

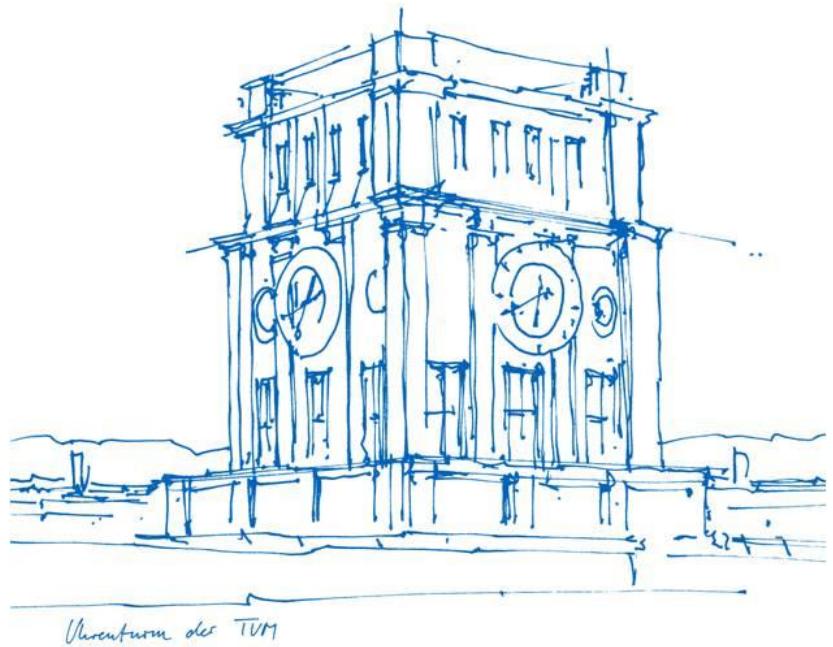
# Deep Virtual Stereo Odometry: Leveraging Deep Depth Prediction for Monocular Direct Sparse Odometry

Nan Yang, Rui Wang, Jörg Stückler, Daniel Cremers

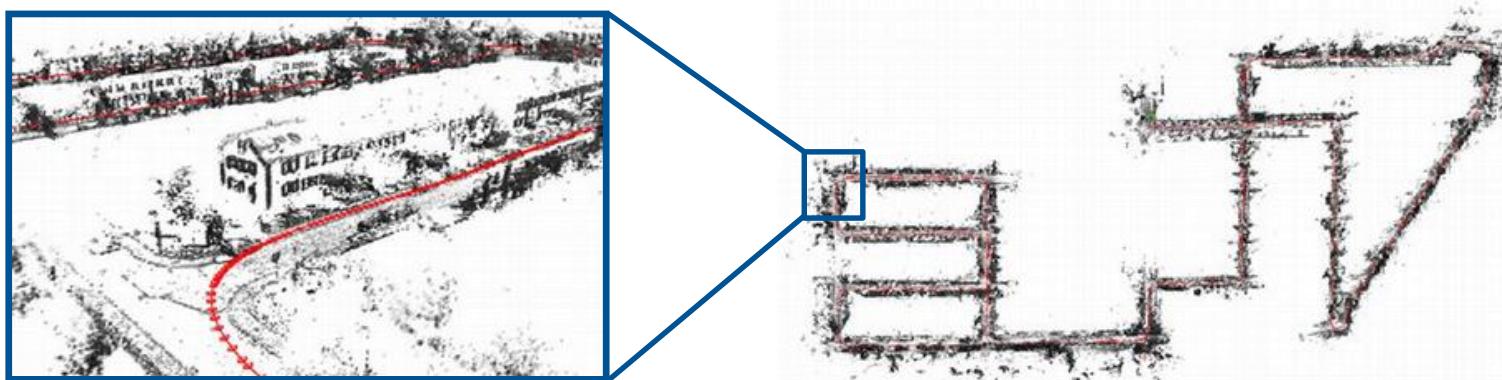
Lars Carius

Technical University of Munich

Munich, March 16th 2020



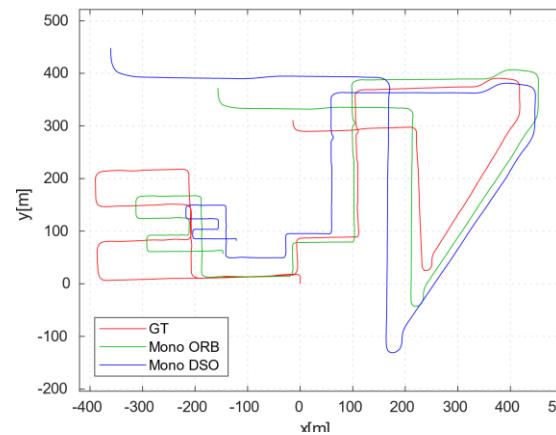
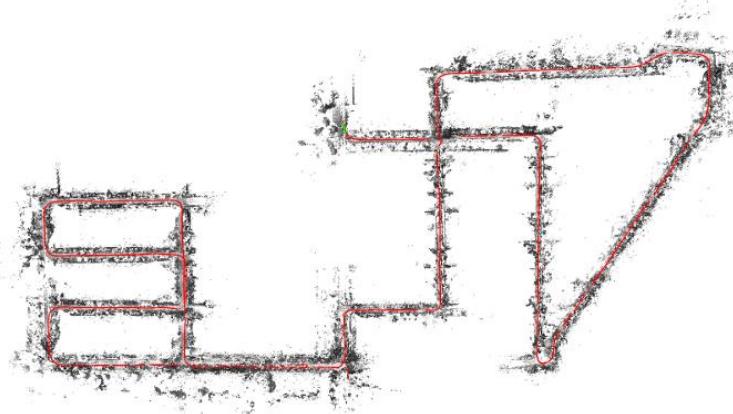
# Intro – Visual Odometry



- **VO:** Determine position and orientation of camera from visual input
- **VSLAM:** Globally optimize both map and camera pose

# Intro – Shortcomings of Existing Methods

- **Mono camera setups:** Scale Drift
  - Geometrically impossible to recover scale!



- **End-to-end trained Neural Networks:** Performance
- **Stereo Camera, RGB-D, LiDAR:** Cost & Calibration
  - **This paper:** Hybrid method (Single camera enhanced with Deep Learning)

# Outline

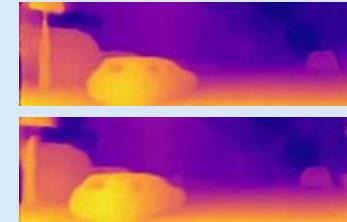
- Introduction
- Method
  - High-Level Concept
  - Depth Estimation
  - Bundle Adjustment
  - Deep Virtual Stereo Odometry
- Experiments & Results
  - Monocular Depth Estimation
  - Monocular Visual Odometry
- Personal Comments
- Summary

# Method – High-Level Concept

## Deep Learning Pipeline



Mono camera image



Left disparity map

Right disparity map

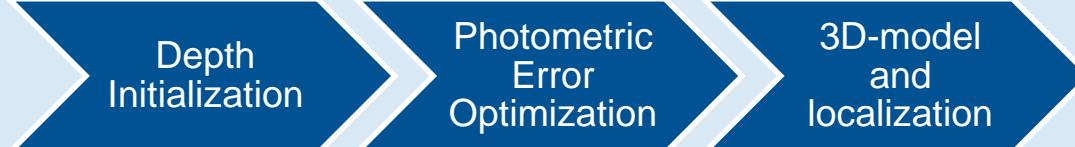
Consistent metric  
scale initialization

Virtual stereo  
photometric error

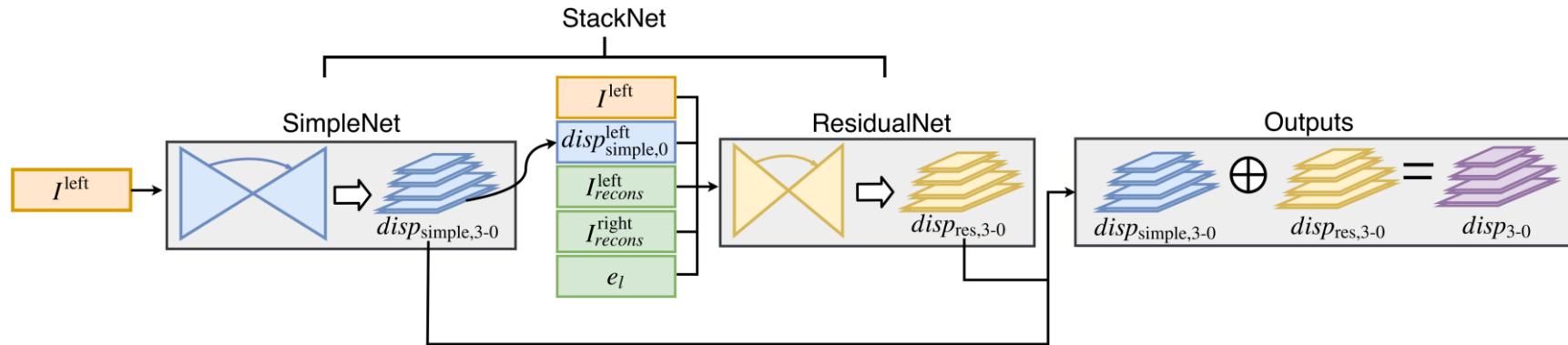
## Classic Visual Odometry Pipeline



Mono camera image



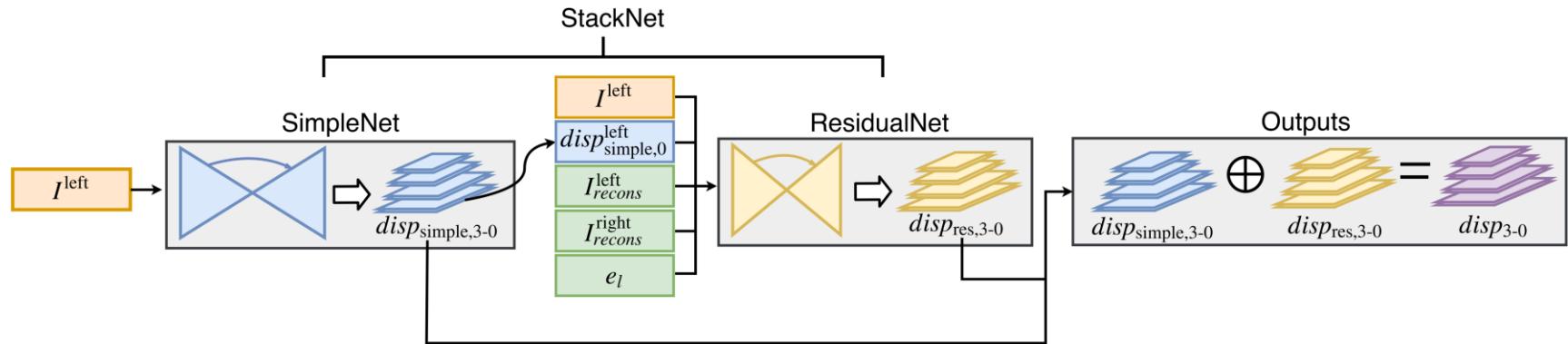
# Method – Depth Estimation



## Architecture:

- 2 fully-convolutional encoder-decoder networks with skip connections
- ResidualNet refines disparity maps output by SimpleNet

# Method – Depth Estimation



## Architecture:

- 2 fully-convolutional encoder-decoder networks with skip connections
- ResidualNet refines disparity maps output by SimpleNet

## Loss Function:

$$\mathcal{L}_s = \underbrace{\alpha_U (\mathcal{L}_U^{\text{left}} + \mathcal{L}_U^{\text{right}})}_{\text{Self-supervised loss}} + \underbrace{\alpha_S (\mathcal{L}_S^{\text{left}} + \mathcal{L}_S^{\text{right}})}_{\text{Supervised loss}} + \underbrace{\alpha_{lr} (\mathcal{L}_{lr}^{\text{left}} + \mathcal{L}_{lr}^{\text{right}})}_{\text{Left-right consistency loss}} + \underbrace{\alpha_{smooth} (\mathcal{L}_{\text{smooth}}^{\text{left}} + \mathcal{L}_{\text{smooth}}^{\text{right}})}_{\text{Disparity smoothness regularization}} + \underbrace{\alpha_{occ} (\mathcal{L}_{\text{occ}}^{\text{left}} + \mathcal{L}_{\text{occ}}^{\text{right}})}_{\text{Occlusion regularization}}$$

# Method – Deep Virtual Stereo Odometry

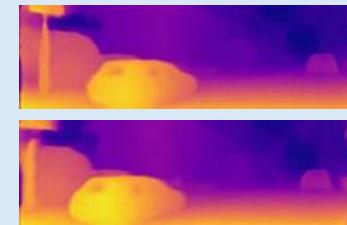
Deep Learning Pipeline



Mono camera image

SimpleNet

ResidualNet



Left disparity map

Right disparity map

Consistent metric  
scale initialization

Virtual stereo  
photometric error

Classic Visual Odometry Pipeline



Mono camera image

Depth  
Initialization

Photometric  
Error  
Optimization

3D-model  
and  
localization



# Method – Deep Virtual Stereo Odometry

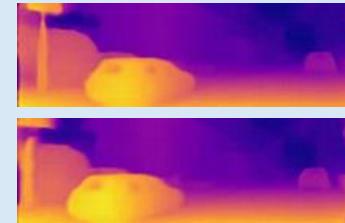
Deep Learning Pipeline



Mono camera image

SimpleNet

ResidualNet



Left disparity map

Right disparity map

Consistent metric  
scale initialization  
→ mitigates scale  
drift

Virtual stereo  
photometric error

Classic Visual Odometry Pipeline



Mono camera image

Depth  
Initialization

Photometric  
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# Method – Deep Virtual Stereo Odometry

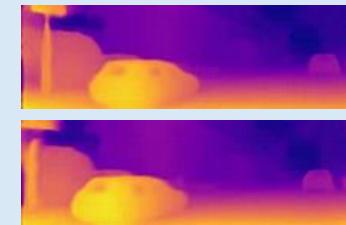
Deep Learning Pipeline



Mono camera image

SimpleNet

ResidualNet



Left disparity map

Right disparity map

Consistent metric  
scale initialization  
→ mitigates scale  
drift

Virtual stereo  
photometric error  
→ increases accuracy  
& mitigates scale drift

Classic Visual Odometry Pipeline



Mono camera image

Depth  
Initialization

Photometric  
Error  
Optimization

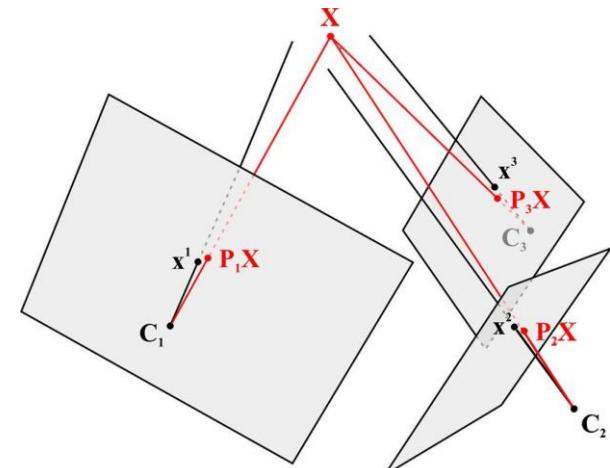
3D-model  
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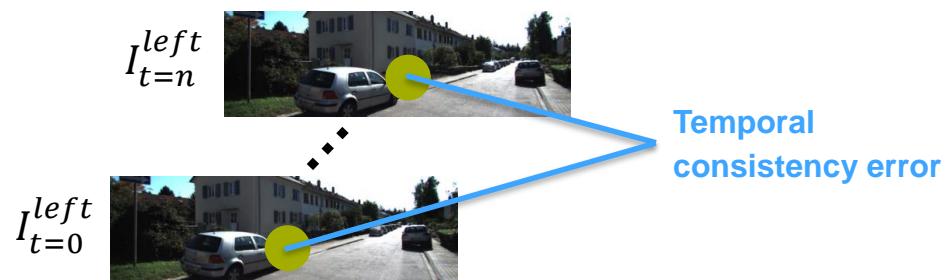
# Method – Definitions

- **Bundle adjustment (BA):** Optimize 3D points, camera motion & camera params based on 2D images
- **Direct bundle adjustment:** No reprojection error, optimize in image space
- **Sparse bundle adjustment:** Use only a subset of pixels
- **Windowed bundle adjustment:** BA with sliding-window (heuristic keyframes)

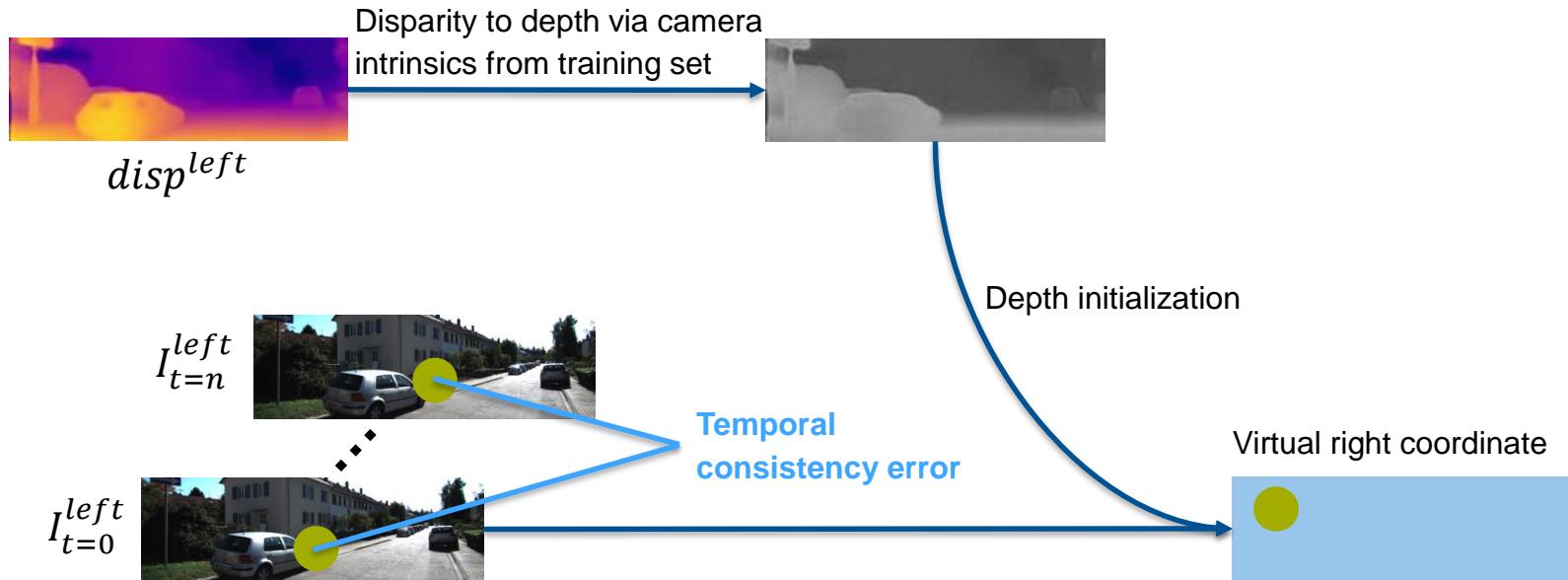
➤ Here: Windowed direct sparse BA



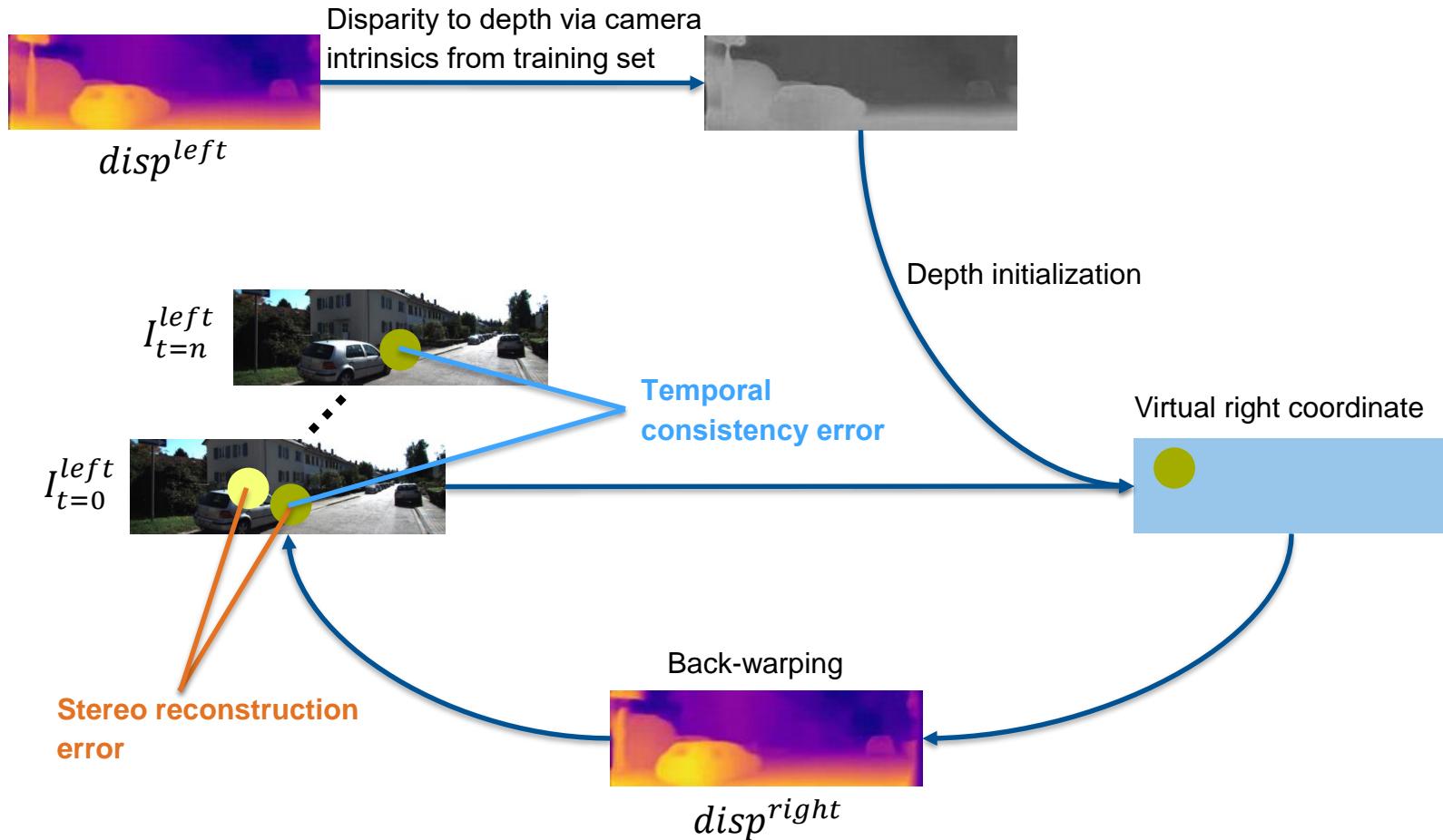
# Method – Virtual Stereo Photometric Error



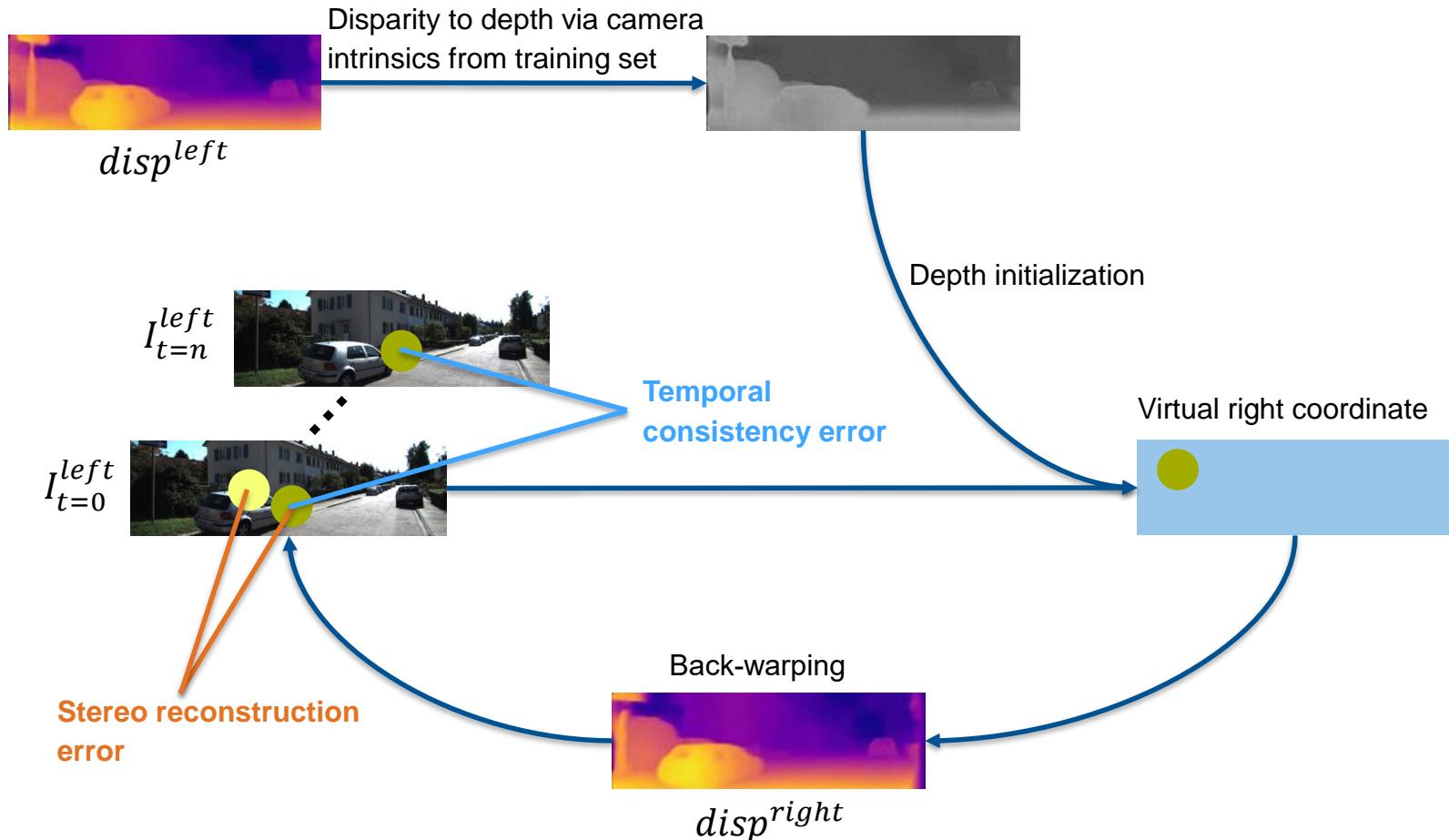
# Method – Virtual Stereo Photometric Error



# Method – Virtual Stereo Photometric Error



# Method – Virtual Stereo Photometric Error



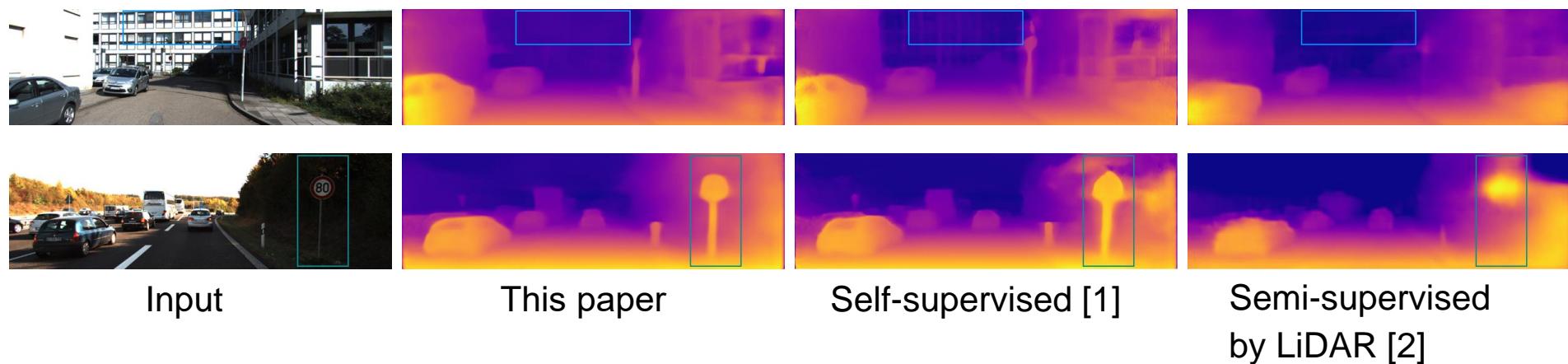
3D-points and camera motion are recovered by jointly optimizing **temporal consistency** and **stereo reconstruction error** using Gauss-Newton

# Experiments & Results – Depth Estimation

**Training schedule** („easy task first, then harder task, then easy again to smooth outliers“):

1. Train SimpleNet: semi-supervised → self-supervised → semi-supervised
2. Freeze SimpleNet, train ResidualNet: semi-supervised → self-supervised → semi-supervised

## Results:



Source:

[1] Godard, C., Mac Aodha, O., Brostow, G.J.: Unsupervised monocular depth estimation with left-right consistency. arXiv preprint arXiv:1609.03677 (2016)

[2] Kuznetsov, Y., Stuckler, J., Leibe, B.: Semi-supervised deep learning for monocular depth map prediction. arXiv preprint arXiv:1702.02706 (2017)

# Experiments & Results – Monocular Visual Odometry

## Ablation study:

1. Initializing depth with left disparity prediction
2. Using right disparity for virtual stereo term in windowed bundle adjustment
3. Checking left-right disparity consistency for sparse point selection
4. Tuning virtual stereo baseline

## Results:

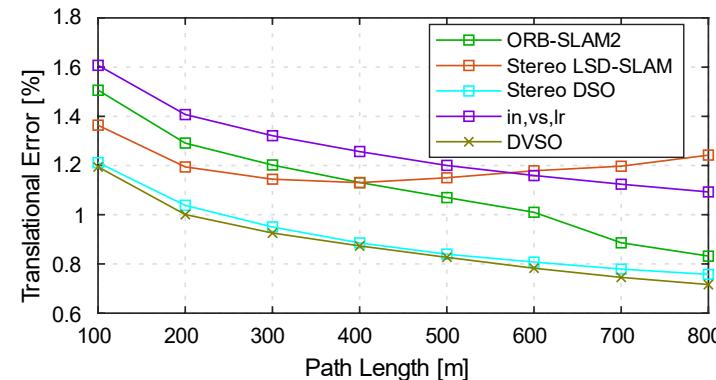
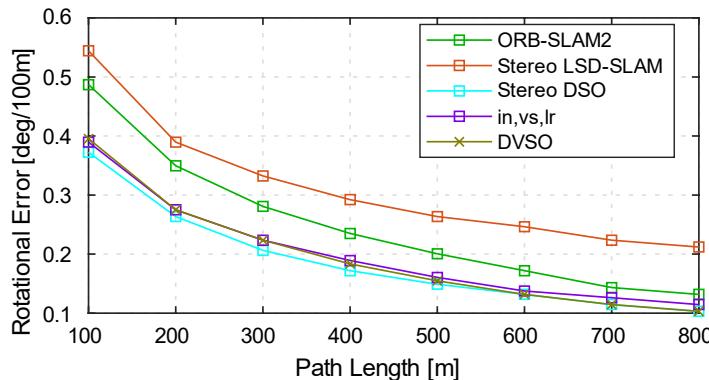
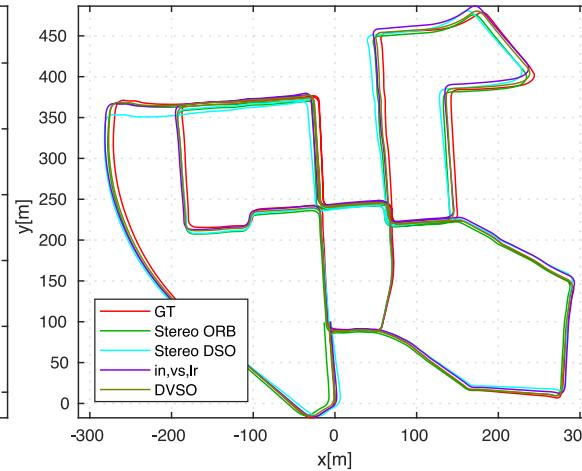
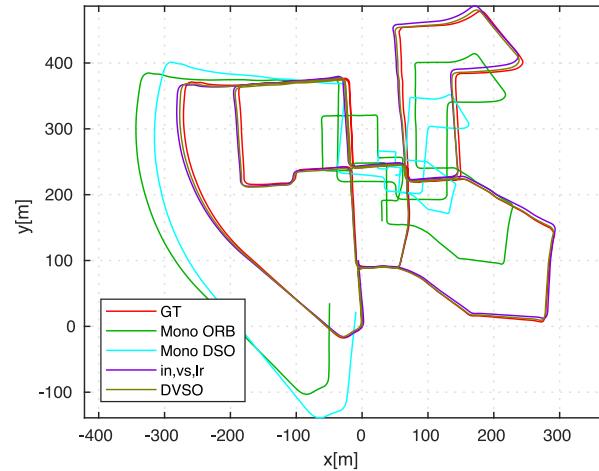
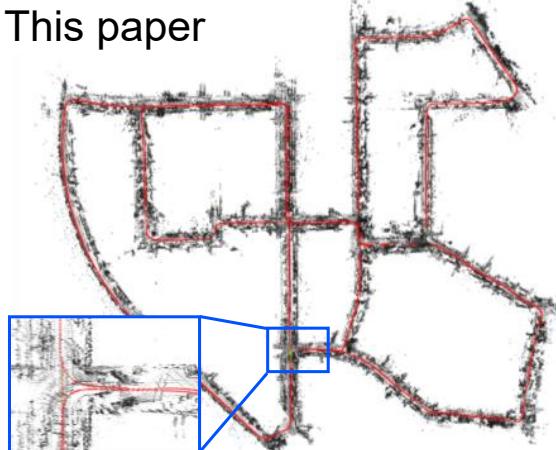


Image source: Stereo DSO: Large-Scale Direct Sparse Visual Odometry with Stereo Cameras, Rui Wang, Martin Schwörer, Daniel Cremers, <https://arxiv.org/abs/1708.07878>

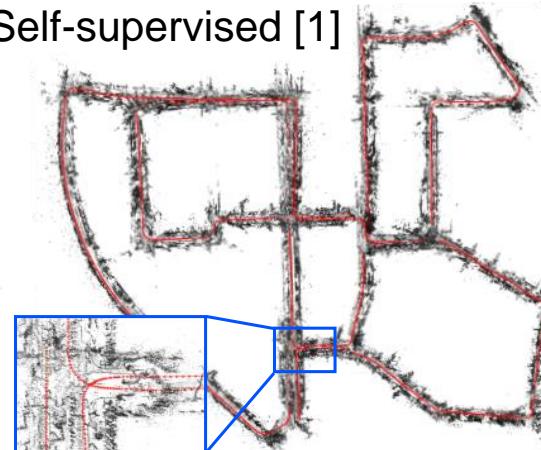
# Experiments & Results – Monocular Visual Odometry



This paper



Self-supervised [1]



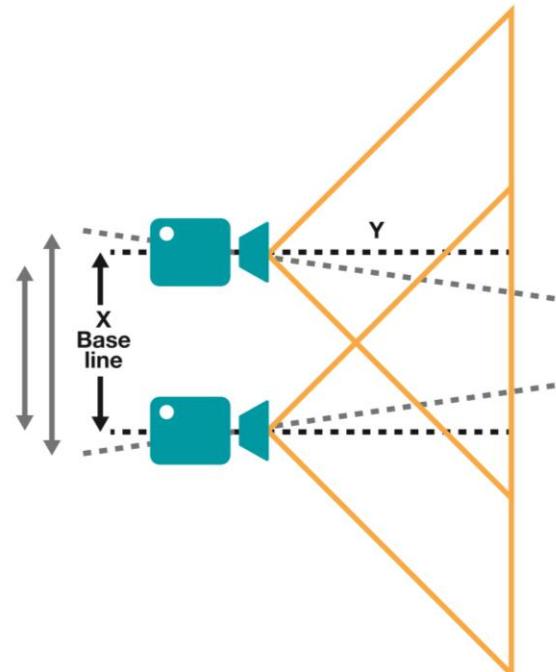
Source:

[1] Godard, C., Mac Aodha, O., Brostow, G.J.: Unsupervised monocular depth estimation with left-right consistency. arXiv preprint arXiv:1609.03677 (2016)

# Personal Comments

## Baseline tuning is cheating

- Stereo information at test time required
- Future work: Online fine tuning



# Personal Comments

## Necessity for Deep Learning

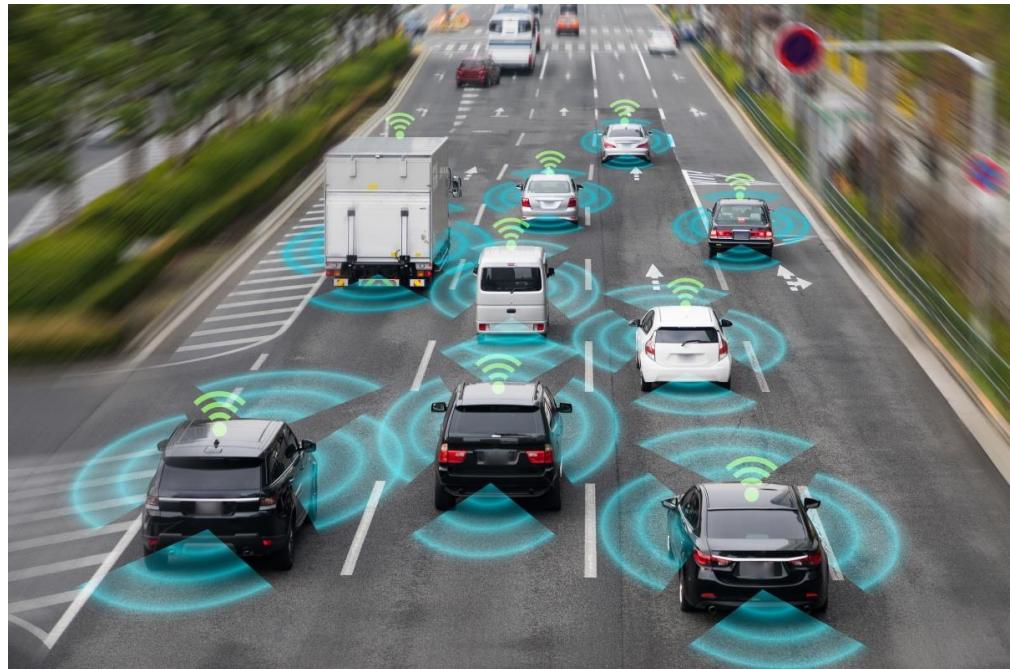
- Stereo cameras cheap
- Deep Learning needs good training data
- Safety & error accountability



# Personal Comments

## Enables fleet learning

- Few vehicles with stereo camera to provide training data
- Remaining vehicles use DL and operate in a similar enough domain



# Summary: Deep Virtual Stereo Odometry

- **Monocular Input + Deep Depth Predictions → Stereo Performance**
  - Scale drift eliminated
- **Semi-Supervised Disparity Predictions**
  - Stereo reconstruction for self-supervision
  - Sparse DSO for supervision
- **Incorporation into Visual Odometry Pipeline**
  - Metric scale initialization
  - Virtual stereo error

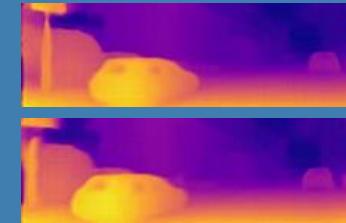


# Discussion

## Deep Learning Pipeline



Mono camera image



Left disparity map

Right disparity map

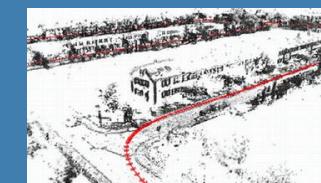
Consistent metric  
scale initialization

Virtual stereo  
photometric error

## Classic Visual Odometry Pipeline



Mono camera image



# Backup: From Disparity to Depth

$$d(\vec{p}) = \frac{b \cdot f_x}{disp(\vec{p})}$$

- $d(\vec{p})$ : Depth at point  $\mathbf{p}$
- $b$ : Baseline
- $f_x$ : Focal length (camera intrinsic)
- $disp(\vec{p})$ : Disparity at point  $\mathbf{p}$

