

Augmentation-based Domain Generalization for Semantic Segmentation

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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	Color Jitter	Gaussian Blur
Hor. Flip	Brightness & Contrast	Gaussian Noise
Cutout	Grayscale	Random Snow
Elastic Transform	CLAHE	Random Rain
Shift-Scale-Rotate		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 + Grayscale	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 Cityscapes (© 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)		29.3 (29.6)
RandomCrop (Ours)		35.4 (35.7)
IBN [19]	ResNet-101	34.2
SW [21]		31.6
DRPC [23]		37.6
GTR [27]		39.7
RobustNet [20]		37.2
FSDR [4]		40.8
AdvStyle [29]		37.6
WEDGE [28]		40.9
SAN&SAW [22]		40.9
RRCrop + ET (Ours)		37.8 (39.5)
Baseline (Ours)	DAFormer	39.6 (40.3)
RandomCrop		42.6
RRC,GB,CJitter		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



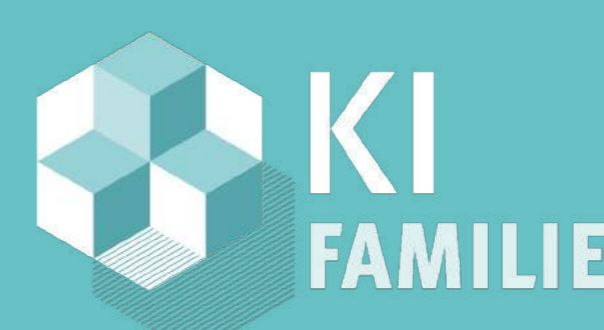
External partners



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