008
NWPU-VHR-10	232	1	10	800	3,775	1000	HBB	2014
VEDAI	3,270	6	9	1,210	3,640	1024	OBB	2015
UCAS-AOD	2,819	1	2	910	6,029	1280	HBB	2015
DLR-3K-Vehicle	14,232	2	2	20	14,235	5616	OBB	2015
COWC	32,716	1	1	53	32,716	2000-19,000	One-Dot	2016
HRSC2016	0	0	1	1,070	2,976	1000	OBB	2016
RSOD	0	0	4	976	6,950	1000	HBB	2017
DOTA	43,462	2	15	2,806	188,282	300-4000	RBB	2017
EAGLE (ours)	215,986	2	2	8,280	215,986	936	OBB	2020

Current datasets for vehicle detection not only lacks high number of instances, but also they lack

- *High-quality annotation esp. occluded vehicles*
- *Scenarios with poor visibility and weather condition*
- *Large-scale for #images, resolution variation, location, time, camera angle*
- *Real disasters*

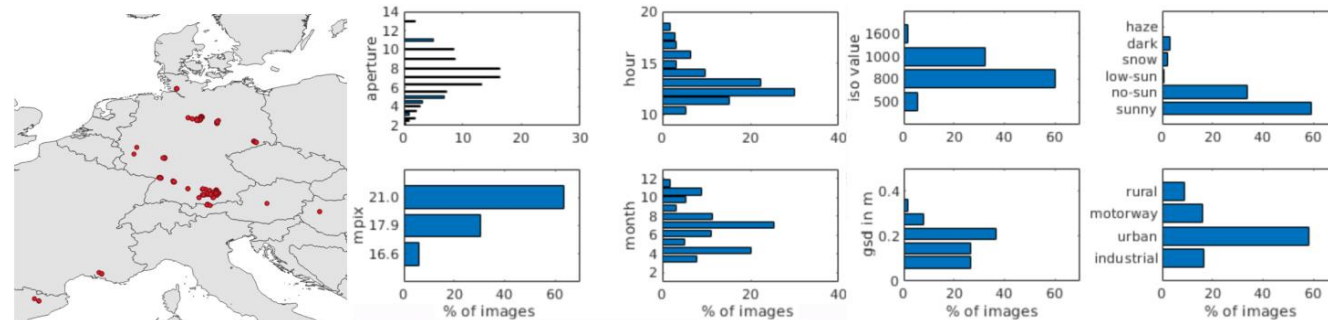


Addressing Current Issues with the Introduction of EAGLE

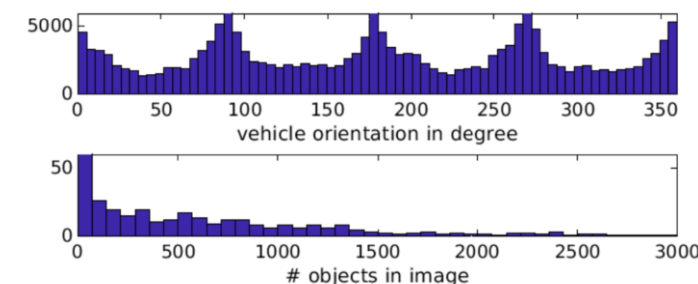


Comparison with the state-of-the-art Dataset DOTA

Sample Images



Distribution and Variation



Statistic

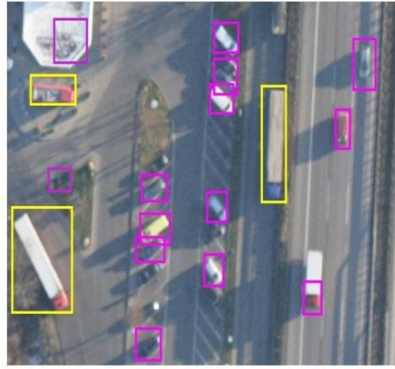
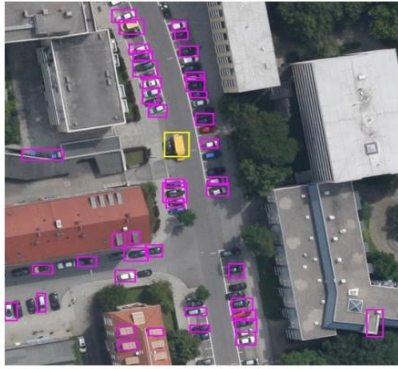
Benchmark Results

Method	Backbone	AP [%] (HBB)			AP [%] (RBB)		
		Mean	SV	LV	Mean	SV	LV
Yolov3	Darknet-53	20.29	30.45	10.13	13.28	21.34	5.23
SSD	InceptionV2	12.06	20.67	3.45	7.31	12.34	2.28
RefineDet	VGG16	22.23	32.25	12.21	14.78	22.67	6.89
R-FCN	ResNet101	30.61	46.85	14.37	21.06	35.56	6.56
Faster-RCNN	ResNet101	31.84	48.34	15.34	23.15	39.29	7.02
Mask-RCNN	ResNet101	30.81	46.51	15.11	22.54	36.65	8.43
Cascade-RCNN	ResNet101	33.49	49.65	17.34	23.58	38.97	8.19
SNIPER	ResNet101	30.74	48.34	13.14	21.97	38.23	5.72
FPN	ResNet101	37.10	50.76	23.45	27.11	39.78	14.45
TridenNet	ResNet101	30.53	47.16	13.91	22.53	37.16	7.91
FCOS	ResNeXt101	38.80	52.94	24.67	27.67	41.24	14.10
Cascade Mask-RCNN-H	Triple-ResNeXt152	39.29	53.45	25.14	30.22	43.84	16.60
Cascade Mask-RCNN-R [Ours]	Triple-ResNeXt152	-	-	-	37.23	51.27	23.19

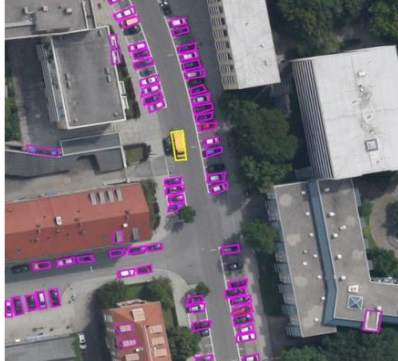
Method	Task	mAP [%]	AP [%]		Training set	Test set	Avg.	SV	LV
			small-vehicle	large-vehicle					
Cascade Mask-RCNN-H	HBB	33.54	50.16	16.92	DOTA	DOTA	59.95	61.23	58.67
Cascade Mask-RCNN-R	RBB	30.18	46.82	13.54	DOTA	EAGLE	28.23	38.89	17.57
Cascade Mask-RCNN-O	OBB	32.02	48.13	15.91	EAGLE	DOTA	53.25	57.34	49.16
					EAGLE	EAGLE	39.29	53.45	25.14



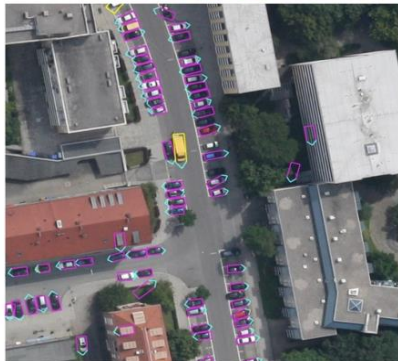
Qualitative Performance



Horizontal
Bounding Box



Quadrilateral
Rotated
Bounding Box



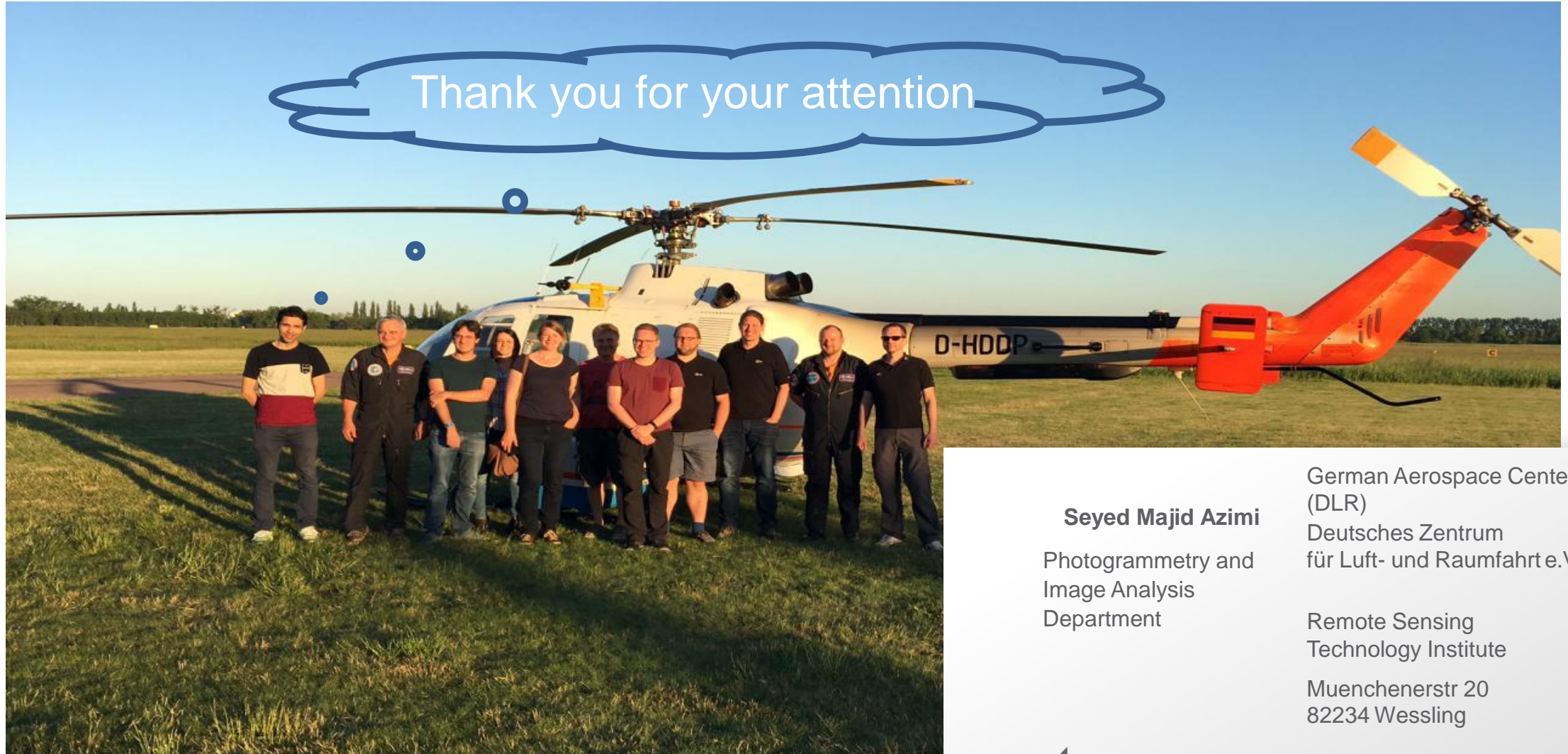
Oriented
Bounding Box



Generalization on Satellite imagery



Thank you for your attention



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