UNSUPERVISED DOMAIN ADAPTATION FOR URBAN SCENES SEGMENTATION

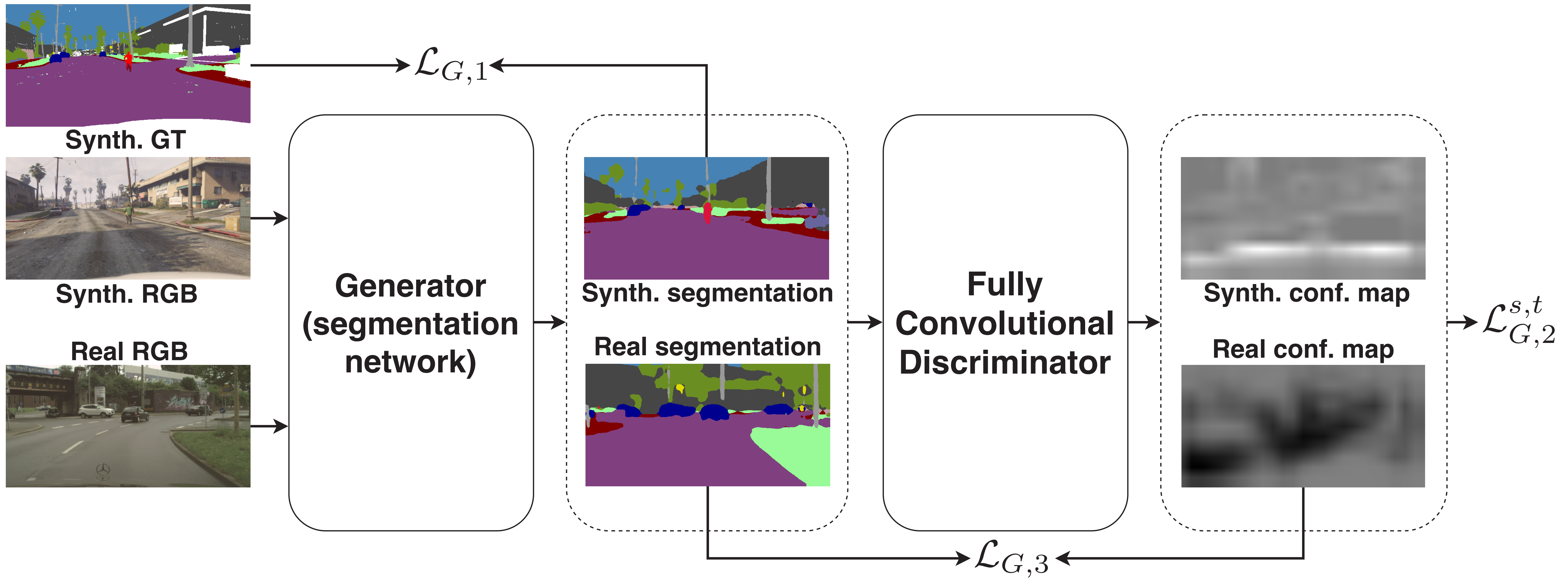
Biasetton M., Michieli U., Agresti G., Zanuttigh P. - University of Padova
{biasetto, michieli, agrestig, zanuttigh}@dei.unipd.it

Università degli Studi di Padova

Abstract

The semantic understanding of urban scenes is one of the key components for an autonomous driving system. Deep neural networks require to be trained with a huge amount of labeled data, which is difficult and expensive to acquire. A recently proposed workaround is the usage of synthetic data, however the differences between real world and synthetic scenes limit the performance. We propose an unsupervised domain adaptation strategy from a synthetic supervised training to real data exploiting three components: supervised learning on synthetic data, adversarial learning strategy and finally self-teaching strategy working on unlabeled data. Experimental results prove that the proposed approach is able to adapt a network trained on synthetic dataset to a real one.

Proposed Approach



Dataset

SOURCE (SYNTHETIC)

GTA

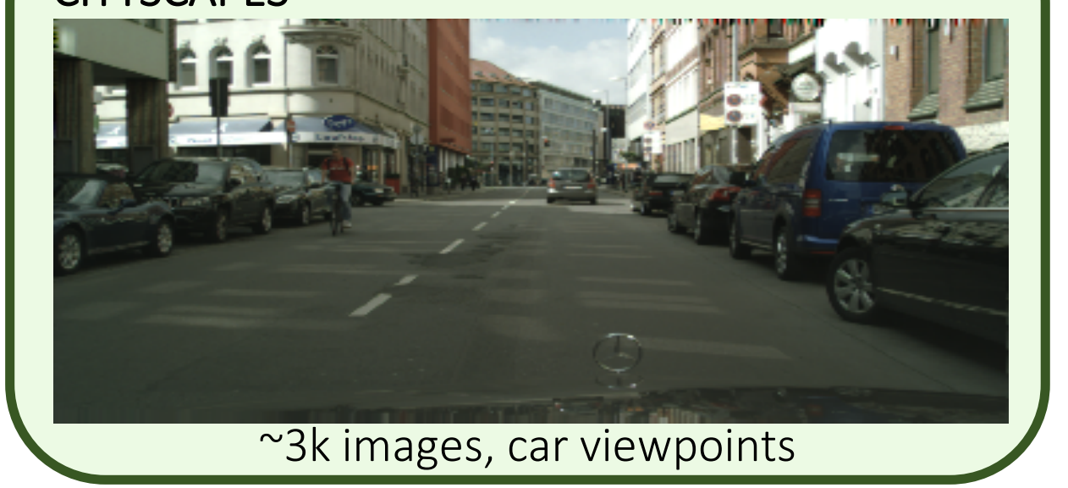
~25k images, high quality, car viewpoints

SYNTHIA

~9k images, medium quality, different viewpoints

TARGET (REAL)

CITYSCAPES



~3k images, car viewpoints

Cross-Entropy Loss

$$\mathcal{L}_{G,1} = -\sum_{c\in\mathcal{C}} \mathbf{Y}_n^s[c] \cdot \log\left(G(\mathbf{X}_n^s)[c]\right)$$

s: source dataset

Adversarial Training

$$\mathcal{L}_{G,2}^{s,t} = -\log(D(G(\mathbf{X}_n^{s,t})))$$

$$\mathcal{L}_D = -\log(1 - D(G(\mathbf{X}_n^{s,t}))) + \log(D(\mathbf{Y}_n^s))$$

t: target dataset

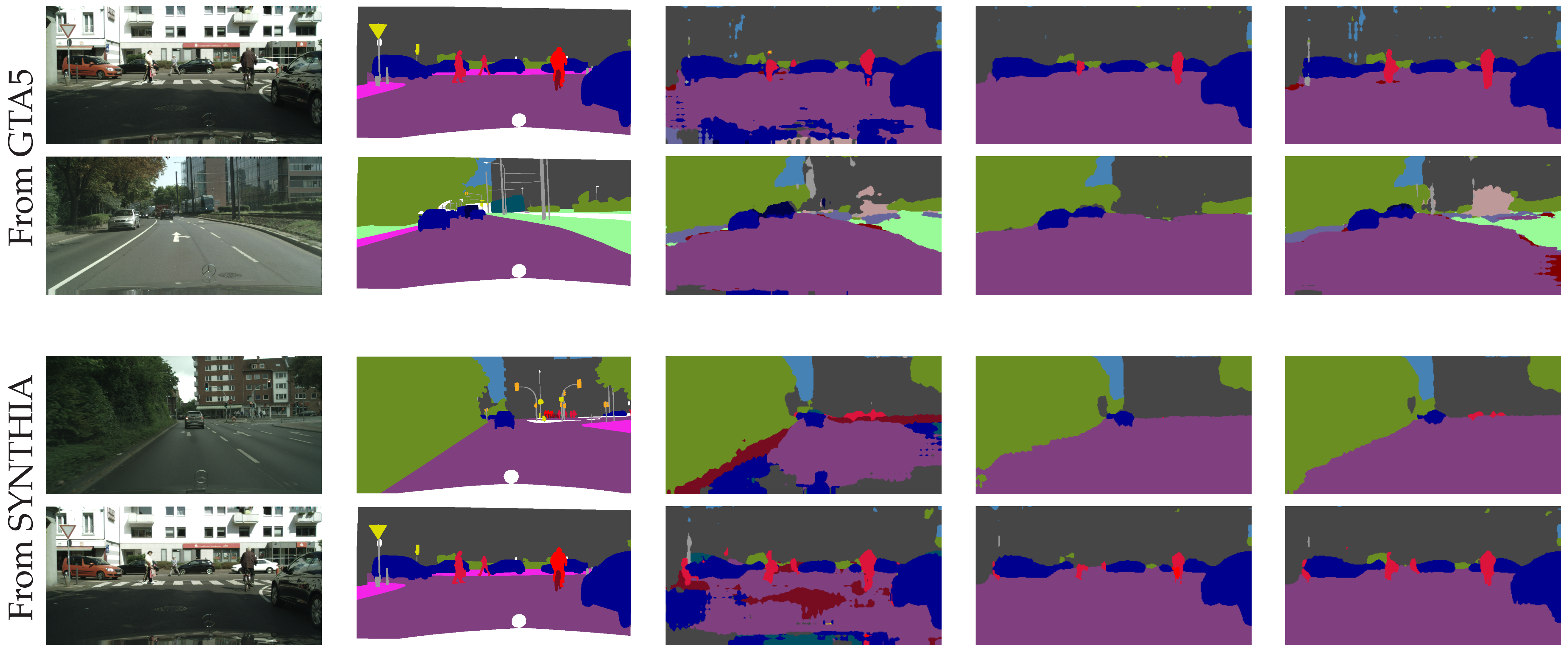
Self-Taught Loss

Predictions of G are more reliable where D marks them as GT with high accuracy

$$\mathcal{L}_{G,3} = -\underbrace{I_{T_u}}_{\text{threshold on confidence maps from } D} \cdot \underbrace{W_c^t}_{\text{class weigthing}} \cdot \hat{\mathbf{Y}}_n[c] \cdot \log\left(G(\mathbf{X}_n^t)[c]\right)$$

c: classes

Qualitative Results



RGB | annotation | baseline ($\mathcal{L}_{G,1}$) | Hung et al. [2] | $\mathcal{L}_{full}$ [1]

Quantitative Results

From GTA	road	sidewalk	building	wall	fence	pole	t light	t sign	veg	terrain	sky	person	rider	car	truck	bus	train	mbike	bike	mIoU
Ours ($\mathcal{L}_{G,1}$ only)	45.3	20.6	50.1	9.3	12.7	19.5	4.3	0.7	81.9	21.1	63.3	52.0	1.7	77.9	26.0	39.8	0.1	4.7	0.0	27.9
Ours ($\mathcal{L}_{full}$) [1]	54.9	23.8	50.9	16.2	11.2	20.0	3.2	0.0	79.7	31.6	64.9	52.5	7.9	79.5	27.2	41.8	0.5	10.7	1.3	**30.4**
Hung et al. [2]	81.7	0.3	68.4	4.5	2.7	8.5	0.6	0.0	82.7	21.5	67.9	40.0	3.3	80.7	34.2	45.9	0.2	8.7	0.0	29.0

From SYNTHIA	road	sidewalk	building	wall	fence	pole	t light	t sign	veg	sky	person	rider	car	bus	mbike	bike	mIoU
Ours ($\mathcal{L}_{G,1}$ only)	10.3	20.5	35.5	1.5	0.0	28.9	0.0	1.2	83.1	74.8	53.5	7.5	65.8	18.1	4.7	1.0	25.4
Ours ($\mathcal{L}_{full}$) [1]	78.4	0.1	73.2	0.0	0.0	16.9	0.0	0.2	84.3	78.8	46.0	0.3	74.9	30.8	0.0	0.1	**30.2**
Hung et al. [2]	72.5	0.0	63.8	0.0	0.0	16.3	0.0	0.5	84.7	76.9	45.3	1.5	77.6	31.3	0.0	0.1	29.4

[1] Biasetton M., Michieli U., Agresti G., Zanuttigh P., "Unsupervised Domain Adaptation for Semantic Segmentation of Urban Scenes", CVPR Workshop on Autonomous Driving (WAD), 2019.

[2] Hung W., Tsai Y., Liou Y., Lin Y., Yang M., "Adversarial Learning for Semi-Supervised Semantic Segmentation", BMVC, 2018.