Leveraging Synthetic Data in Object Detection Training using Style-Transfer

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KI DATA TOOLING
The Data Kit for Automotive AI

Style-transfer for Domain Adaptation

Domain adaptation aims at transferring knowledge from a labeled source dataset to an unlabeled target dataset. One specific use case is leveraging synthetic data, as labels for such type of data could be acquired almost automatically. A typical approach to shrink the domain gap between synthetic and real data is to apply a so-called style-transfer. Style-transfer aims at translating the source domain style to a target domain style, because synthetic data lack in realism due to biased simulation environments.

Figure 1: Example of style-transfer from GTA5 to Cityscapes images. [1]

Figure 1 shows qualitative results of style-transfer from the GTA5 dataset to Cityscapes using our proposed modifications to style-transfer networks.

All previous methods for style-transfer aim at generating realistic images by using generative adversarial networks. We find that style-transfer networks are unstable and produce visual artifacts. Addressing this problem, we transfer a well-known style-transfer network CyCADA [2] from Semantic Segmentation to Object Detection. CyCADA aims at enforcing semantic consistency by introducing a pre-trained semantic Segmentation Network into the CycleGAN framework. We have investigated that such additional consistency regularization also improves object detection performance.

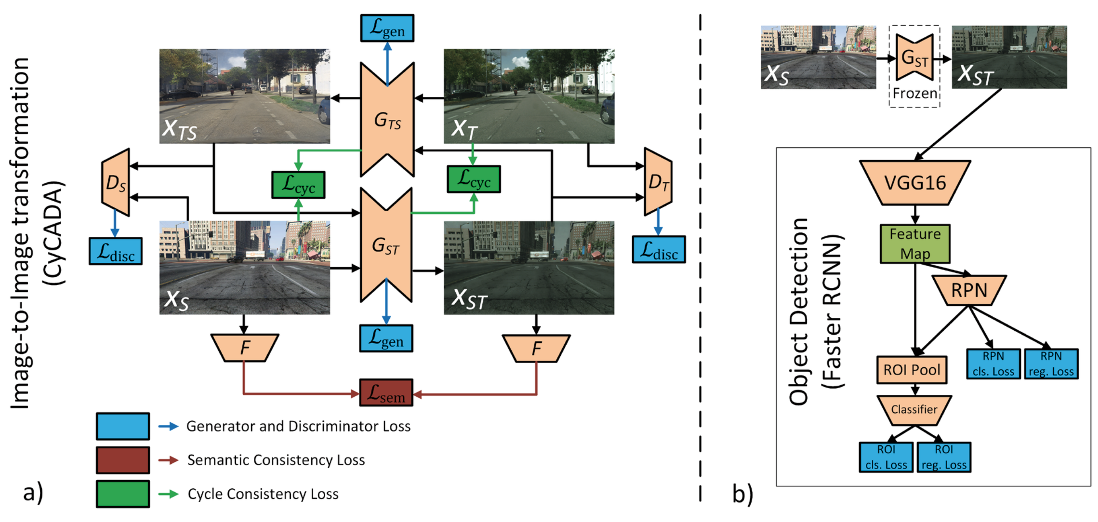

Figure 2: a) CyCADA framework for enforcing semantic consistency in style-transfer networks.
b) Training of Object Detectors based on stylized-source images for Domain Adaptation

Figure 2 shows our proposed domain adaptation framework for object detection. CyCADA includes adversarial generator and discriminator loss functions, a cycle-constistency loss and a semantic consistency loss term. We have investigated, that the CyCADA framework is more regularized than the standard CycleGAN framework.

We also investigate, how the patch-size of CycleGAN based frameworks behave on object detection performance. When patch-size is small, more local style-transformation is applied. For object detection we aim at reducing global content change, which leads to visual artifacts and hindering object detection training.

Method	Sem. Cons.	Patch-Size	Car AP
Baseline	-	-	33.2
CycleGAN	-	600px	42.5
CyCADA [2]	✓	600px	42.6
CycleGAN Low Patch-Size	-	128px	45.5
Our Method [1]	✓	**128px**	**48.9**

Table 1: Experimental Results of GTA-to-Cityscapes Domain Adaptation Benchmarks using mAP with IoU of 0.5. [1]

Table 1 shows our domain adaptation performance in the GTA to Cityscapes. We compare our proposed framework to a baseline (naively trained on source data) as a lower.

Our results show that our framework outperforms our baseline on the given benchmark for about 15.7 average precision. We have also investigated, that especially the reduced patch-size improves the quality of generated images as shown in Figure 1.

References:

[1] Menke, Maximilian, et al. “Improving GAN-based Domain Adaptation for Object Detection.” In Review at European Conference on Computer Vision (ECCV) 2022

[2] Hoffman, Judy, et al. „Cycada: Cycle-consistent adversarial domain adaptation.“ International conference on machine learning. PMLR, 2018.

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