KI DELTA LEARNING
Scalable AI for Automated Driving

Augmentation-based Domain Generalization for Semantic Segmentation

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Semi- and Unsupervised Learning

Motivation

- Domain Generalization (DG) has no access to any target domains and needs to learn generalized features on a source domain
- Style randomization and instance normalization and whitening are used
- We propose to simple utilize rule-based image augmentations for DG
- we evaluate an extensive set of augmentations on the problem of synthetic-to-real domain generalization
- we evaluate the best performing set of augmentations in a full factorial manner and statistically analyze their interactions

Approach

We choose a 2-step approach:

1. Evaluate stand-alone augmentations
2. Combine best performing augmentations in a full factorial manner and analyze their interactions

Geometric	Color	Texture
Crop Hor. Flip Cutout Elastic Transform Shift-Scale-Rotate	Color Jitter Brightness & Contrast Grayscale CLAHE	Gaussian Blur Gaussian Noise Random Snow Random Rain Random Fog Random Sun Flare

Figure 1: Augmentations for Step I-Experiments (© CARIAD SE)

Results: Stand-Alone Augmentation

Augmentation	CS I	CS II	Synthia II
Geometric			
Resize	29.6	29.3	45.9
RandomCrop	35.7	35.4	60.3
RandomResizedCrop	36.3	35.8	61.9
RCrop + HFlip	33.7	33.3	60.8
RCrop + Cutout	34.3	33.6	60.7
RCrop + ElasticTransform	37.7	36.4	61.8
RCrop + ShiftScaleRotate	36.6	35.8	61.6
Color			
RCrop + Brightness/Contrast	35.0	34.2	61.2
RCrop + ColorJitter	35.0	34.2	61.2
RCrop + CLAHE	37.9	35.8	60.9
RCrop + Grayscaling	35.4	34.2	60.6
AutoAugment	34.8	33.3	60.1
Texture			
RCrop + GaussNoise	33.9	32.5	60.8
RCrop + GaussBlur	37.9	37.0	60.7
RCrop + RandomFog	36.6	36.1	59.8
RCrop + RandomRain	36.8	34.8	60.3
RCrop + RandomSnow	35.5	34.5	60.3
RCrop + RandomSunFlare	34.0	31.7	60.1
RCrop + CannyEdge	34.4	33.7	60.0

Figure 2: mIoU for stand-alone augmentations on Synthia and Ciytscapes (© CARIAD SE)

Backbone	lr	Synthia		
		to CS	to BDD	to Synthia
DAFormer	0.0007	34.4	22.5	68.8
	0.0005	38.8	24.2	70.6
	0.0001	42.5	31.1	70.1
	0.00008	40.7	29.3	69.6

Figure 3: learning rate dependency of generalization (© CARIAD SE)

- Learning rate and random cropping cause significant improvement
- Stand-alone augmentation → small gains

Results: Full Factorial Experiments

Out-of-Domain Generalization Cityscapes	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	35.9869	0.4995	72.04	0.0000
GB	0.3800	0.5585	0.68	0.5060
RRain	-1.1100	0.5585	-1.99	0.0643
ET	1.2850	0.5585	2.30	0.0352
CLAHE	0.0100	0.5585	0.02	0.9859
RRC	0.3850	0.5585	0.69	0.5005
GB:RRain	-0.0150	0.4995	-0.03	0.9764
GB:ET	-0.7075	0.4995	-1.42	0.1758
GB:CLAHE	-0.4350	0.4995	-0.87	0.3967
GB:RRC	-0.7700	0.4995	-1.54	0.1427
RRain:ET	-0.5600	0.4995	-1.12	0.2788
RRain:CLAHE	-0.2825	0.4995	-0.57	0.5795
RRain:RRC	-0.9175	0.4995	-1.84	0.0849
ET:CLAHE	-0.7850	0.4995	-1.57	0.1356
ET:RRC	-0.6250	0.4995	-1.25	0.2288
CLAHE:RRC	-0.6025	0.4995	-1.21	0.2453

Figure 4: Statistical Analysis of a quadratic model (© CARIAD SE)

- Combination of augmentations provide significant better out-of-domain generalization
- Mostly negative interaction factors due to similar augmentations effects
- Combination of gaussian blur and elastic transform provide best absolute performance
- Statistical significance is not as good as expected
- Higher degree of interaction also of interest for application

Results: SOTA Comparison

Method		Synthia
		to Cityscapes
Baseline (Ours)	ResNet-101	29.3 (29.6)
RandomCrop (Ours)	ResNet-101	35.4 (35.7)
IBN [19]	ResNet-101	34.2
SW [21]	ResNet-101	31.6
DRPC [23]	ResNet-101	37.6
GTR [27]	ResNet-101	39.7
RobustNet [20]	ResNet-101	37.2
FSDR [4]	ResNet-101	40.8
AdvStyle [29]	ResNet-101	37.6
WEDGE [28]	ResNet-101	**40.9**
SAN&SAW [22]	ResNet-101	**40.9**
RRCrop + ET (Ours)	ResNet-101	37.8 (39.5)
Baseline (Ours)	DAFormer	39.6 (40.3)
RandomCrop	DAFormer	42.6
RRC,GB,CJitter	DAFormer	**44.2**

Figure 5: Comparison with State-of-the-Art approaches (© CARIAD SE)

- Augmentations perform competitive to state-of-the-art DG approaches
- Utilizing DAFormer all other benchmarks are clearly outperformed

Conclusions & Future Work

- Augmentations offer simple but competitive alternative to recent DG approaches
- More research necessary to better understand how augmentations DG
- Cross-dataset and cross architecture transfer is important for future work

Partners

External partners

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KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

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Supported by:
Federal Ministry for Economic Affairs and Climate Action
on the basis of a decision by the German Bundestag