Introduction of Computer Vision Benchmark for Autonomous Driving

Automotive Cyber-Physical Systems

Cheng-Yang Fu

01/04/2015

State-of-the-Art

- Localization, Path Planning, and Obstacle avoidance

State-of-the-Art

- Heavy usage of **Valodyne** and detailed Maps

May 2014 Embedded Vision Summit Keynote Presentation: "Self-Driving Cars," Nathaniel Fairfield, Google

State-of-the-Art

- Heavy usage of Valodyne and **detailed Maps**

May 2014 Embedded Vision Summit Keynote Presentation: "Self-Driving Cars," Nathaniel Fairfield, Google

State-of-the-Art

- **Do we have cheaper solutions?**

3D Laser-scanner

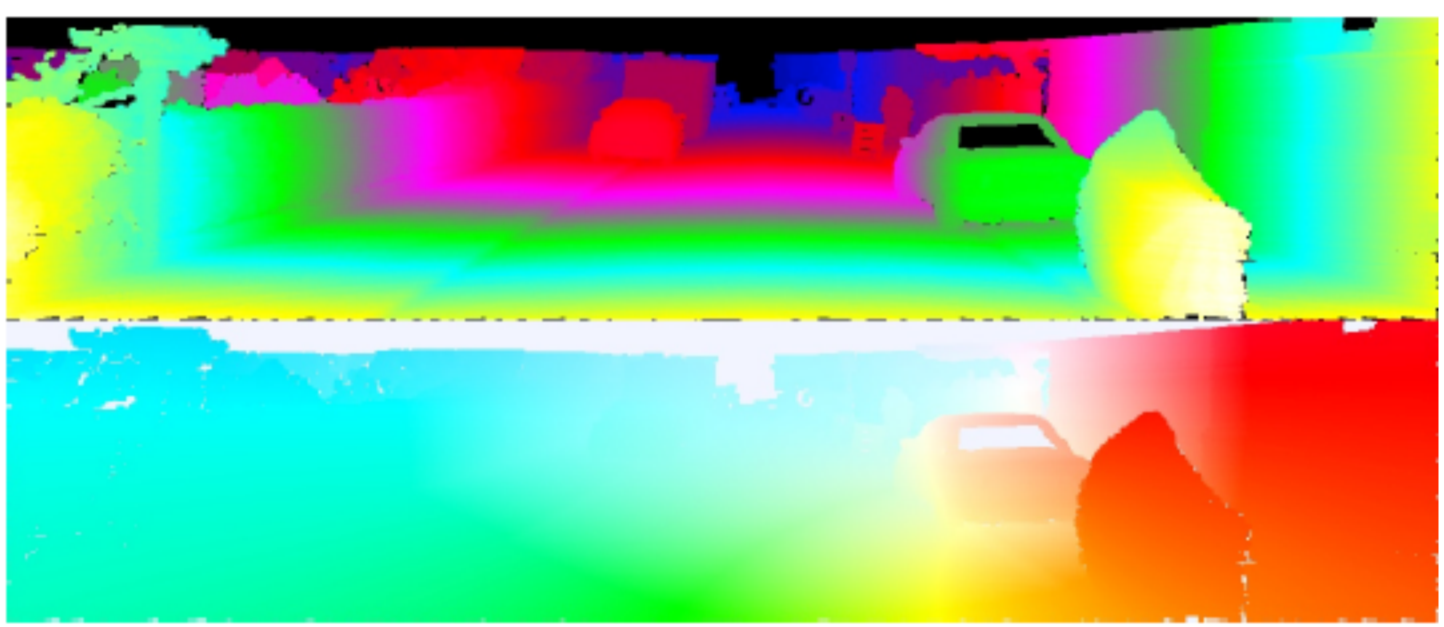
May 2014 Embedded Vision Summit Keynote Presentation: "Self-Driving Cars," Nathaniel Fairfield, Google

KITTI Vision Benchmark Suite

Karlsruhe Institute of Technology (KIT) and Toyota Technological Institute at Chicago (TTI-C)

- **Goal** : Autonomous driving cheap sensors
- Problem for Computer vision
    - Stereo, optical flow , Visual Odometry

Karlsruhe Institute of Technology



KITTI Vision Benchmark Suite

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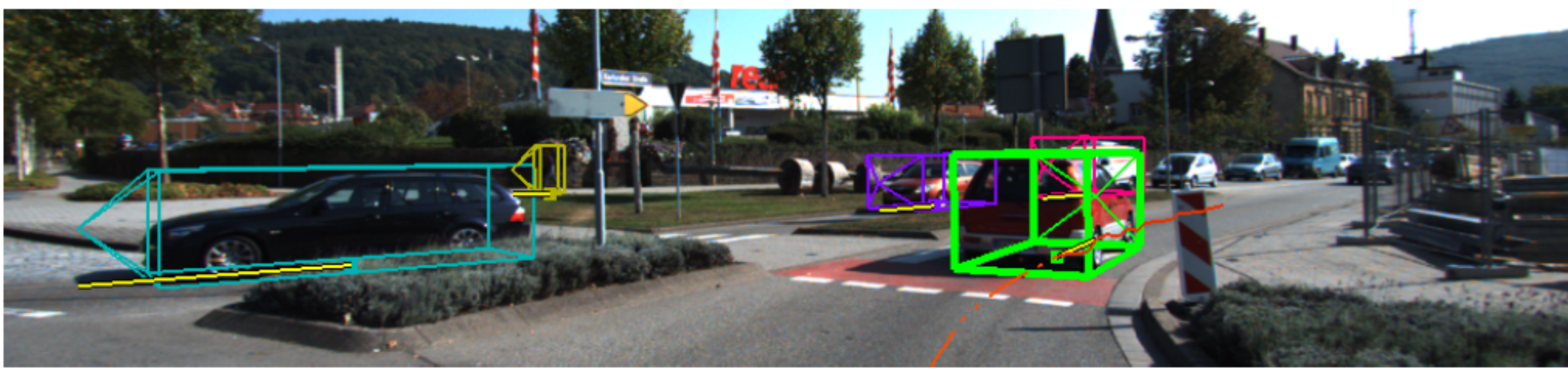
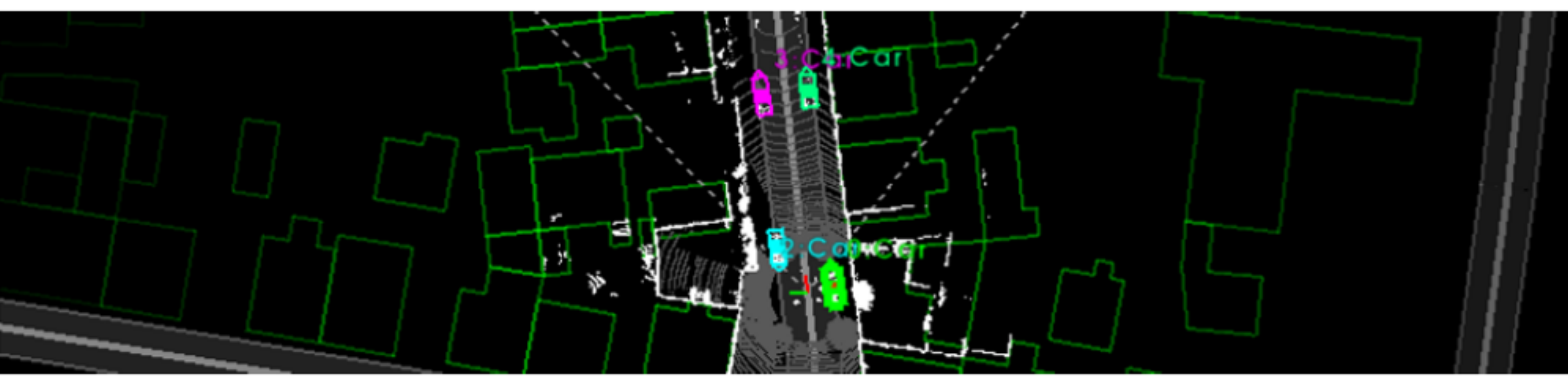
Karlsruhe Institute of Technology



KITTI Vision Benchmark Suite

Karlsruhe Institute of Technology (KIT) and Toyota Technological Institute at Chicago (TTI-C)

- **Goal** : Autonomous driving cheap sensors
- Problem for Computer vision
    - Stereo, optical flow , Visual Odometry
    - Object Detection, Recognition, and Tracking
    - scene Understanding

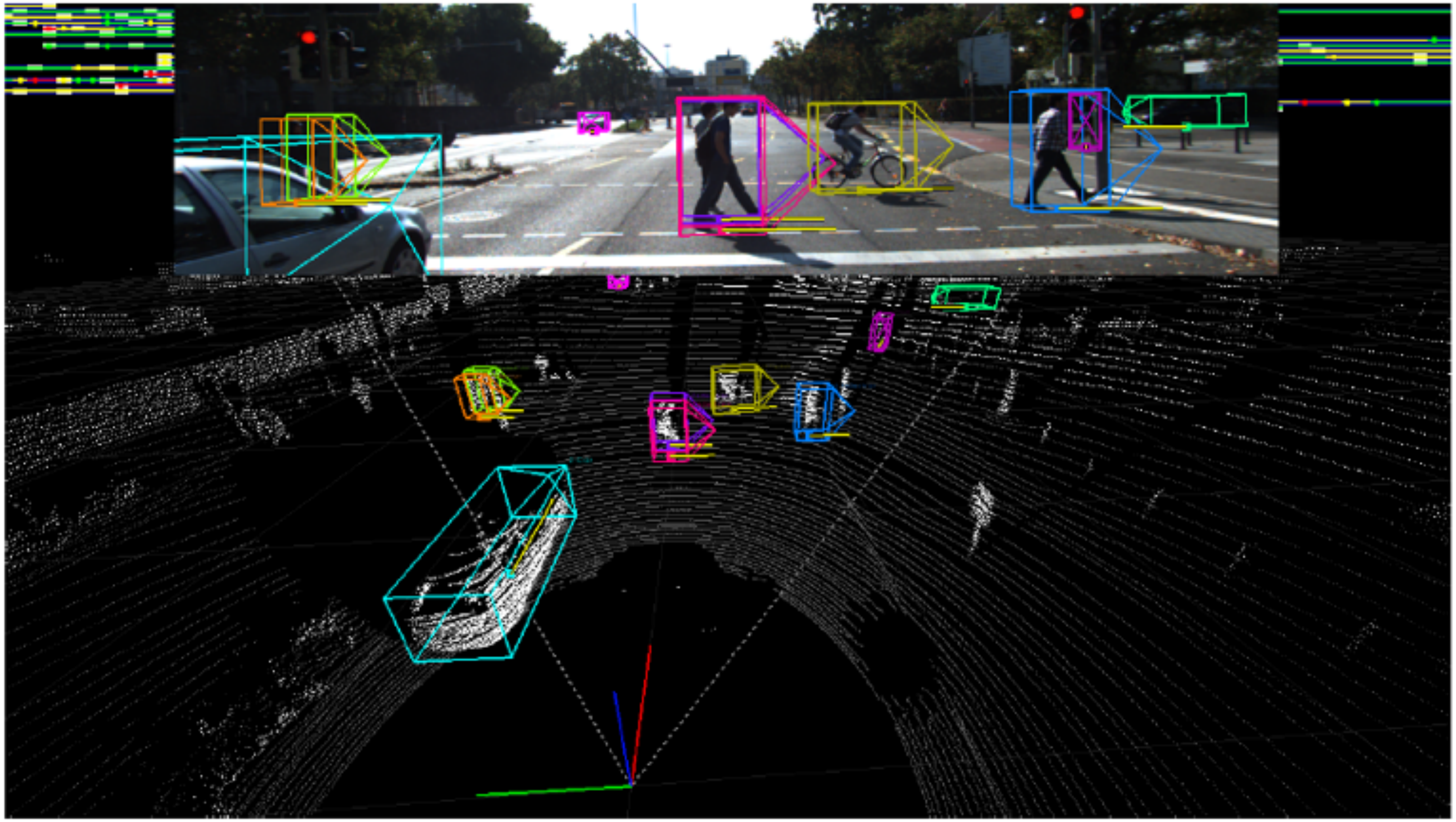


KITTI Vision Benchmark : Data Collection

- Two **stereo** rigs(1392x512 pixels, 54 cm , 90° opening)
- **Velodyne** laser scanner, **GPS +IMU**
- 6 hours at 10 frame per second

Annotation

- 3D object labels, Occlusion labels



Evaluation

The KITTI Vision Benchmark Suite

A project of Karlsruhe Institute of Technology and Toyota Technological Institute at Chicago

Toyota Technological Institute Chicago | Karlsruhe Institute of Technology

home | setup | stereo | flow | odometry | object | tracking | road | semantics | raw data | submit results | jobs

Andreas Geiger (MPI Tübingen) | Philip Lenz (KIT) | Christoph Stiller (KIT) | Raquel Urtasun (University of Toronto)

Welcome to the KITTI Vision Benchmark Suite!

We take advantage of our autonomous driving platform Annieway to develop novel challenging real-world computer vision benchmarks. Our tasks of interest are: stereo, optical flow, visual odometry, 3D object detection and 3D tracking. For this purpose, we equipped a standard station wagon with two high-resolution color and grayscale video cameras. Accurate ground truth is provided by a Velodyne laser scanner and a GPS localization system. Our datsets are captured by driving around the mid-size city of Karlsruhe, in rural areas and on highways. Up to 15 cars and 30 pedestrians are visible per image. Besides providing all data in raw format, we extract benchmarks for each task. For each of our benchmarks, we also provide an evaluation metric and this evaluation website. Preliminary experiments show that methods ranking high on established benchmarks such as Middlebury perform below average when being moved outside the laboratory to the real world. Our goal is to reduce this bias and complement existing benchmarks by providing real-world benchmarks with novel difficulties to the community.

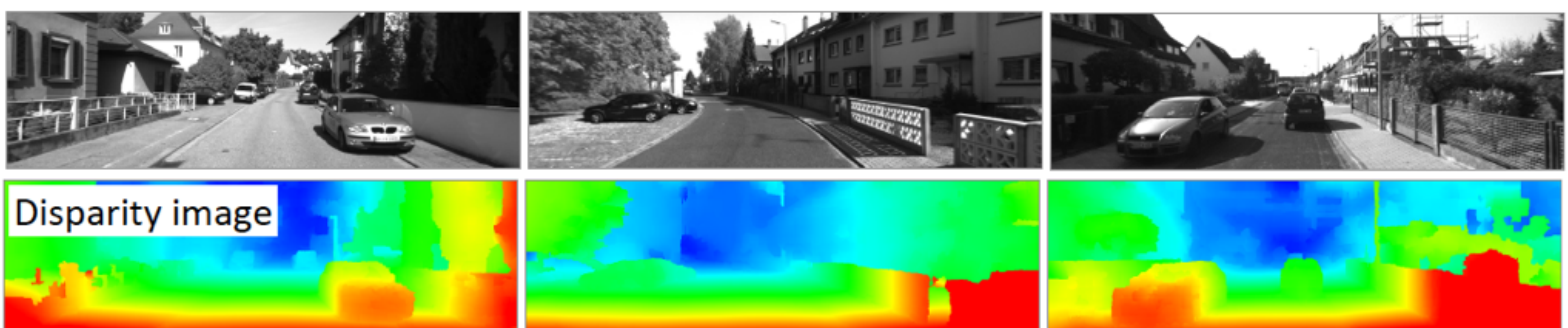
http://www.cvlibs.net/datasets/kitti/index.php

3D Reconstruction

Goal: given **2 cameras** mounted on top of the car, reconstruct the environment in 3D.

Stereo

- Input Data : Stereo Images
- Output : Depth

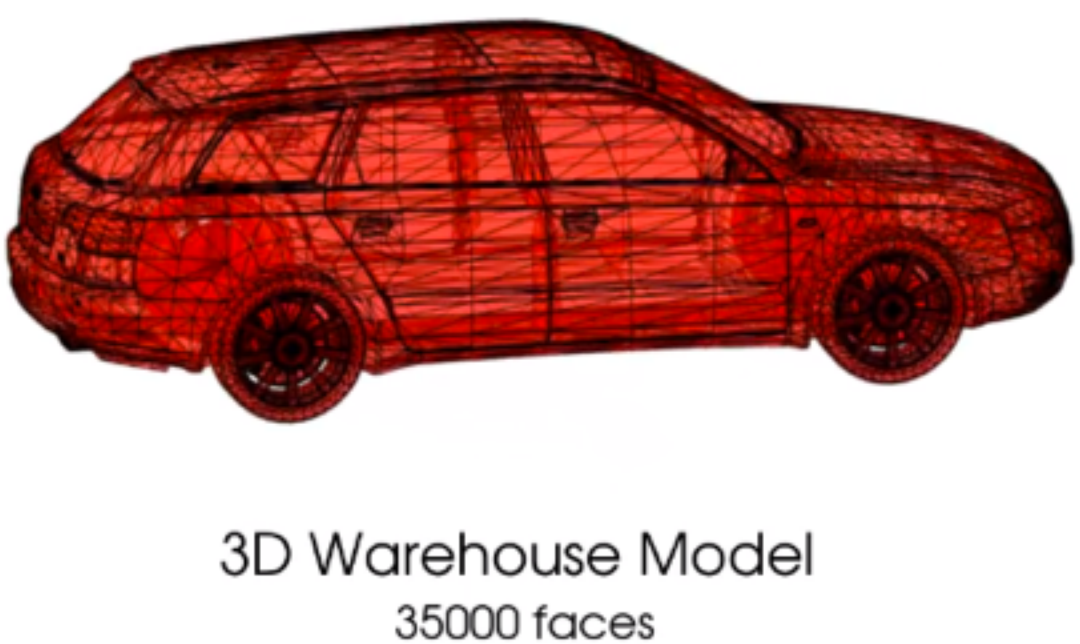


Stereo Evaluation

Rank	Method	Setting	Code	Out-Noc	Out-All	Avg-Noc	Avg-All	Density	Runtime	Environment	Compare
1	Displets		code	**2.47 %**	**3.27 %**	**0.7 px**	0.9 px	100.00 %	265 s	>8 cores @ 3.0 Ghz (Matlab + C/C++)	
F. Guney and A. Geiger: Displets: Resolving Stereo Ambiguities using Object Knowledge. Conference on Computer Vision and Pattern Recognition (CVPR) 2015.											
2	MC-CNN			2.61 %	3.84 %	0.8 px	1.0 px	100.00 %	100 s	Nvidia GTX Titan (CUDA, Lua/Torch7)	
Anonymous submission											
3	SPS-StFl			2.83 %	3.64 %	0.8 px	0.9 px	100.00 %	35 s	1 core @ 3.5 Ghz (C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Efficient Joint Segmentation, Occlusion Labeling, Stereo and Flow Estimation. ECCV 2014.											
4	VC-SF			3.05 %	3.31 %	0.8 px	0.8 px	100.00 %	300 s	1 core @ 2.5 Ghz (C/C++)	
C. Vogel, S. Roth and K. Schindler: View-Consistent 3D Scene Flow Estimation over Multiple Frames. Proceedings of European Conference on Computer Vision. Lecture Notes in, Computer Science 2014.											
5	OSF		code	3.28 %	4.07 %	0.8 px	0.9 px	99.98 %	50 min	1 core @ 3.0 Ghz (Matlab + C/C++)	
M. Menze and A. Geiger: Object Scene Flow for Autonomous Vehicles. Conference on Computer Vision and Pattern Recognition (CVPR) 2015.											
6	CoR			3.30 %	4.10 %	0.8 px	0.9 px	100.00 %	6 s	6 cores @ 3.3 Ghz (Matlab + C/C++)	
A. Chakrabarti, Y. Xiong, S. Gortler and T. Zickler: Low-level Vision by Consensus in a Spatial Hierarchy of Regions. CVPR 2015.											
7	SPS-St		code	3.39 %	4.41 %	0.9 px	1.0 px	100.00 %	2 s	1 core @ 3.5 Ghz (C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Efficient Joint Segmentation, Occlusion Labeling, Stereo and Flow Estimation. ECCV 2014.											
8	PCBP-SS			3.40 %	4.72 %	0.8 px	1.0 px	100.00 %	5 min	4 cores @ 2.5 Ghz (Matlab + C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Robust Monocular Epipolar Flow Estimation. CVPR 2013.											
9	DDS-SS			3.83 %	4.59 %	0.9 px	1.0 px	100.00 %	1 min	1 core @ 2.5 Ghz (Matlab + C/C++)	
D. Wei, C. Liu and W. Freeman: A Data-driven Regularization Model for Stereo and Flow. 3DTV-Conference, 2014 International Conference on 2014.											
10	StereoSLIC			3.92 %	5.11 %	0.9 px	1.0 px	99.89 %	2.3 s	1 core @ 3.0 Ghz (C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Robust Monocular Epipolar Flow Estimation. CVPR 2013.											

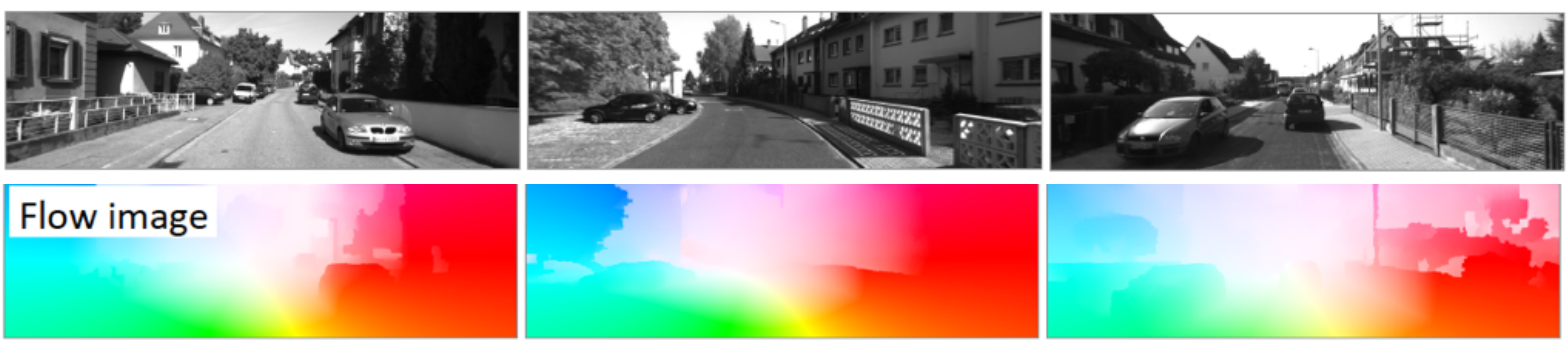
Displets

Displets: Resolving Stereo Ambiguities using Object Knowledge (CVPR 2015)



Optical Flow

- Input Data : Two Temporally Adjacent Images
- Output : Depth



Optical Flow Evaluation

This table ranks general optical flow methods, performing a full 2D search, as compared to the motion stereo methods below.

Rank	Method	Setting	Code	Out-Noc	Out-All	Avg-Noc	Avg-All	Density	Runtime	Environment	Compare
1	VC-SF			**2.72 %**	**4.84 %**	0.8 px	1.3 px	100.00 %	300 s	1 core @ 2.5 Ghz (Matlab + C/C++)	
C. Vogel, S. Roth and K. Schindler: View-Consistent 3D Scene Flow Estimation over Multiple Frames. Proceedings of European Conference on Computer Vision. Lecture Notes in, Computer Science 2014.											
2	SPS-StFl			2.82 %	5.61 %	**0.8 px**	1.3 px	100.00 %	35 s	1 core @ 3.5 Ghz (C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Efficient Joint Segmentation, Occlusion Labeling, Stereo and Flow Estimation. ECCV 2014.											
3	SPS-Fl			3.38 %	10.06 %	0.9 px	2.9 px	100.00 %	11 s	1 core @ 3.5 Ghz (C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Efficient Joint Segmentation, Occlusion Labeling, Stereo and Flow Estimation. ECCV 2014.											
4	OSF		code	3.47 %	6.34 %	1.0 px	1.5 px	100.00 %	50 min	1 core @ 3.0 Ghz (Matlab + C/C++)	
M. Menze and A. Geiger: Object Scene Flow for Autonomous Vehicles. Conference on Computer Vision and Pattern Recognition (CVPR) 2015.											
5	PR-Sf+E			3.57 %	7.07 %	0.9 px	1.6 px	100.00 %	200 s	4 cores @ 3.0 Ghz (Matlab + C/C++)	
C. Vogel, S. Roth and K. Schindler: Piecewise Rigid Scene Flow. International Conference on Computer Vision (ICCV) 2013.											
6	PCBP-Flow			3.64 %	8.28 %	0.9 px	2.2 px	100.00 %	3 min	4 cores @ 2.5 Ghz (Matlab + C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Robust Monocular Epipolar Flow Estimation. CVPR 2013.											
7	PR-Sceneflow			3.76 %	7.39 %	1.2 px	2.8 px	100.00 %	150 sec	4 core @ 3.0 Ghz (Matlab + C/C++)	
C. Vogel, S. Roth and K. Schindler: Piecewise Rigid Scene Flow. International Conference on Computer Vision (ICCV) 2013.											
8	MotionSLIC			3.91 %	10.56 %	0.9 px	2.7 px	100.00 %	11 s	1 core @ 3.0 Ghz (C/C++)	
K. Yamaguchi, D. McAllester and R. Urtasun: Robust Monocular Epipolar Flow Estimation. CVPR 2013.											
9	PPR-Flow			5.76 %	10.57 %	1.3 px	2.9 px	100.00 %	800 s	1 core @ 3.5 Ghz (Matlab + C/C++)	
Anonymous submission											
10	NLTGV-SC			5.93 %	11.96 %	1.6 px	3.8 px	100.00 %	16 s	GPU @ 2.5 Ghz (Matlab + C/C++)	
R. Ranftl, K. Bredies and T. Pock: Non-Local Total Generalized Variation for Optical Flow Estimation. Proceedings of the 13th European Conference on Computer Vision 2014.											

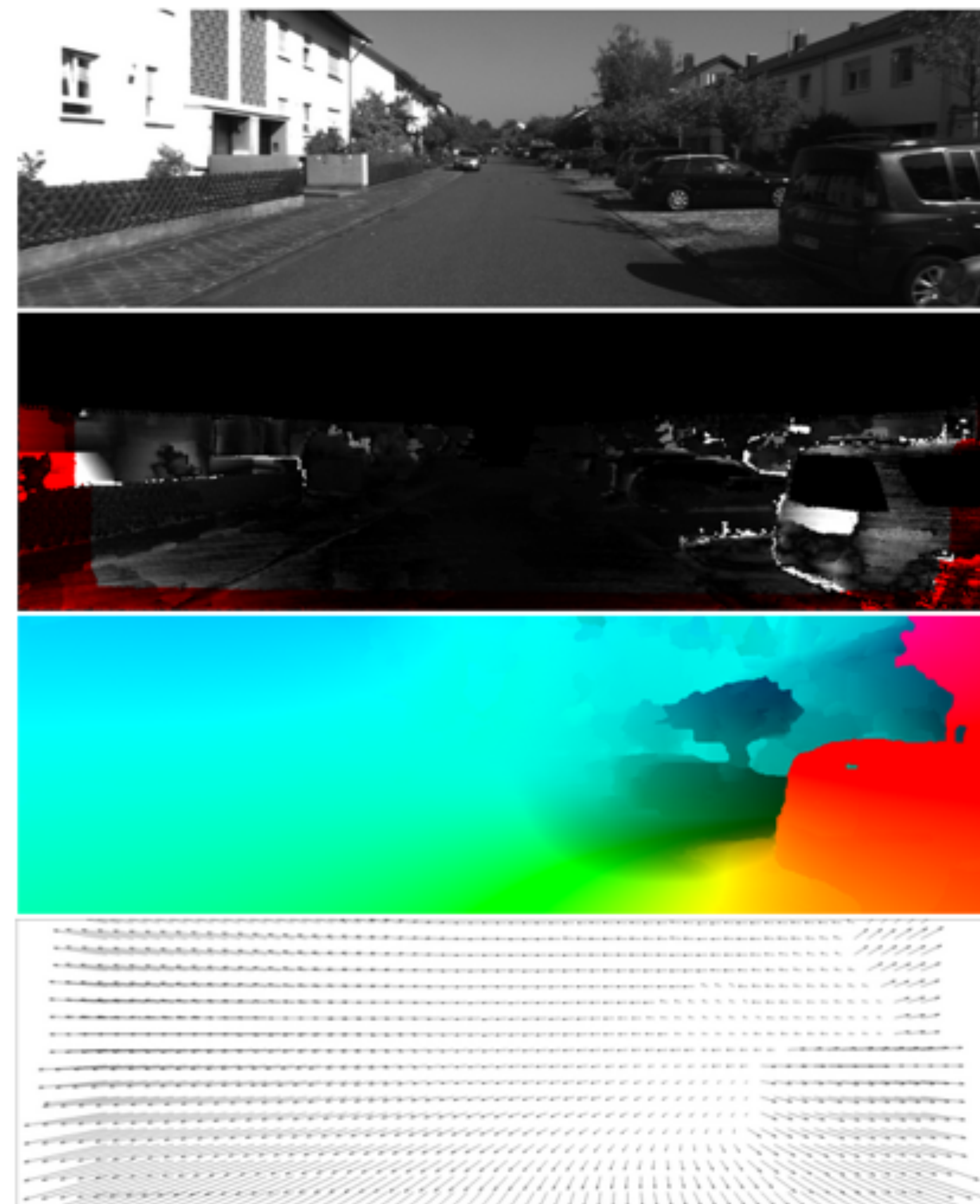
VC-SF

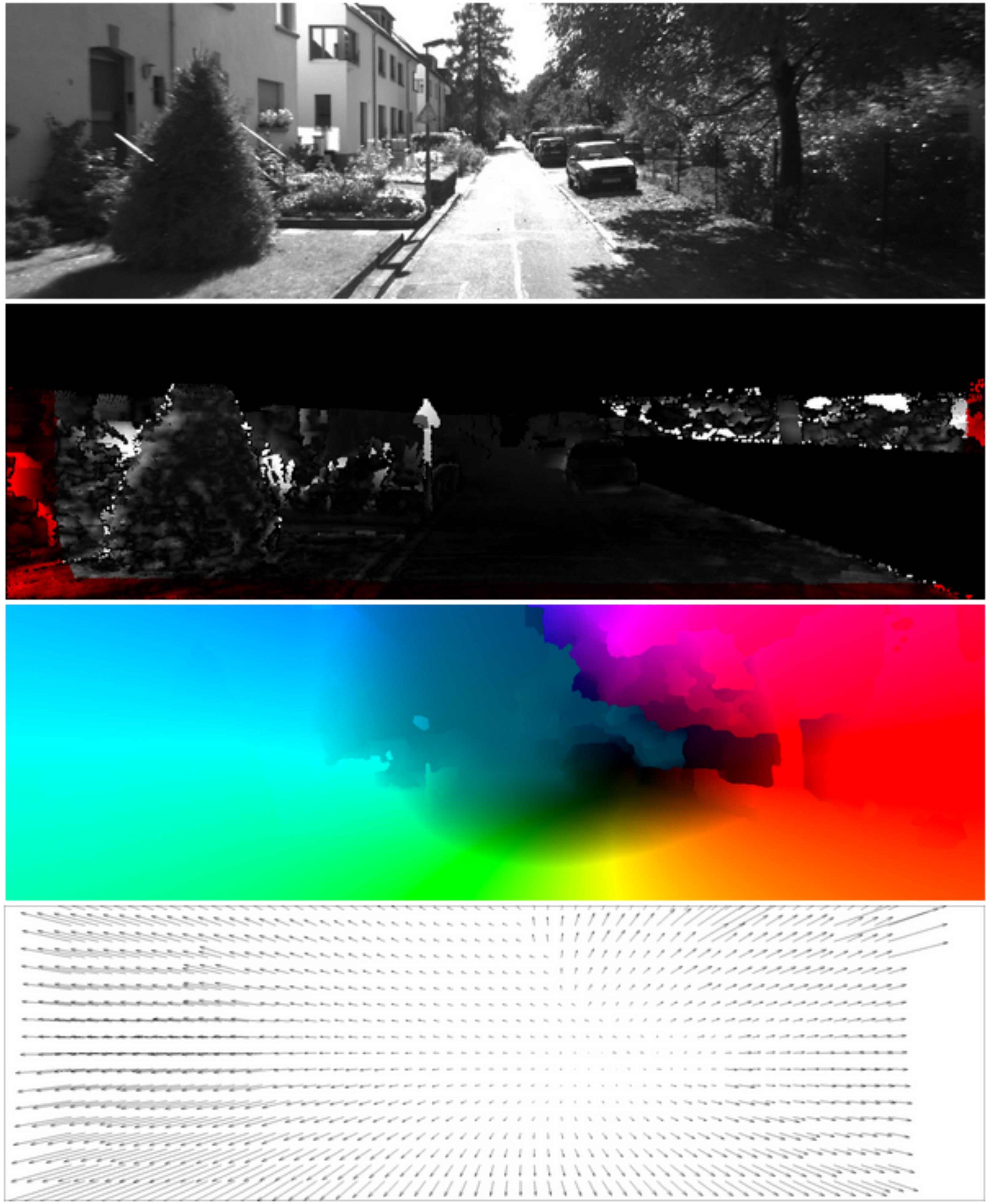
View-Consistent 3D Scene Flow Estimation
over Multiple Frames
, ECCV 2014

Test Image 0

Error	Out-Noc	Out-All	Avg-Noc	Avg-All
2 pixels	3.52 %	5.25 %	0.5 px	0.7 px
3 pixels	2.24 %	2.81 %	0.5 px	0.7 px
4 pixels	1.84 %	2.38 %	0.5 px	0.7 px
5 pixels	1.33 %	1.89 %	0.5 px	0.7 px

This table as LaTeX





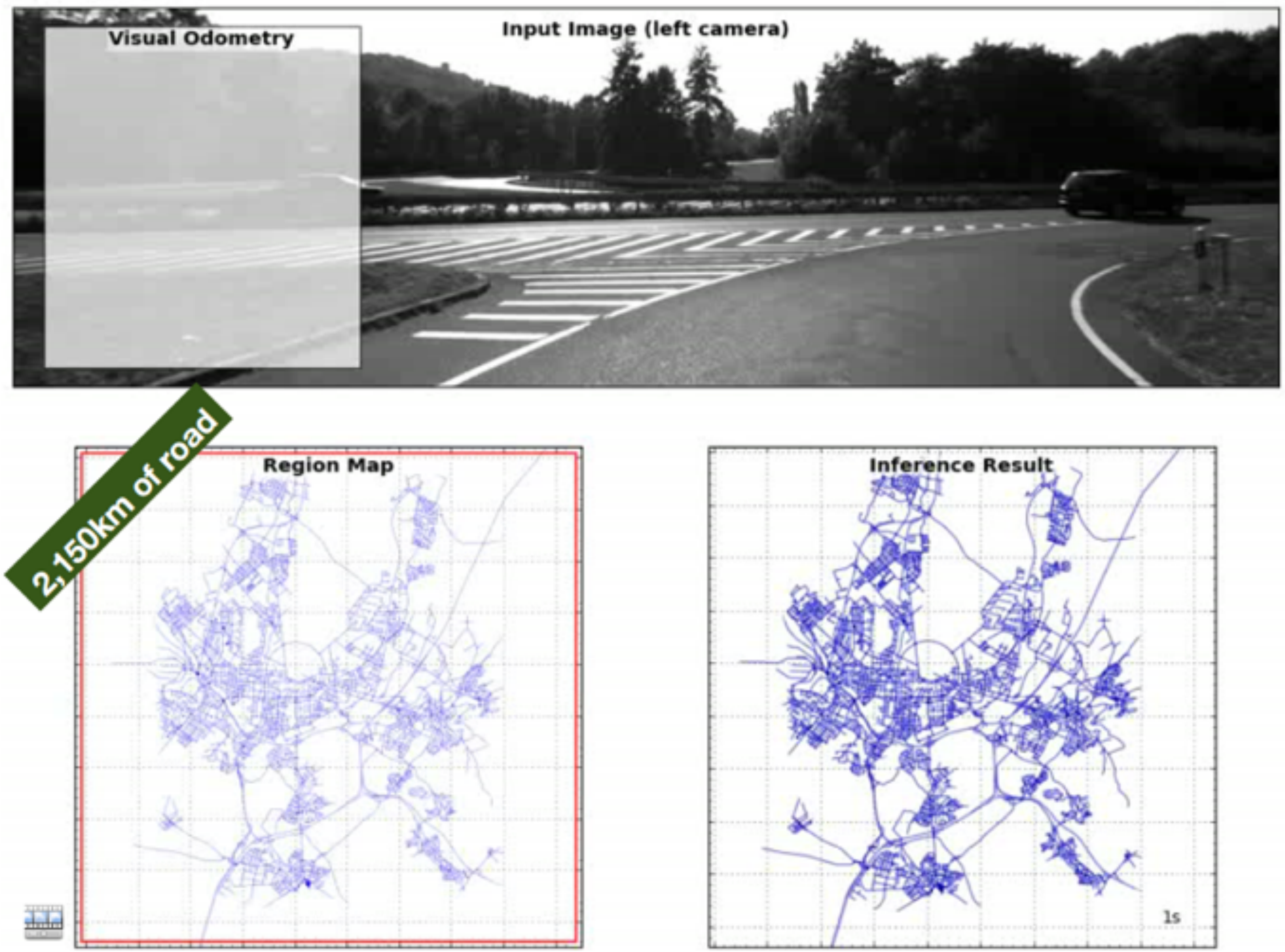
Odometry:motivation

- **Localization** is crucial for autonomous systems
- GPS has limitations in terms of **reliability and availability**
- Place recognition techniques use i**mage features** or depth maps and a **database** of previously collected images

Odometry:motivation

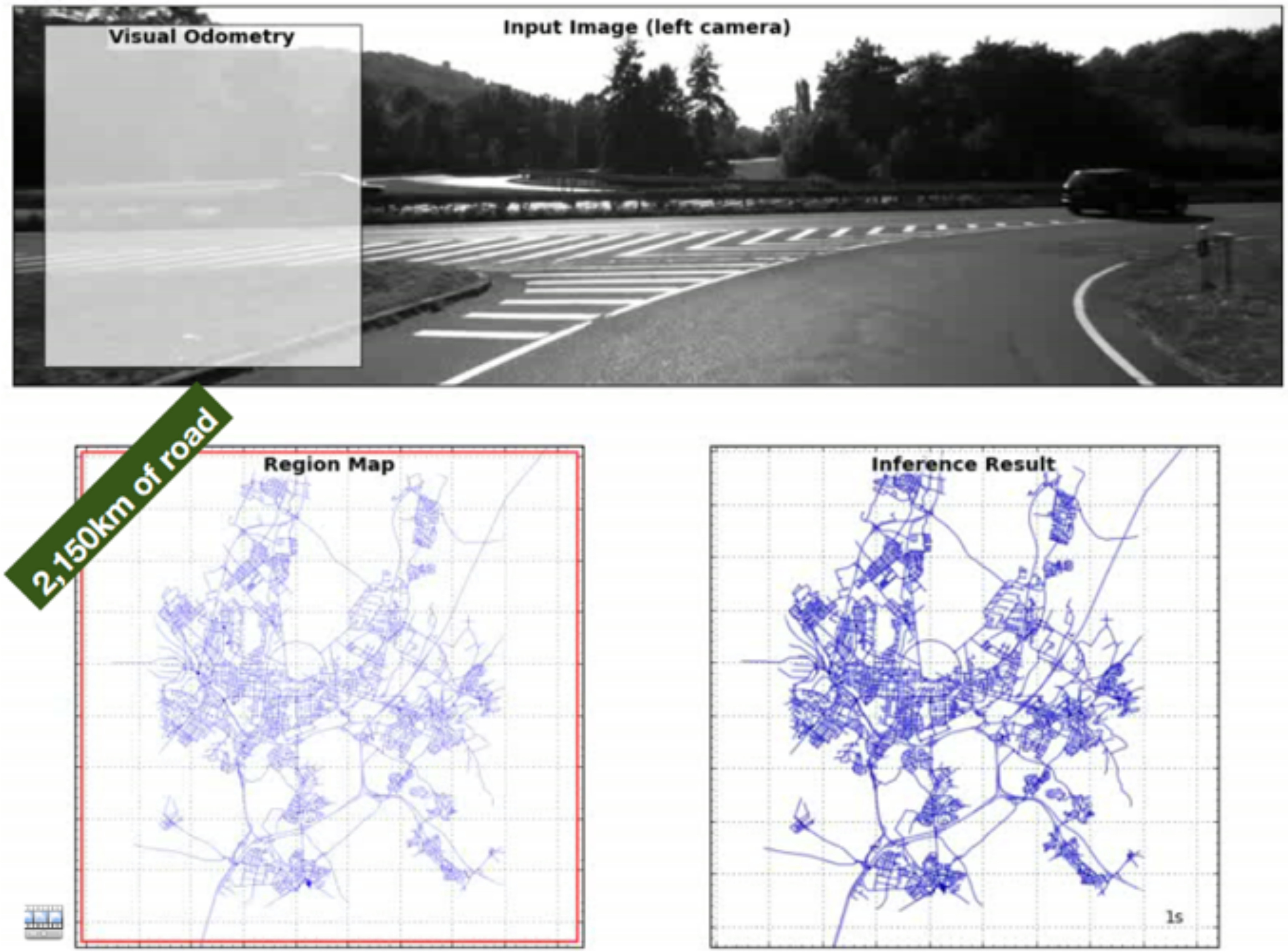
- Use **visual input** to localize a vehicle

Visual Odometry



[M. Brubaker, A. Geiger and R. Urtasun, CVPR13 best paper runner up award]

Visual Odometry

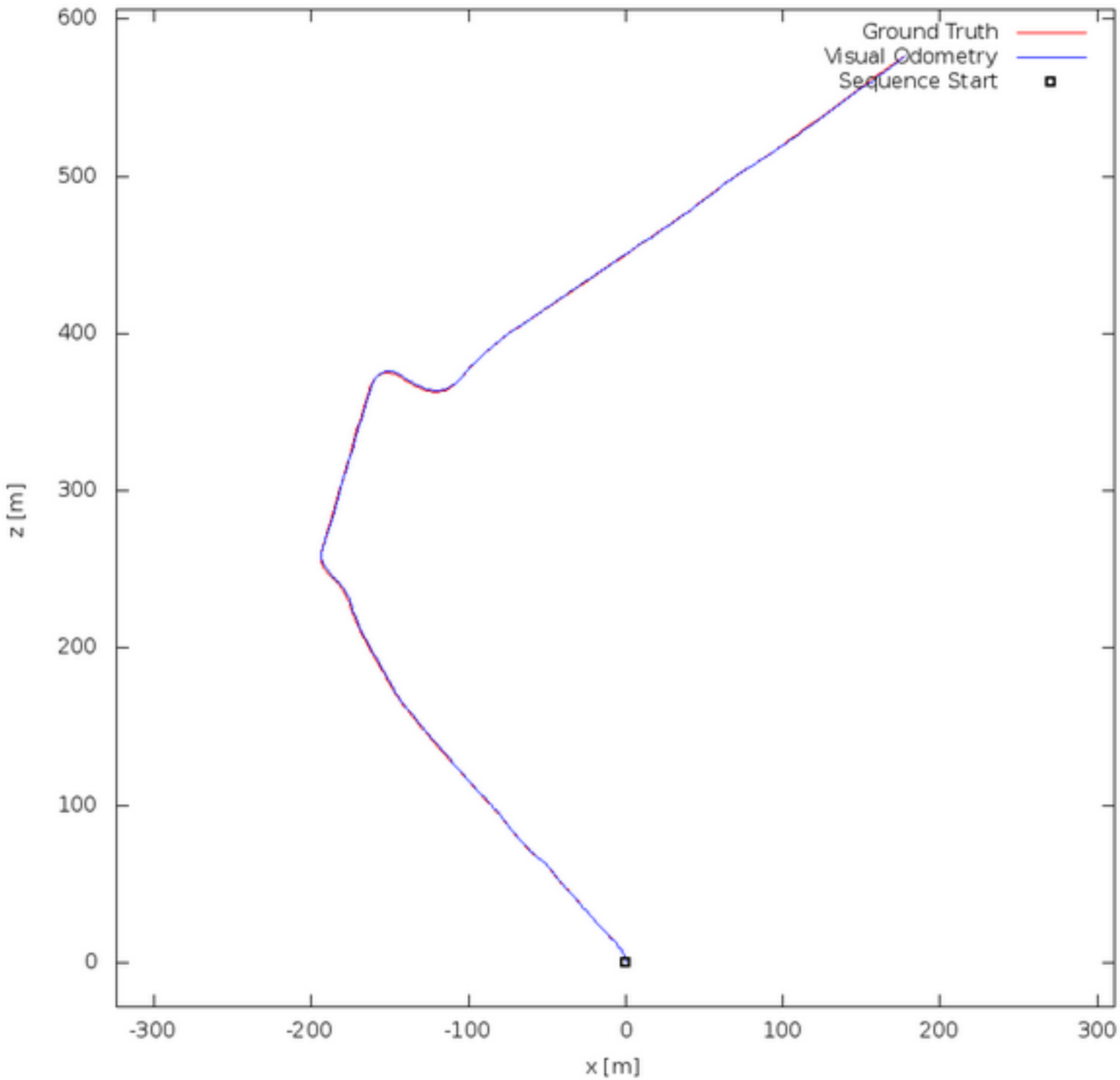


- Velocity
- Direction

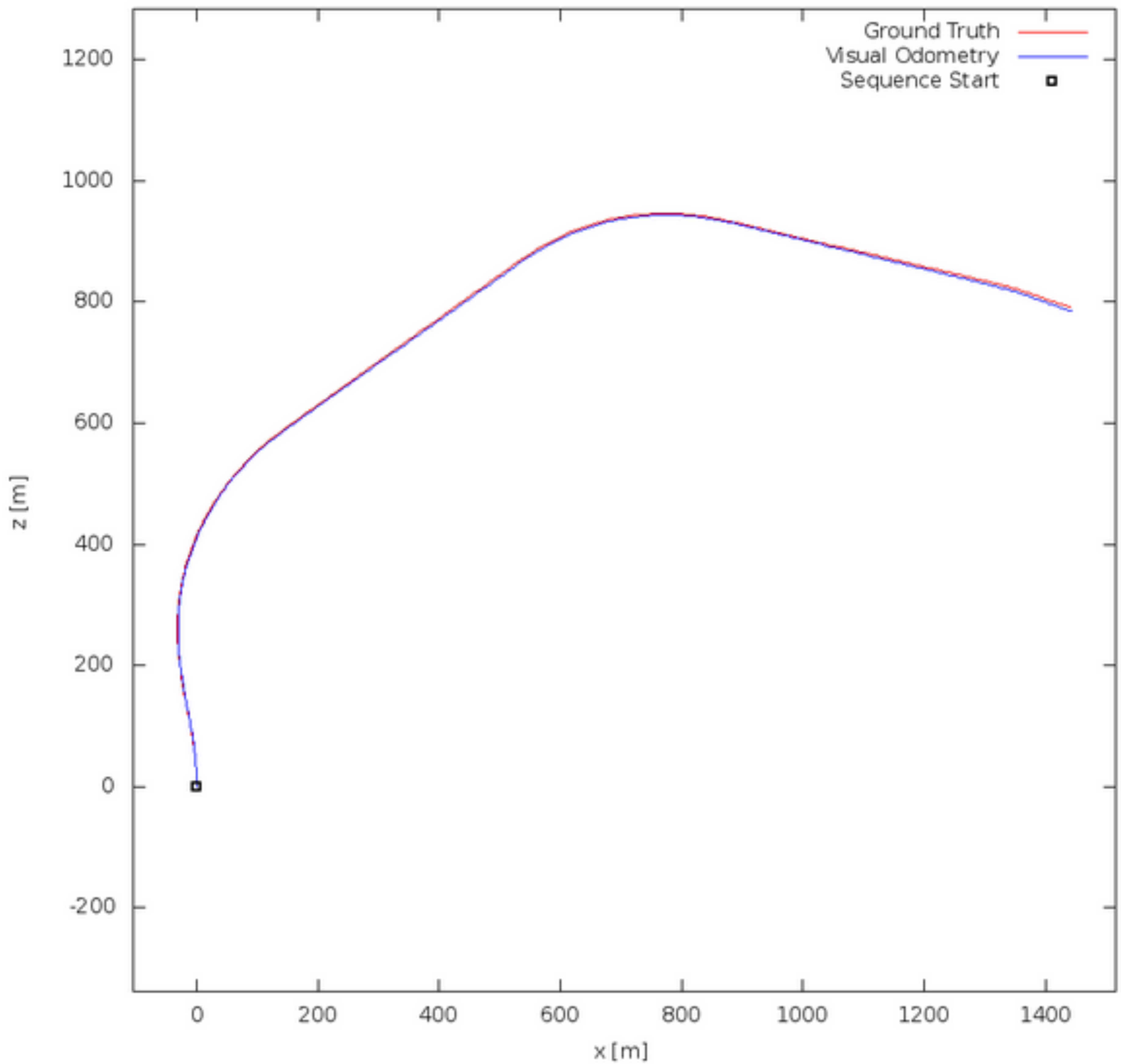
[M. Brubaker, A. Geiger and R. Urtasun, CVPR13 best paper runner up award]

Rank	Method	Setting	Code	Translation	Rotation	Runtime	Environment	Compare
1	V-LOAM			**0.75 %**	**0.0018 [deg/m]**	0.3 s	4 cores @ 2.5 Ghz (C/C++)	
J. Zhang and S. Singh: Visual-lidar Odometry and Mapping: Low- rift, Robust, and Fast. IEEE International Conference on Robotics and Automation(ICRA) 2015.								
2	LOAM		code	0.88 %	0.0022 [deg/m]	1.0 s	2 cores @ 2.5 Ghz (C/C++)	
J. Zhang and S. Singh: LOAM: Lidar Odometry and Mapping in Real-time. Robotics: Science and Systems Conference (RSS) 2014.								
3	SOFT			1.03 %	0.0029 [deg/m]	0.1 s	2 cores @ 2.5 Ghz (C/C++)	
Anonymous submission								
4	cv4xv1-sc			1.09 %	0.0029 [deg/m]	0.145 s	GPU @ 3.5 Ghz (C/C++)	
Anonymous submission								
5	DEMO		code	1.14 %	0.0049 [deg/m]	0.1 s	4 cores @ 2.5 Ghz (C/C++)	
J. Zhang, M. Kaess and S. Singh: Real-time Depth Enhanced Monocular Odometry. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2014.								
6	MFI			1.30 %	0.0030 [deg/m]	0.1 s	1 core @ 2.2 Ghz (C/C++)	
H. Badino, A. Yamamoto and T. Kanade: Visual Odometry by Multi-frame Feature Integration. First International Workshop on Computer Vision for Autonomous Driving at ICCV 2013. H. Badino and T. Kanade: A Head-Wearable Short-Baseline Stereo System for the Simultaneous Estimation of Structure and Motion. IAPR Conference on Machine Vision Application 2011.								
7	TLBBA			1.36 %	0.0038 [deg/m]	0.1 s	1 Core @2.8GHz (C/C++)	
W. Lu, Z. Xiang and J. Liu: High-performance visual odometry with two- stage local binocular BA and GPU. Intelligent Vehicles Symposium (IV), 2013 IEEE 2013.								
8	2FO-CC			1.37 %	0.0035 [deg/m]	0.1 s	1 core @ 3.0 Ghz (C/C++)	
I. Krešo and S. Šegvić: Improving the Egomotion Estimation by Correcting the Calibration Bias. VISAPP 2015.								
9	VoBa			1.46 %	0.0030 [deg/m]	0.1 s	1 core @ 2.0 Ghz (C/C++)	
10	SSLAM			1.57 %	0.0044 [deg/m]	0.5 s	8 cores @ 3.5 Ghz (C/C++)	
F. Bellavia, M. Fanfani, F. Pazzaglia and C. Colombo: Robust Selective Stereo SLAM without Loop Closure and Bundle Adjustment.. ICIAP (1) 2013.								

Sequence 11

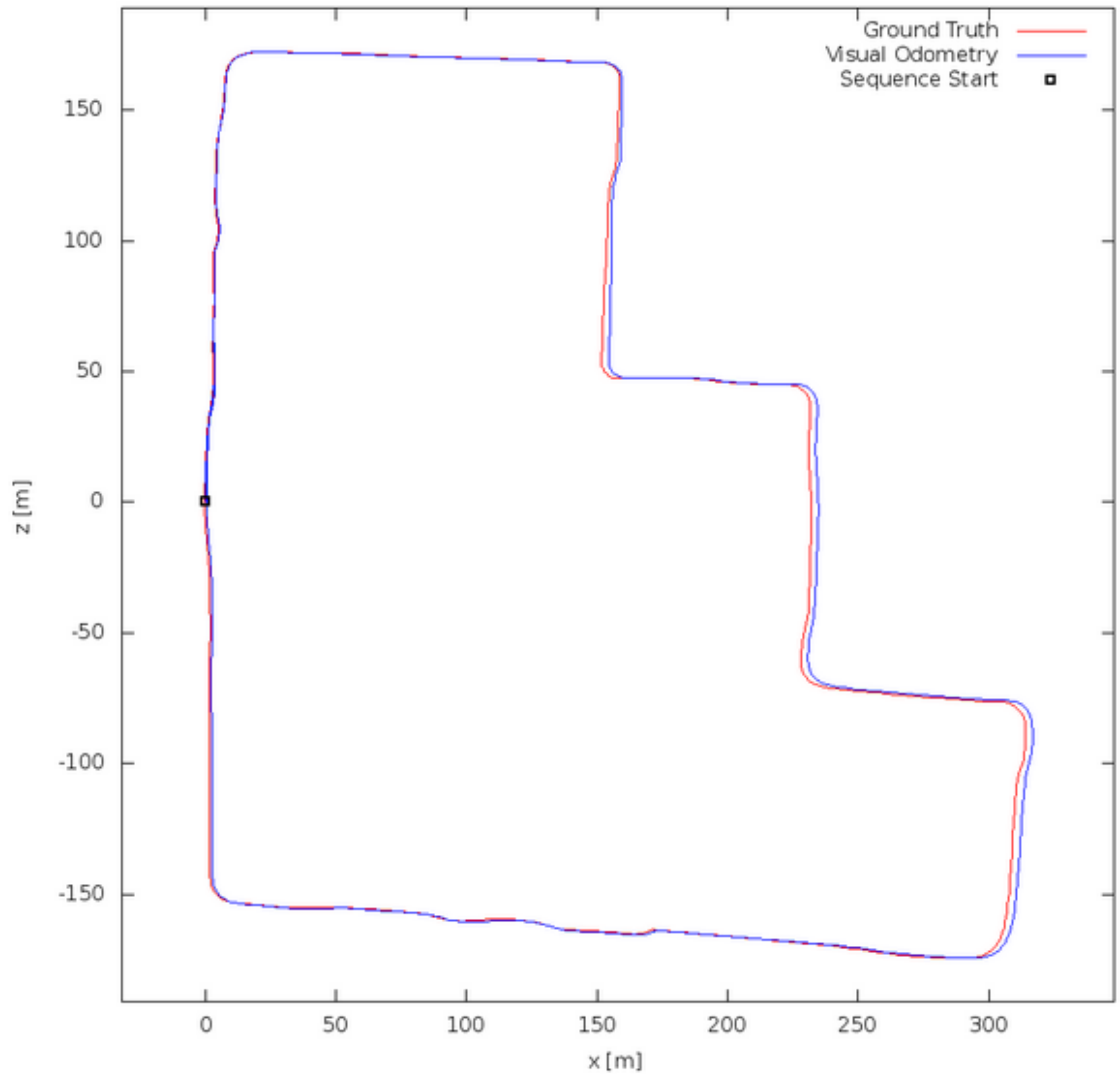

Ground Truth
Visual Odometry
Sequence Start
z [m]
x [m]
600
500
400
300
200
100
0
-300
-200
-100
0
100
200
300

Sequence 12



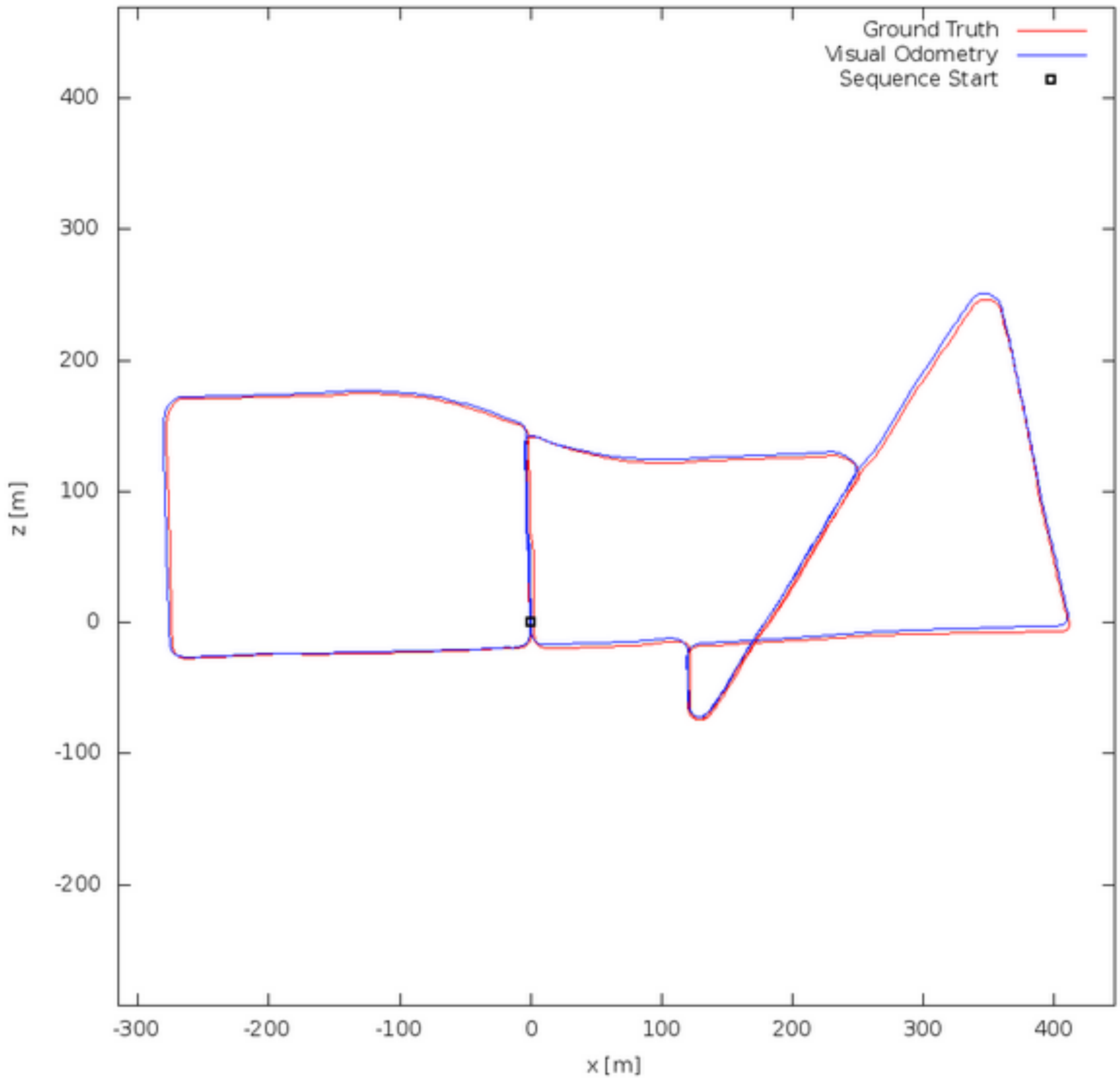
Ground Truth
Visual Odometry
Sequence Start
1200
1000
800
600
400
200
0
-200
z [m]
0
200
400
600
800
1000
1200
1400
x [m]

Sequence 15



Ground Truth
Visual Odometry
Sequence Start
150
100
50
0
-50
-100
-150
z [m]
0
50
100
150
200
250
300
x [m]

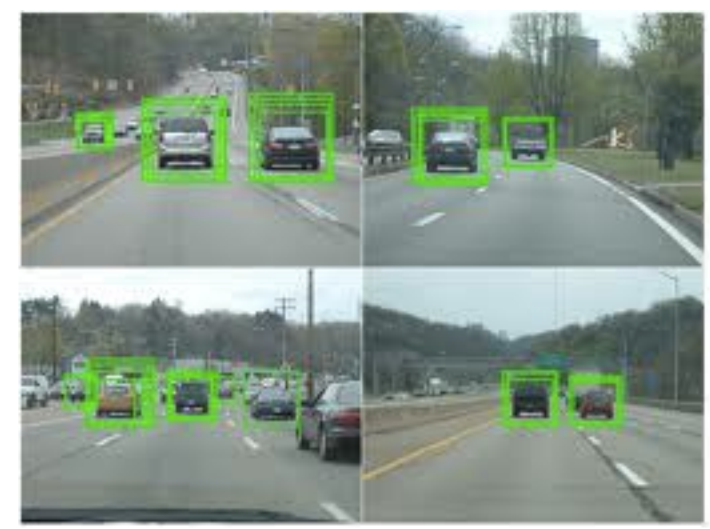
Sequence 13



Ground Truth
Visual Odometry
Sequence Start
400
300
200
100
0
-100
-200
z [m]
-300
-200
-100
0
100
200
300
400
x [m]

Detection

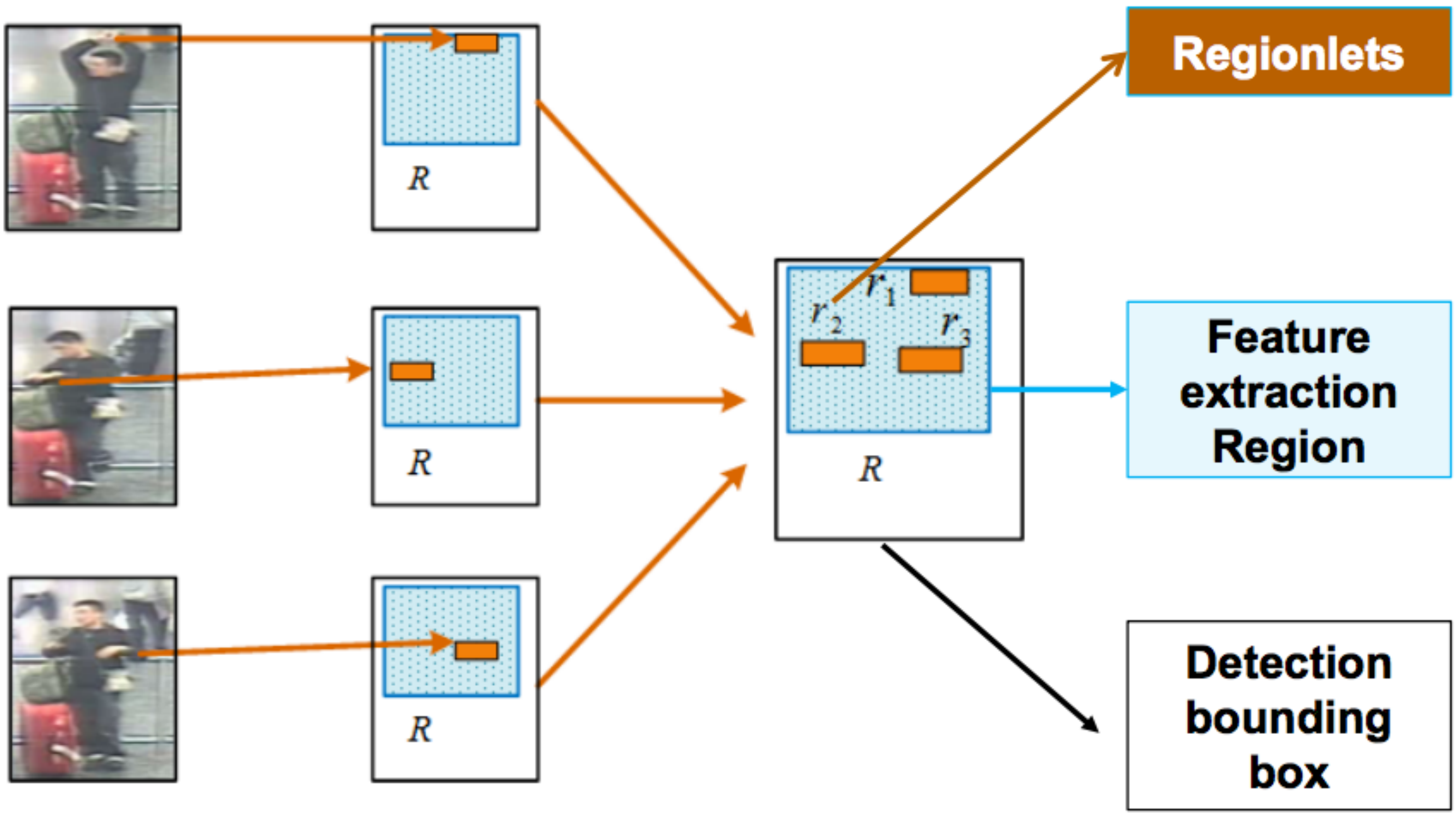
- Car, Pedestrian, Cyclist detection
- Object Detection and Orientation Estimation



Car

<table>
<tr><th>Rank</th><th>Method</th><th>Setting</th><th>Code</th><th>Moderate</th><th>Easy</th><th>Hard</th><th>Runtime</th><th>Environment</th><th>Compare</th></tr>
<tr><td>1</td><td>V C</td><td></td><td></td><td>85.74 %</td><td>83.63 %</td><td>76.71 %</td><td>15 s</td><td>GPU @ 2.5 Ghz (C/C++)</td><td></td></tr>
<tr><td>2</td><td>DeepInsight</td><td></td><td></td><td>84.40 %</td><td>84.59 %</td><td>76.09 %</td><td>2 s</td><td>>8 core @ 2.5 Ghz (C/C++)</td><td></td></tr>
<tr><td>3</td><td>Regionlets</td><td></td><td></td><td>76.45 %</td><td>84.75 %</td><td>59.70 %</td><td>1 s</td><td>>8 cores @ 2.5 Ghz (C/C++)</td><td></td></tr>
<tr><td colspan="10">X. Wang, M. Yang, S. Zhu and Y. Lin: Regionlets for Generic Object Detection. International Conference on Computer Vision 2013.
C. Long, X. Wang, G. Hua, M. Yang and Y. Lin: Accurate Object Detection with Location Relaxation and Regionlets Relocalization. Asian Conference on Computer Vision 2014.</td></tr>
<tr><td>4</td><td>3DVP</td><td></td><td></td><td>75.77 %</td><td>87.46 %</td><td>65.38 %</td><td>40 s</td><td>8 cores @ 3.5 Ghz (Matlab + C/C++)</td><td></td></tr>
<tr><td colspan="10">Y. Xiang, W. Choi, Y. Lin and S. Savarese: Data-Driven 3D Voxel Patterns for Object Category Recognition. IEEE Conference on Computer Vision and Pattern Recognition 2015.</td></tr>
<tr><td>5</td><td>SubCat</td><td></td><td>code</td><td>75.46 %</td><td>84.14 %</td><td>59.71 %</td><td>0.7 s</td><td>6 cores @ 2.5 Ghz (Matlab + C/C++)</td><td></td></tr>
<tr><td colspan="10">E. Ohn-Bar and M. Trivedi: Learning to Detect Vehicles by Clustering Appearance Patterns. T-ITS 2015.</td></tr>
<tr><td>6</td><td>SS</td><td></td><td></td><td>74.30 %</td><td>85.03 %</td><td>59.48 %</td><td>0.3 s</td><td>4 cores @ 2.5 Ghz (Matlab + C/C++)</td><td></td></tr>
<tr><td colspan="10">Anonymous submission</td></tr>
<tr><td>7</td><td>AOG</td><td></td><td>code</td><td>71.88 %</td><td>84.36 %</td><td>59.27 %</td><td>3 s</td><td>4 cores @ 2.5 Ghz (Matlab)</td><td></td></tr>
<tr><td colspan="10">B. Li, T. Wu and S. Zhu: Integrating Context and Occlusion for Car Detection by Hierarchical And-Or Model. ECCV 2014.</td></tr>
<tr><td>8</td><td>SVM-Res</td><td></td><td></td><td>67.49 %</td><td>78.11 %</td><td>54.28 %</td><td>10 s</td><td>4 cores @ 2.5 Ghz (Matlab)</td><td></td></tr>
<tr><td colspan="10">Anonymous submission</td></tr>
<tr><td>9</td><td>SubCat</td><td></td><td></td><td>66.32 %</td><td>81.94 %</td><td>51.10 %</td><td>0.3 s</td><td>6 cores @ 2.5 Ghz (Matlab + C/C++)</td><td></td></tr>
<tr><td colspan="10">E. Ohn-Bar and M. Trivedi: Learning to Detect Vehicles by Clustering Appearance Patterns. T-ITS 2015.
E. Ohn-Bar and M. Trivedi: Fast and Robust Object Detection Using Visual Subcategories. Computer Vision and Pattern Recognition Workshops Mobile Vision 2014.</td></tr>
<tr><td>10</td><td>OC-DPM</td><td></td><td></td><td>65.95 %</td><td>74.94 %</td><td>53.86 %</td><td>10 s</td><td>8 cores @ 2.5 Ghz (Matlab)</td><td></td></tr>
<tr><td colspan="10">B. Pepik, M. Stark, P. Gehler and B. Schiele: Occlusion Patterns for Object Class Detection. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2013.</td></tr>
</table>

Regionlets for Generic Object Detection, ICCV 2013



Tracking

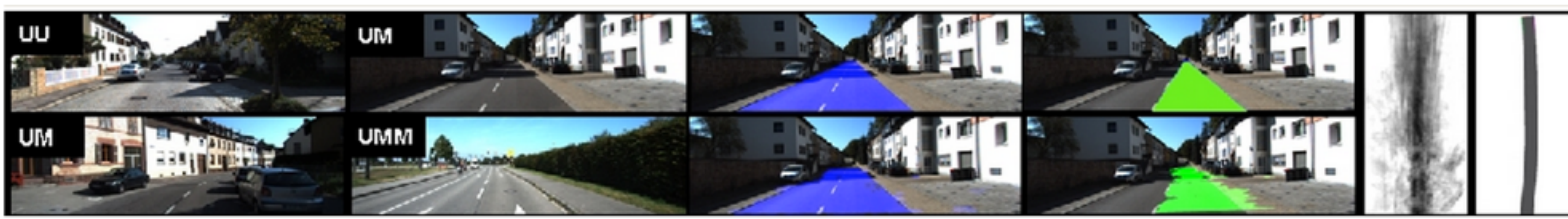
- Car and Pedestrian classes

CAR

Method	Setting	Code	MOTA	MOTP	MT	ML	IDS	FRAG	Runtime	Environment	Compare
DP_MCF		code	43.77 %	78.49 %	11.08 %	39.45 %	2738	3241	0.01 s	1 core @ 2.5 Ghz (Matlab)	☐
H. Pirsiavash, D. Ramanan and C. Fowlkes: Globally-Optimal Greedy Algorithms for Tracking a Variable Number of Objects. IEEE conference on Computer Vision and Pattern Recognition (CVPR) 2011.											
HM	O		41.56 %	78.42 %	7.74 %	42.19 %	12	578	0.01 s	1 core @ 2.5 Ghz (Python)	☐
MCF			43.63 %	78.32 %	10.93 %	40.06 %	23	591	0.01 s	1 core @ 2.5 Ghz (Python + C/C++)	☐
L. Zhang, Y. Li and R. Nevatia: Global data association for multi-object tracking using network flows.. CVPR .											
TBD		code	51.73 %	78.47 %	13.81 %	34.60 %	33	540	10 s	1 core @ 2.5 Ghz (Matlab + C/C++)	☐
A. Geiger, M. Lauer, C. Wojek, C. Stiller and R. Urtasun: 3D Traffic Scene Understanding from Movable Platforms. Pattern Analysis and Machine Intelligence (PAMI) 2014. H. Zhang, A. Geiger and R. Urtasun: Understanding High-Level Semantics by Modeling Traffic Patterns. International Conference on Computer Vision (ICCV) 2013.											
SSP			53.85 %	77.78 %	21.24 %	27.31 %	7	717	0.6s	1 core @ 2.7 Ghz (Python)	☐
Anonymous submission											
mbodSSP	O		51.64 %	77.67 %	15.02 %	29.89 %	**0**	708	0.01 s	1 core @ 2.7 Ghz (Python)	☐
Anonymous submission											
DCO		code	35.23 %	74.50 %	10.62 %	33.84 %	223	624	0.03 s	1 core @ >3.5 Ghz (Matlab + C/C++)	☐
A. Andriyenko, K. Schindler and S. Roth: Discrete-Continuous Optimization for Multi-Target Tracking. CVPR 2012.											
CEM		code	47.81 %	77.26 %	14.42 %	33.99 %	125	401	0.09 s	1 core @ >3.5 Ghz (Matlab + C/C++)	☐
A. Milan, S. Roth and K. Schindler: Continuous Energy Minimization for Multitarget Tracking. IEEE TPAMI 2014.											
NOMT			62.44 %	78.32 %	31.56 %	27.77 %	13	**159**	0.09 s	16 core @ 2.5 Ghz (C++)	☐
Anonymous submission											
NOMT-HM	O		57.55 %	78.79 %	26.86 %	30.50 %	28	253	0.09 s	8 cores @ 2.5 Ghz (Matlab + C/C++)	☐
Anonymous submission											
SSP*			66.67 %	78.64 %	40.52 %	**8.95 %**	194	977	0.6 s	1 core @ 2.7 Ghz (Python)	☐
Anonymous submission											
mbodSSP*	O		66.66 %	78.83 %	34.29 %	10.47 %	117	894	0.01 s	1 core @ 2.7 Ghz (Python)	☐
Anonymous submission											

Road Estimation

- UU - Urban unmarked
- UM - Urban Marked
- UMM - Urban Multiple Marked lanes



This benchmark has been created in collaboration with Jannik Fritsch and Tobias Kuehnl from Honda Research Institute Europe GmbH. The road and lane estimation benchmark consists of 289 training and 290 test images. It contains three different categories of road scenes:

- uu - urban unmarked (98/100)
- um - urban marked (95/96)
- umm - urban multiple marked lanes (96/94)

Road Estimation Evaluation

UM_ROAD

Rank	Method	Setting	Code	MaxF	AP	PRE	REC	FPR	FNR	Runtime	Environment	Compare
1	DDN			**93.65 %**	88.55 %	**94.28 %**	93.03 %	**2.57 %**	6.97 %	2 s	GPU @ 2.5 Ghz (Python + C/C++)	
R. Mohan: Deep Deconvolutional Networks for Scene Parsing. 2014.												
2	FusedCRF			89.55 %	80.00 %	84.87 %	**94.78 %**	7.70 %	**5.22 %**	2 s	1 core @ 2.5 Ghz (C/C++)	
Anonymous submission												
3	RD_UM			89.36 %	90.50 %	88.80 %	89.93 %	5.17 %	10.07 %	1s	1 core @ 2.5 Ghz (Python + C/C++)	
Anonymous submission												
4	CB			88.89 %	82.17 %	87.26 %	90.58 %	6.03 %	9.42 %	10 s	1 core @ 2.5 Ghz (Python)	
5	SPRAY			88.14 %	**91.24 %**	88.60 %	87.68 %	5.14 %	12.32 %	45 ms	NVIDIA GTX 580 (Python + OpenCL)	
T. Kuehnl, F. Kummert and J. Fritsch: Spatial Ray Features for Real-Time Ego-Lane Extraction. Proc. IEEE Intelligent Transportation Systems 2012.												
6	ProbBoost			87.48 %	80.13 %	85.02 %	90.09 %	7.23 %	9.91 %	2.5 min	>8 cores @ 3.0 Ghz (C/C++)	
G. Vitor, A. Victorino and J. Ferreira: A probabilistic distribution approach for the classification of urban roads in complex environments. Workshop on Modelling, Estimation, Perception and Control of All Terrain Mobile Robots on IEEE International Conference on Robotics and Automation (ICRA) 2014.												
7	NNP			87.31 %	75.72 %	85.59 %	89.10 %	6.84 %	10.90 %	5 s	4 cores @ 2.5 Ghz (Matlab)	
Anonymous submission												
8	CN24			86.32 %	89.19 %	87.80 %	84.89 %	5.37 %	15.11 %	30 s	>8 cores @ 2.5 Ghz (C/C++)	
C. Brust, S. Sickert, M. Simon, E. Rodner and J. Denzler: Convolutional Patch Networks with Spatial Prior for Road Detection and Urban Scene Understanding. VISAPP 2015 - Proceedings of the 10th International Conference on Computer Vision Theory and Applications, Berlin, Germany, 11-14 March, 2015 2015.												
9	GRES3D+VELO			85.43 %	83.04 %	82.69 %	88.37 %	8.43 %	11.63 %	60 ms	4 cores @ 2.8 Ghz (C/C++)	
Anonymous submission												
10	SPlane + BL			85.23 %	88.66 %	83.43 %	87.12 %	7.89 %	12.88 %	2 s	1 core @ 3.0 Ghz (C/C++)	
N. Einecke and J. Eggert: Block-Matching Stereo with Relaxed Fronto-Parallel Assumption. IV 2014.												

DDN : Deep Deconvolutional Networks for Scene Parsing, arXiv

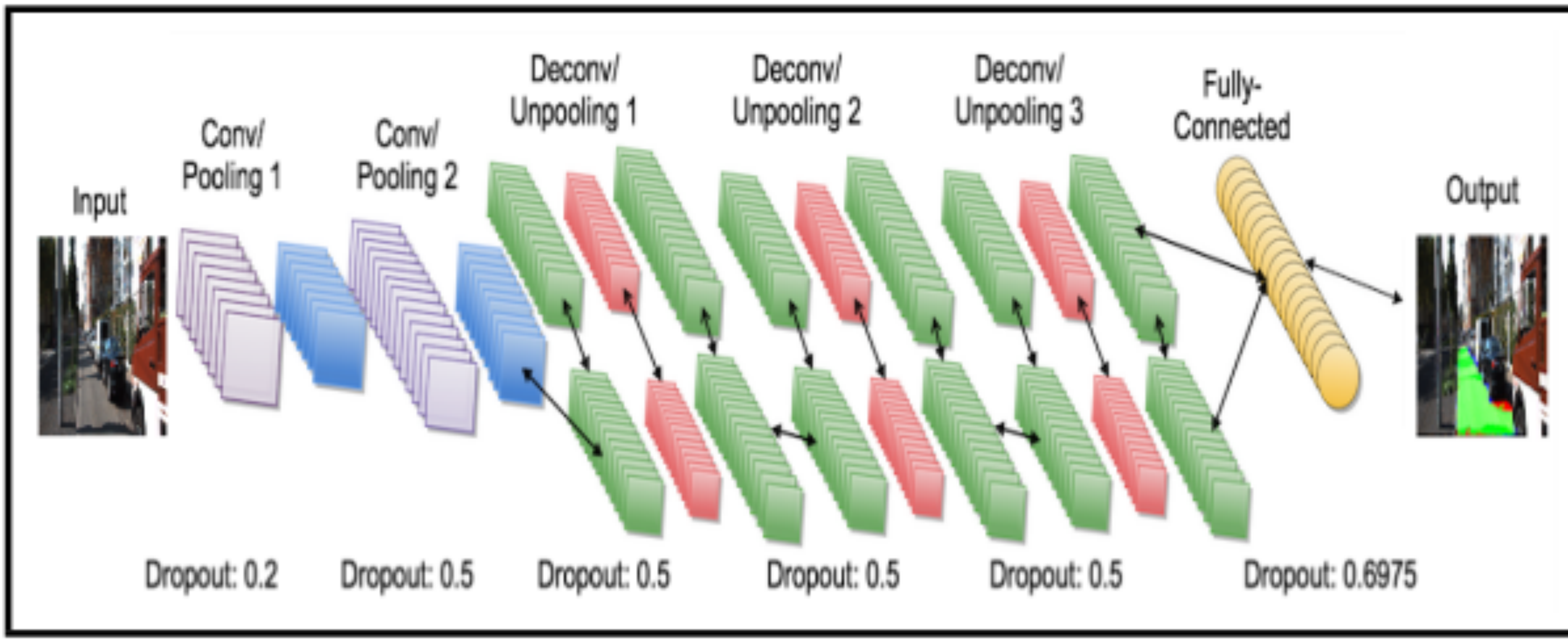
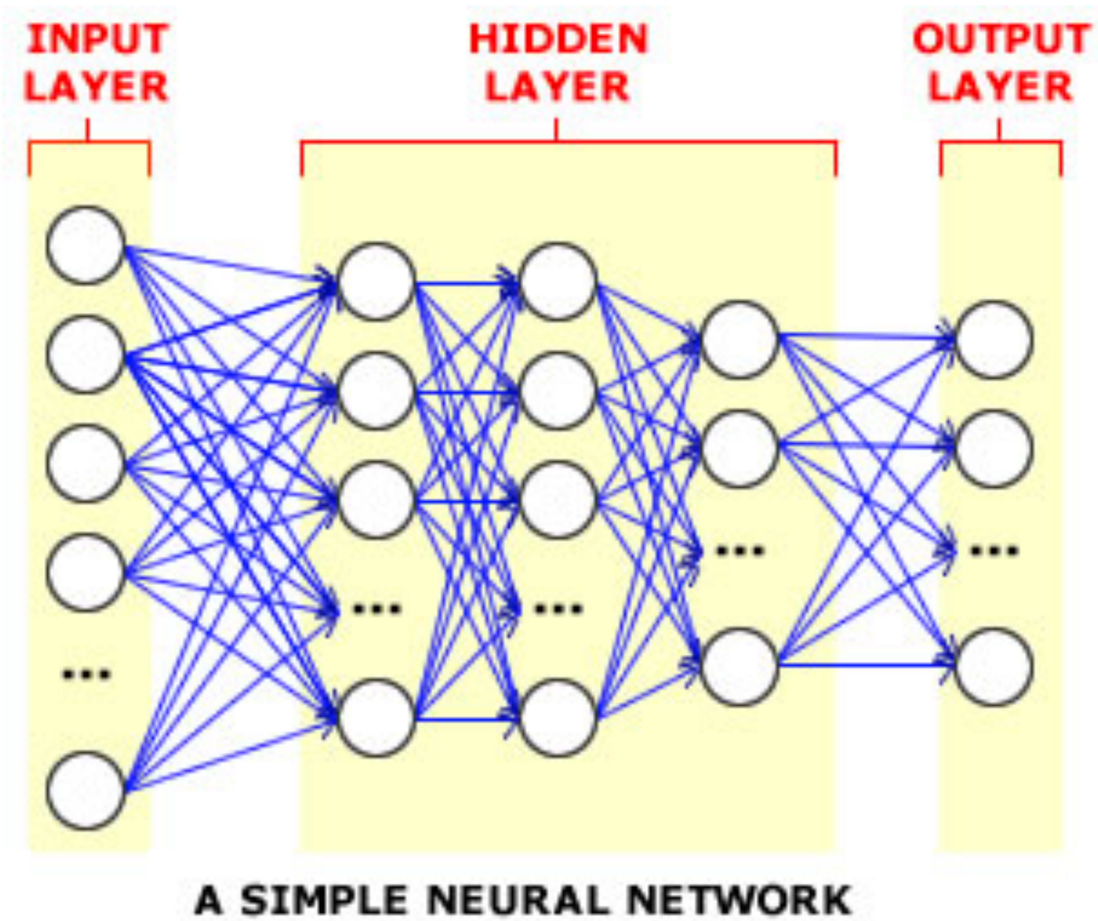


Figure 1. The architecture of our 7-layered deep network.

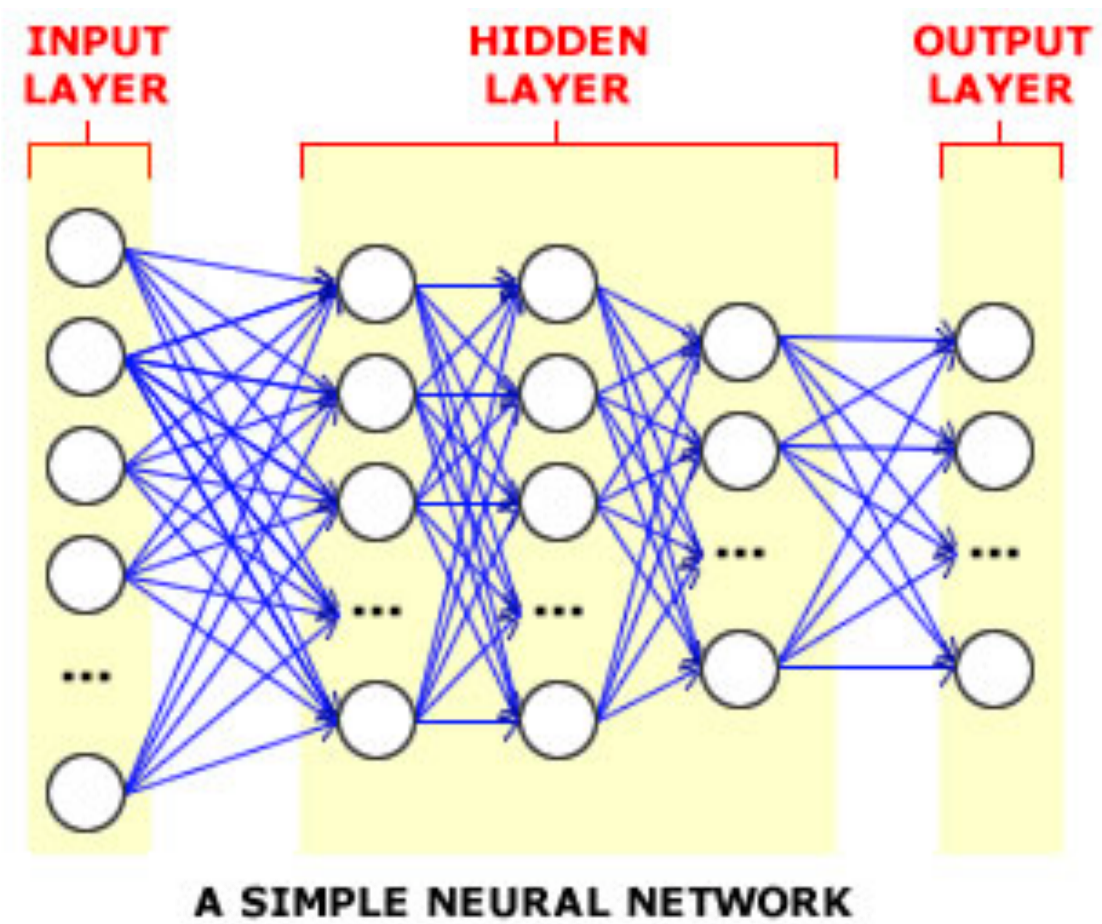
Deep Neural Networks



http://blog.peltarion.com/2014/06/22/deep-learning-and-deep-neural-networks-in-synapse/

Deep Neural Networks : **Why Popular ?**

- **GPU**
- **Large scale Data**



http://blog.peltarion.com/2014/06/22/deep-learning-and-deep-neural-networks-in-synapse/

Visualization of Results

The following images illustrate the performance of the method qualitatively on a couple of test images. We first show results in the perspecti image, followed by evaluation in bird's eye view. Here, red denotes false negatives, blue areas correspond to false positives and green represer true positives.

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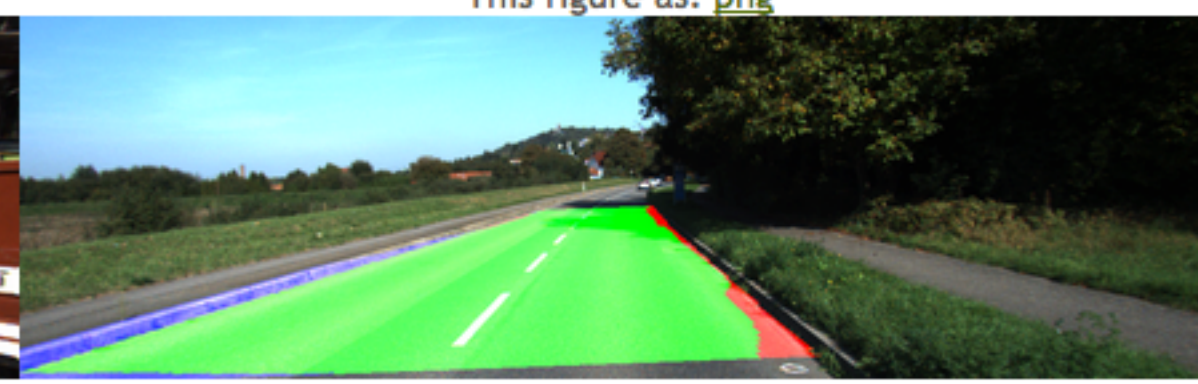

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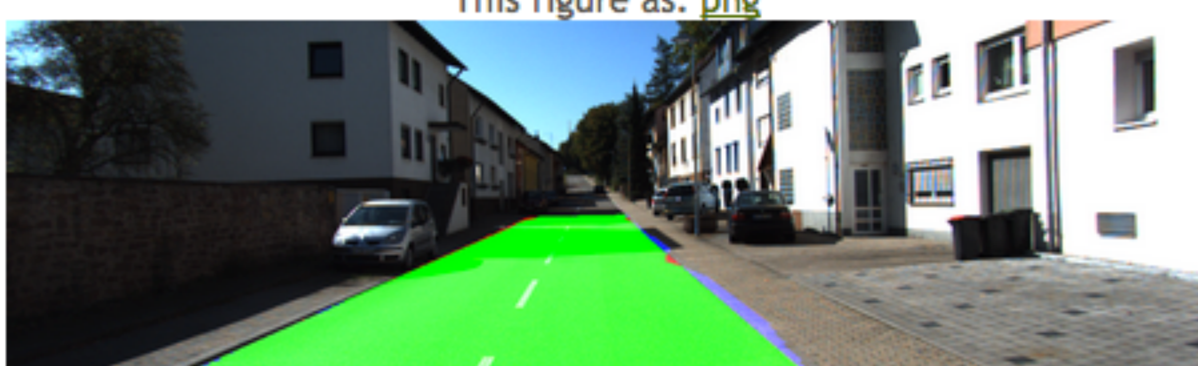

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Reference

- KITTI website : http://www.cvlibs.net/datasets/kitti/
- First International Workshop on Computer Vision for Autonomous Driving
  - Visual Scene Understanding for Autonomous Systems
  - Raquel Urtasun, University of Toronto
- Regionlet
  - http://www.xiaoyumu.com/project/kitti
- DDN
  - http://arxiv.org/pdf/1411.4101v1.pdf