SAGIVTECH IMVC 2021

GM RESEARCH & DEVELOPMENT

Synthetic-to-Real Domain Adaptation for Lane Detection

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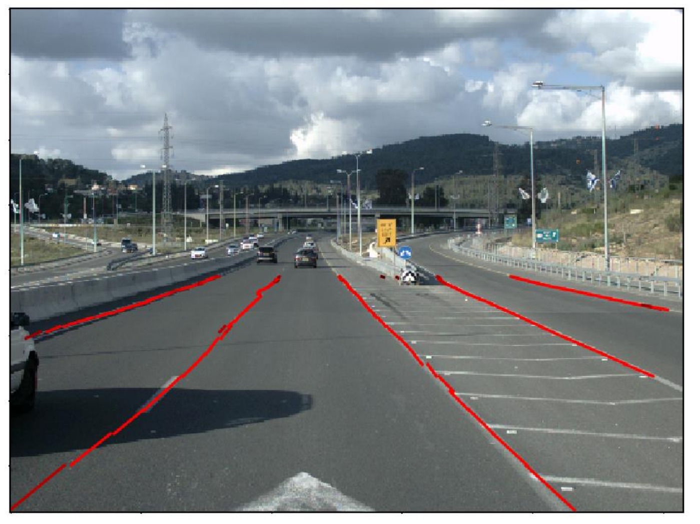
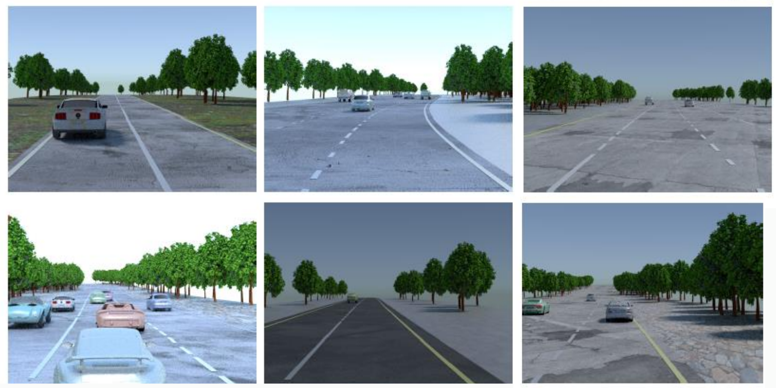
Domain adaptation from synthetic to real

Task: Lane detection



Main idea: leverage "free" synthetic data to enrich training data with additional geometries and topologies of lanes



[Garnett et al. ICCV19]

Photorealism is difficult!

- Unsupervised Domain Adaptation (UDA)
- Semi-Supervised Domain Adaptation (SSDA)

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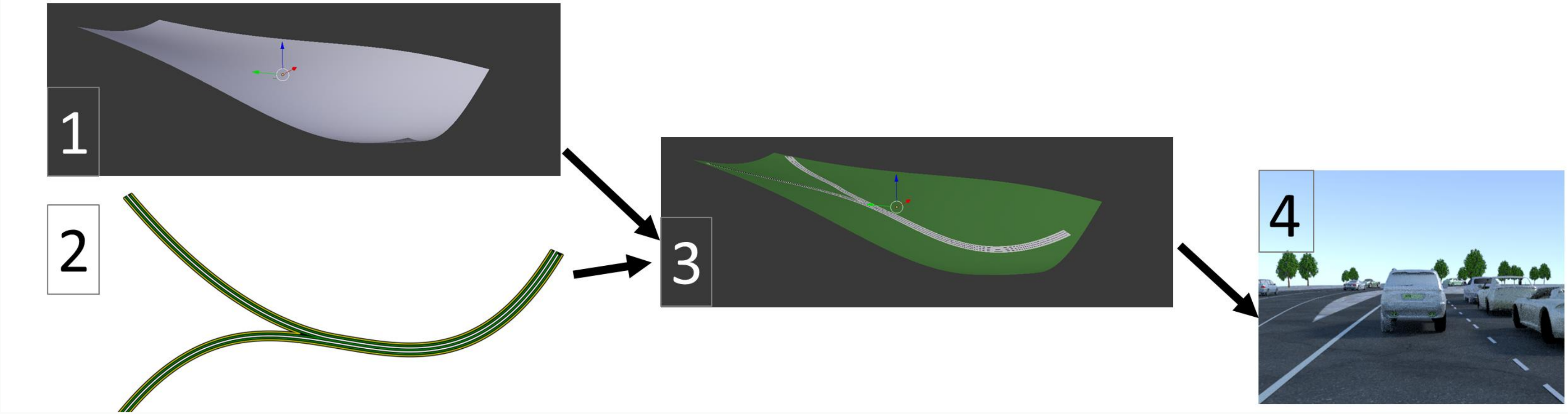
Randomized synthetic data generation



[Garnett et al. ICCV19]

Base architecture for top-view 2D lane detection

labeled sample

$(x, \hat{y})$

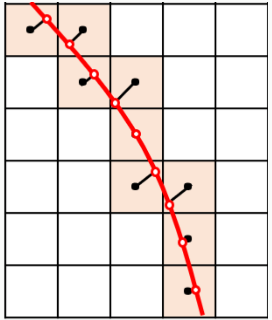
x Top view image

ϕ

f Intermediate feature maps

Ψ

y Top view tile-based lane representation [Efrat et al. 2020]



$$\mathcal{L}_{task} = \sum_{(x,\hat{y}) \in \mathcal{D}^l} \mathcal{L}_{tiles}(\psi \circ \phi(x), \hat{y})$$

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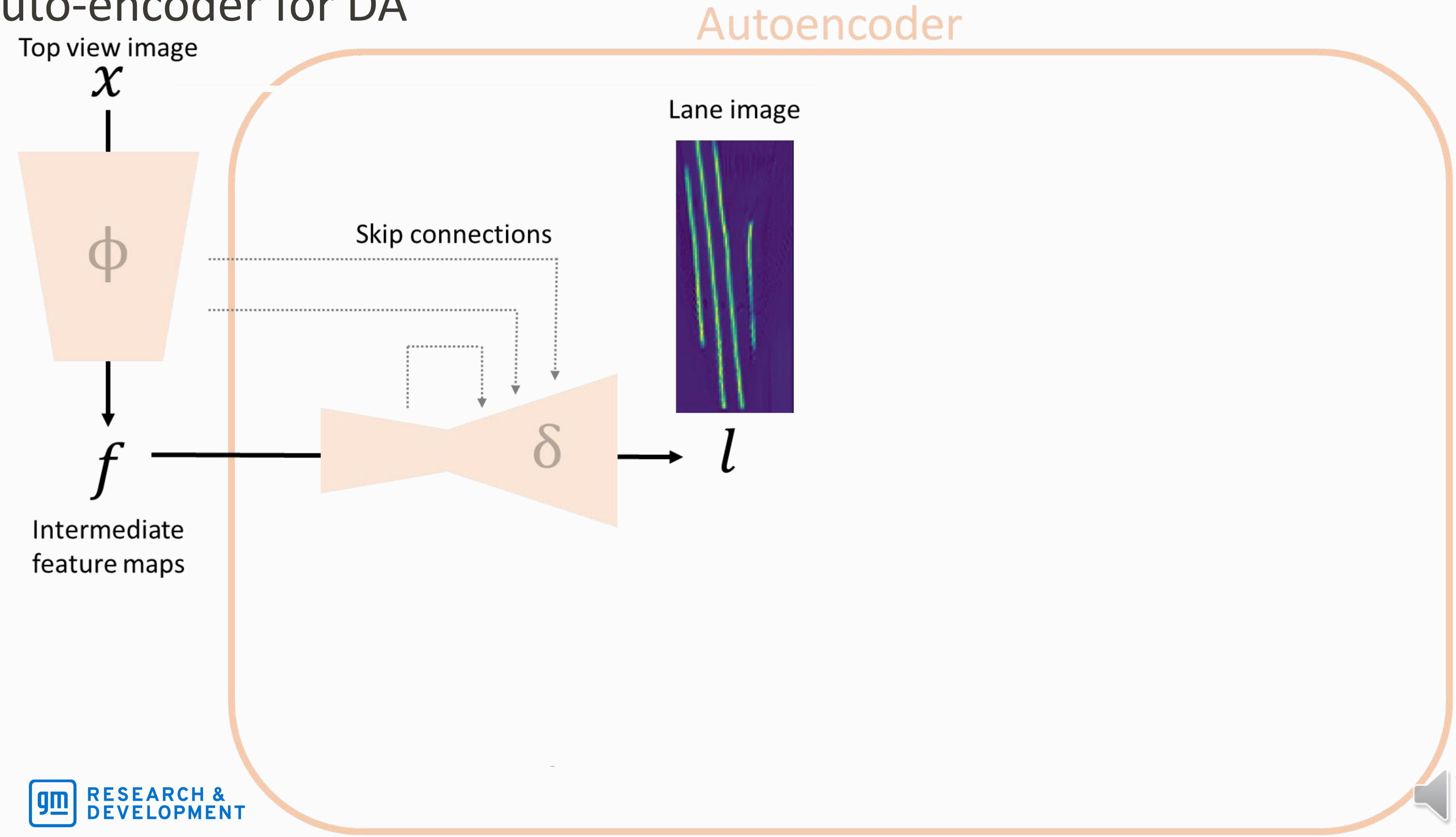
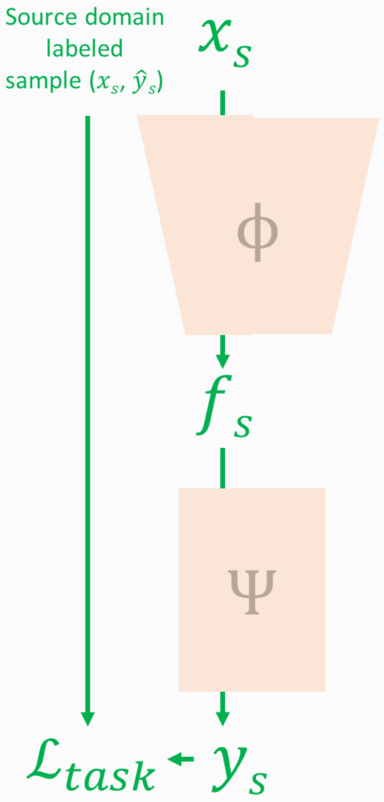
Approaches for domain adaptation for lane detection

1. **A novel autoencoder based approach**
2. **Image translation**
3. **Self-supervision**
4. Feature distribution matching

Auto-encoder for DA



Auto-encoder based domain adaptation



Source domain lane images $\bar{l}$

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Image translation for domain adaptation

- “**Cycada**” [Hoffman et al., ICML 2018]

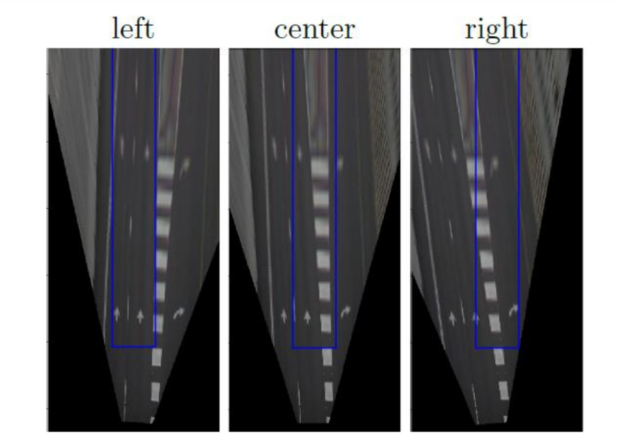
(Labeled) Source domain image

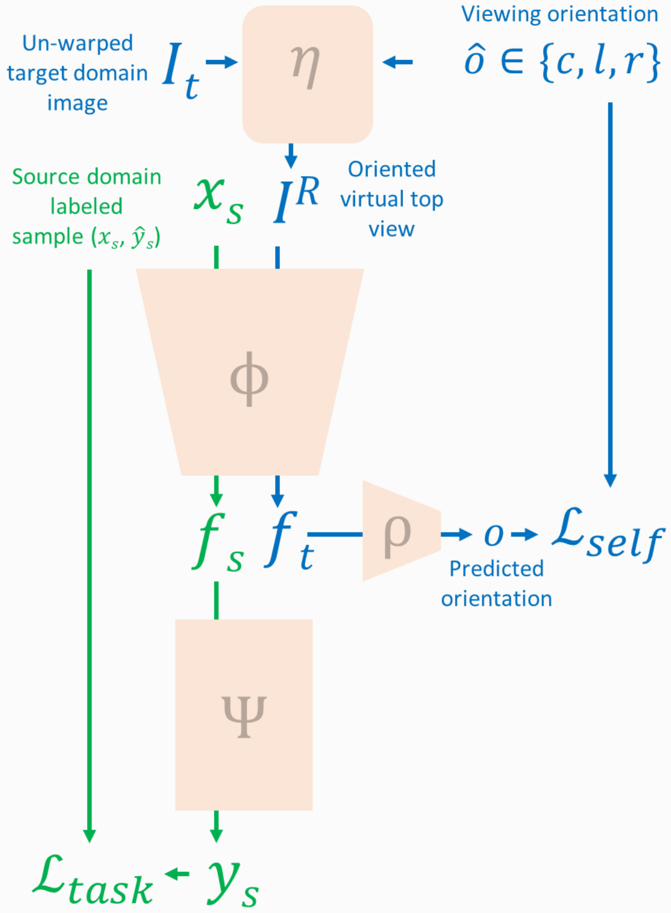
Target domain style image

- Train on **translated images**
- Used **CycleGAN** [Zhu et al., ICCV 2017] to translate all training images to the target domain
- Additional Cycada enhancements did not improve results

Self-supervision for domain adaptation

- Originally proposed in [Sun et al. 2019]
- **We propose viewing orientation as the self supervised task:**





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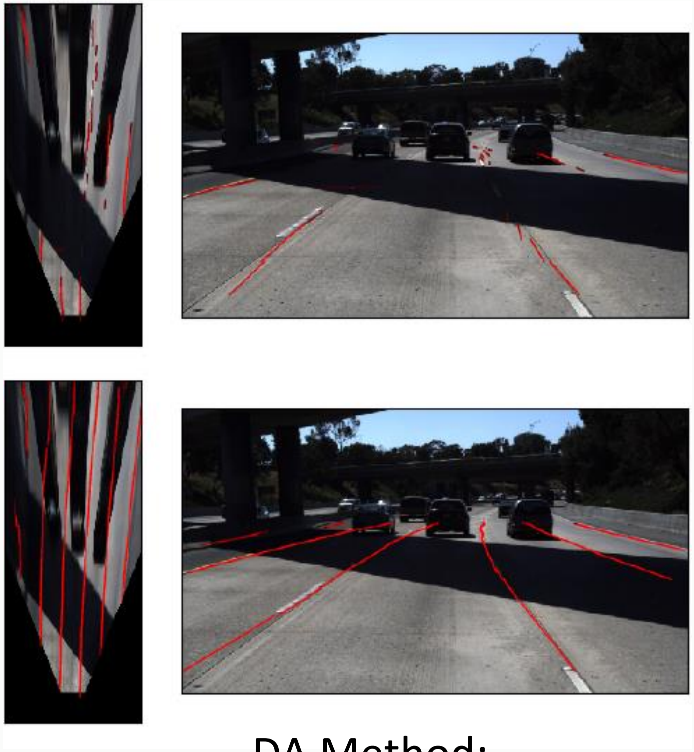
Results – Unsupervised domain adaptation

Method \ Dataset	tuSimple (mAP%)	Llamas (mAP%)	3DLanes (mAP%)
Fully supervised	81.1	73.2	74.5
Synthetic only	60.5	47.8	53.8
Autoencoder	67.7	56.0	57.8
Image translation	**72.0**	62.3	**59.3**
Self supervision	66.3	**63.4**	58.1
Combination of all three	**77.1**	**66.0**	**59.5**

Qualitative results before and after Domain Adaptation

Before DA

After DA



DA Method:
Image Translation

DA Method:
Autoencoder

Semi-supervised domain adaptation

10% labeled target domain training images

Method \ Dataset	tuSimple (mAP%)	Llamas (mAP%)	3DLanes (mAP%)
Fully supervised	81.1	73.2	74.5
Small + synthetic only	77.5	65.5	62.0
Autoencoder	**79.3**	**70.5**	**66.9**
Image translation	78.4	69.1	64.2
Self supervision	77.1	70.2	64.0

- **Our Autoencoder approach** almost recovers full supervision accuracy on tuSimple (-1.8%) and llamas (-2.7%) with a **ten-fold labeling saving**
- Combination of all methods did not improve

Conclusions

- We adjusted existing **domain adaptation** approaches for **lane detection** and tested them on the synthetic-to-real problem
- We presented a **novel autoencoder-based approach** for domain adaptation in the lane detection task
- We conducted our experiments on 3 large datasets
- Our approach achieves **SOTA in the SSDA setting** reflecting a ten-fold saving in labeling effort with minimal performance loss
- We also introduced a new self-supervision objective for lane detection
- In the **UDA** our method is **complementary** with two existing ones and their combination reach state-of-the-art results

Thank you!