KI DELTA LEARNING
Scalable AI for Automated Driving

Semi-supervised domain adaptation with CycleGAN guided by downstream task awareness

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Semi- and Unsupervised Learning

Use-case and Challenges:

Automatically understanding complex visual scenes from RGB images with only a few labeled data since manual labeling is time consuming and error prone

→ Synthetic data from simulations comes with semantic labels for free, but introduces a domain gap

Task: Semantic segmentation with deep neural networks (DNNs) with only a few labeled samples

Technical solution [1]:

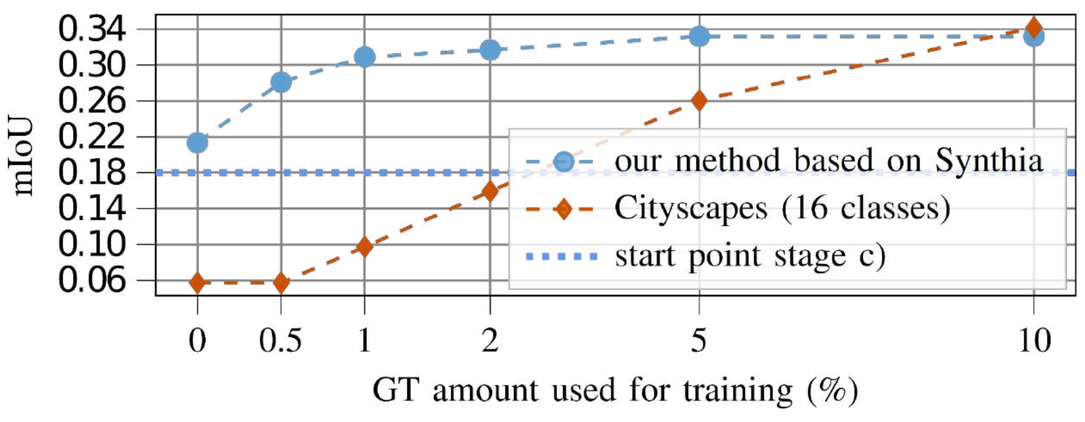
- A modular semi-supervised domain adapation method for semantic segmentation
- Guiding the generator of an Image-to-Image approach (CycleGAN[2]) to a semantic segmentation task awareness.
- Semantic segmentation network is trained from scratch for a less biased domain gap.
- Weights of the semantic segmentation network are fixed after it has been trained on synthetic data (synthetic expert).
- Task awareness is achieved in stage c) by extending the generator loss with the the downstream task loss e.g., cross entropy.

Evaluation I:

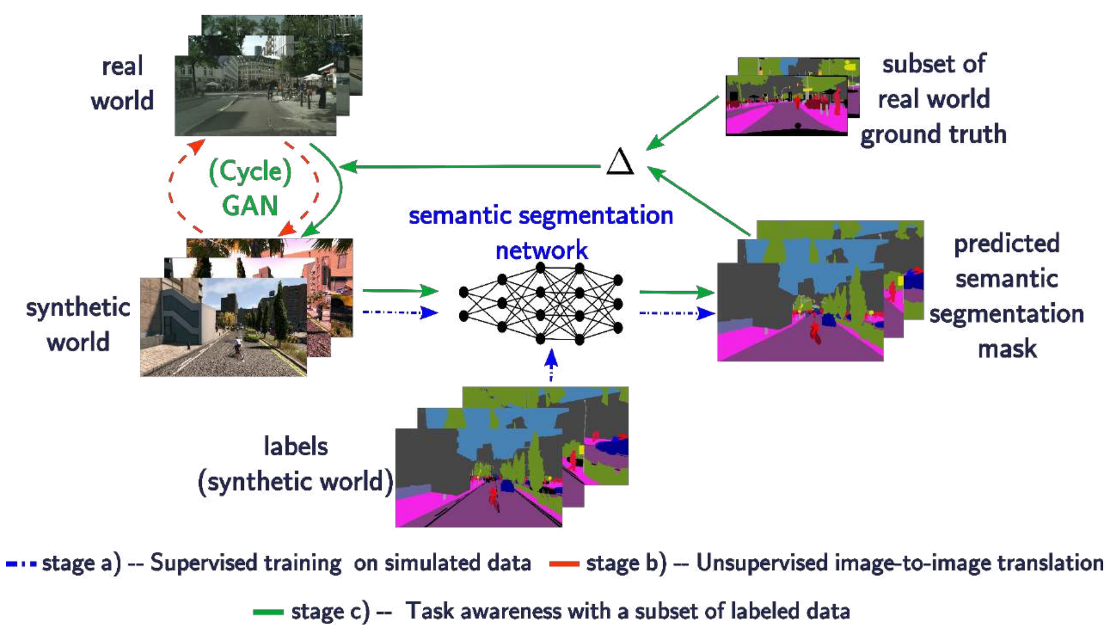
- Influence of pure domain separation

Synthia -> Cityscapes (mIoU in %)			
Method	*Out of domain*	*Oracle*	*gap*
ImageNet pre-trained [5]	*31.8*	*75.6*	*43.8*
From scratch (ours)	*9.9*	*62.7*	*52.8*

- Our method outperforms CycleGAN only and direct Cityscapes (CS) training when only a few labeled samples are available



Concept:

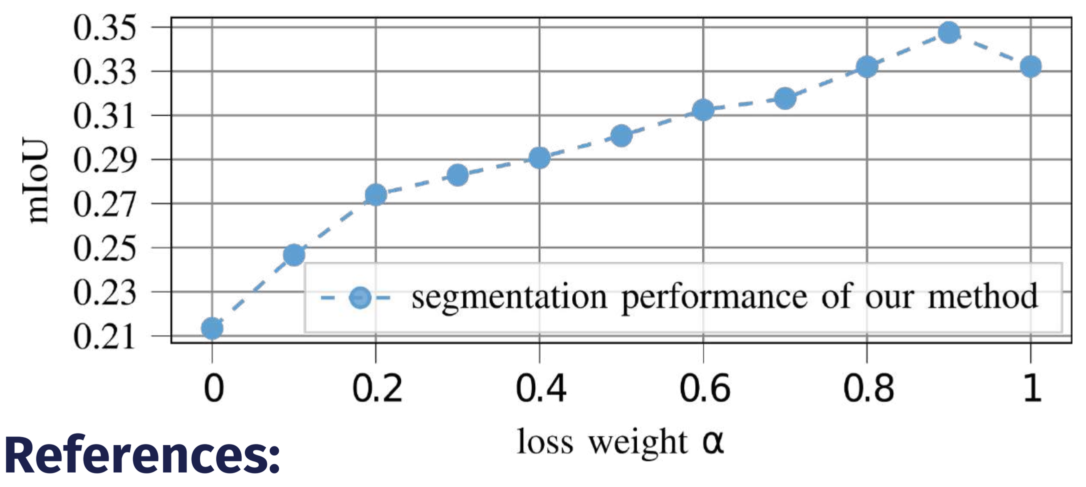


- Extended loss for stage c) – Task awareness

$$\tilde{\mathcal{L}}_{G_{\mathcal{R}\to\mathcal{S}}}((x_i^r, y_i^r)) = (1-\alpha)\underbrace{\left(D_s\left(G_{\mathcal{R}\to\mathcal{S}}(x_i^r)\right)-1\right)^2}_{\text{original LSGAN generator loss}} + \alpha\underbrace{\left(\mathcal{L}_{CE}\left(f(G_{\mathcal{R}\to\mathcal{S}}(x_i^r)), y_i^r\right)\right)}_{\text{task loss}}$$

Evaluation II:

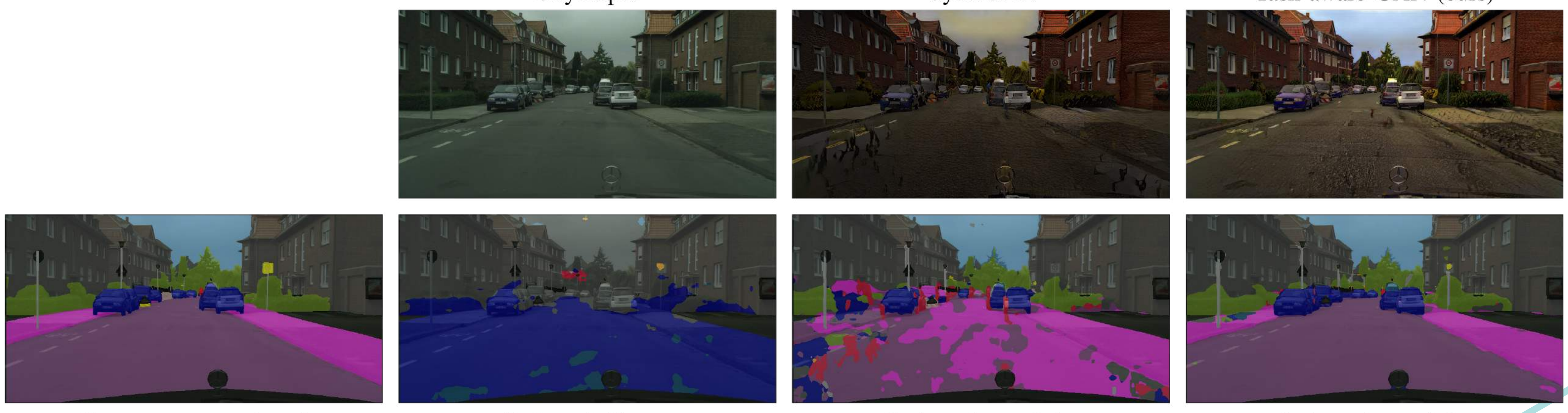
- Influence of task loss
- The weighting represents a linear interpolation between the adversarial generator loss and the task loss, resulting in the original CycleGAN implementation for α = 0 and the pixel-wise cross entropy loss for α = 1.
- Improvement of up to 12.5 percent points with appropriate task awareness weighting



References:

[1] Mütze, A., et al. (2022). Semi-supervised domain adaptation with CycleGAN guided by a downstream task loss. arXiv:2208.08815. (Accepted conference paper at VISAPP 2023).
[2] Zhu, J.-Y., et al. (2017). Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. ICCV.
[3] Ros, G., et al. (2016). The SYNTHIA Dataset: A Large Collection of Synthetic Images for Semantic Segmentation of Urban Scenes. CVPR, pages 3234–3243.
4] Cordts, M., et al. (2016). The Cityscapes Dataset for Semantic Urban Scene Understanding. CVPR, pages 3213–3223.
[5] Dundar, A., et al. (2018). Domain stylization: A strong, simple baseline for synthetic to real image domain adaptation. arXiv:1807.09384.

- Comparison of prediction results (our method was trained with 148 (5%) labeled CS samples)



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Or check out our paper:

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