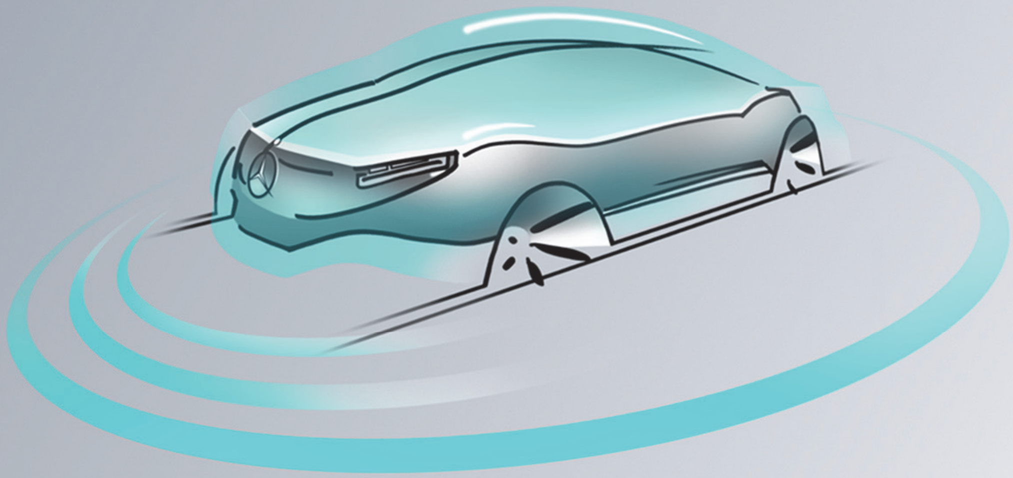


# Measuring the World:

## Designing Robust Vehicle Localization for Autonomous Driving

Frank Schuster, Dr. Martin Haueis

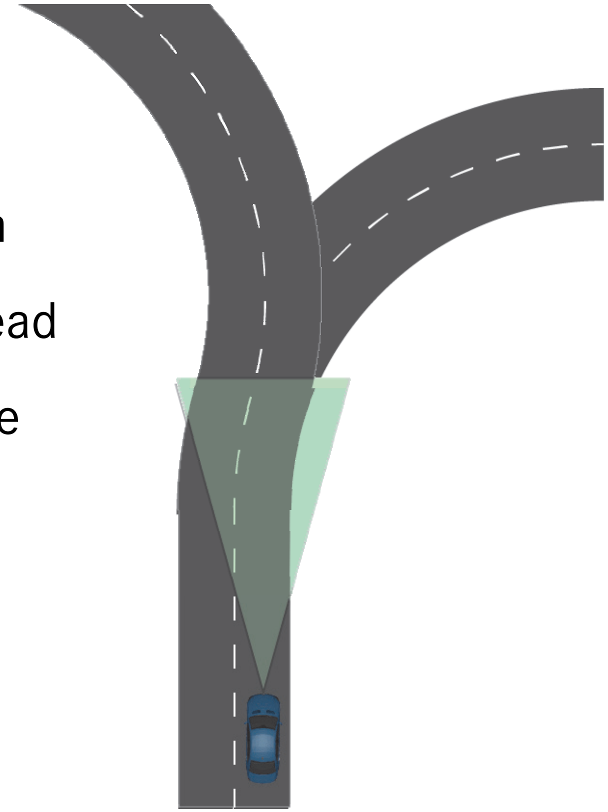
Mercedes-Benz

# Agenda

- **Motivation:** Why measure the world for autonomous driving?
- **Map Content:** What do we need to know about the world for autonomous driving?
- **Mapping Algorithms:** How can we measure the world?
- **Challenges:** But can we really measure the entire world?

# Why measure the world for autonomous driving?

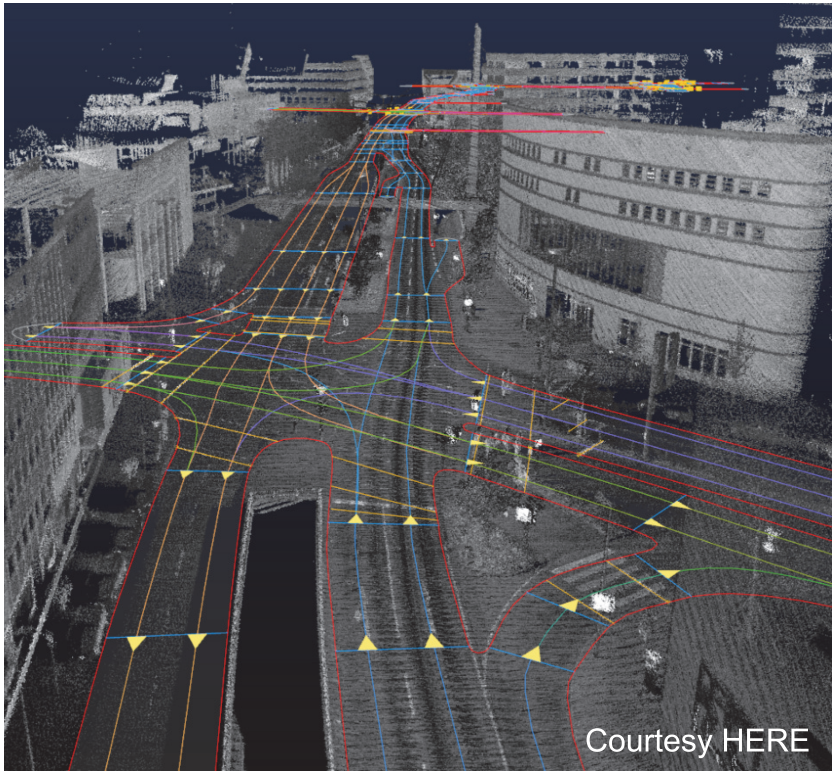
- Typical sensor range (stereo camera) approx. 40 m
- To drive autonomously, planning 5-10 seconds ahead
- Need to know information beyond the sensor range
- Highly accurate and up-to-date maps to calculate drivable area
- Reliable localization algorithms to choose map segment



# What do we need to know about the world for autonomous driving?

- Navigation Maps: Information per road
- Autonomous Driving: Information per lane
  - planning information (speed limits, lane merges, intersections)
  - Localization information (sensor compatible representation of the environment)

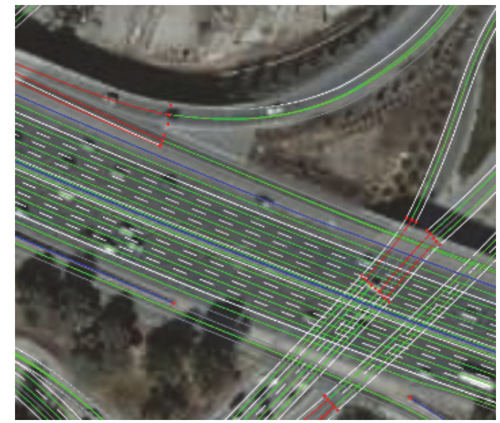
⇒ How can we do this?



# Map Content

1 Courtesy HERE

2 Courtesy Mapillery



3 Courtesy HERE

1. Road Connectivity for navigation
2. Precise road geometry for path planning
3. Semantic information for situation analysis and localization



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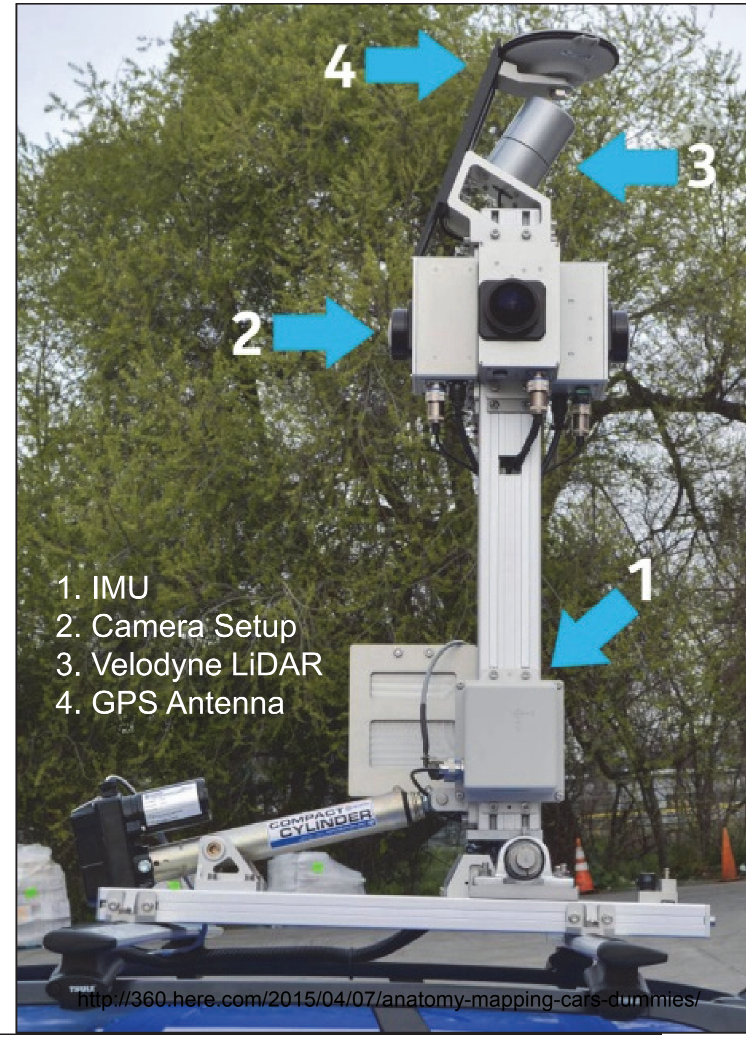
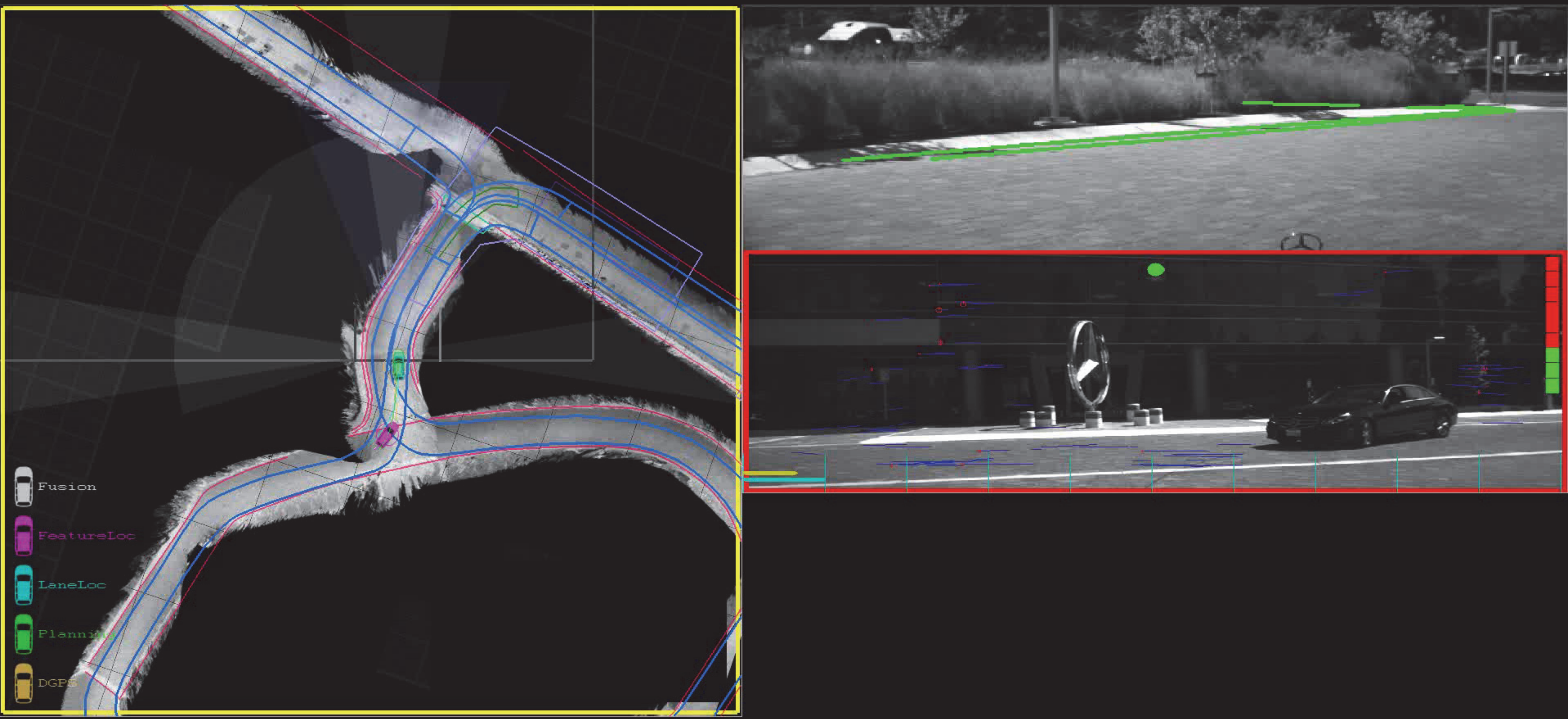
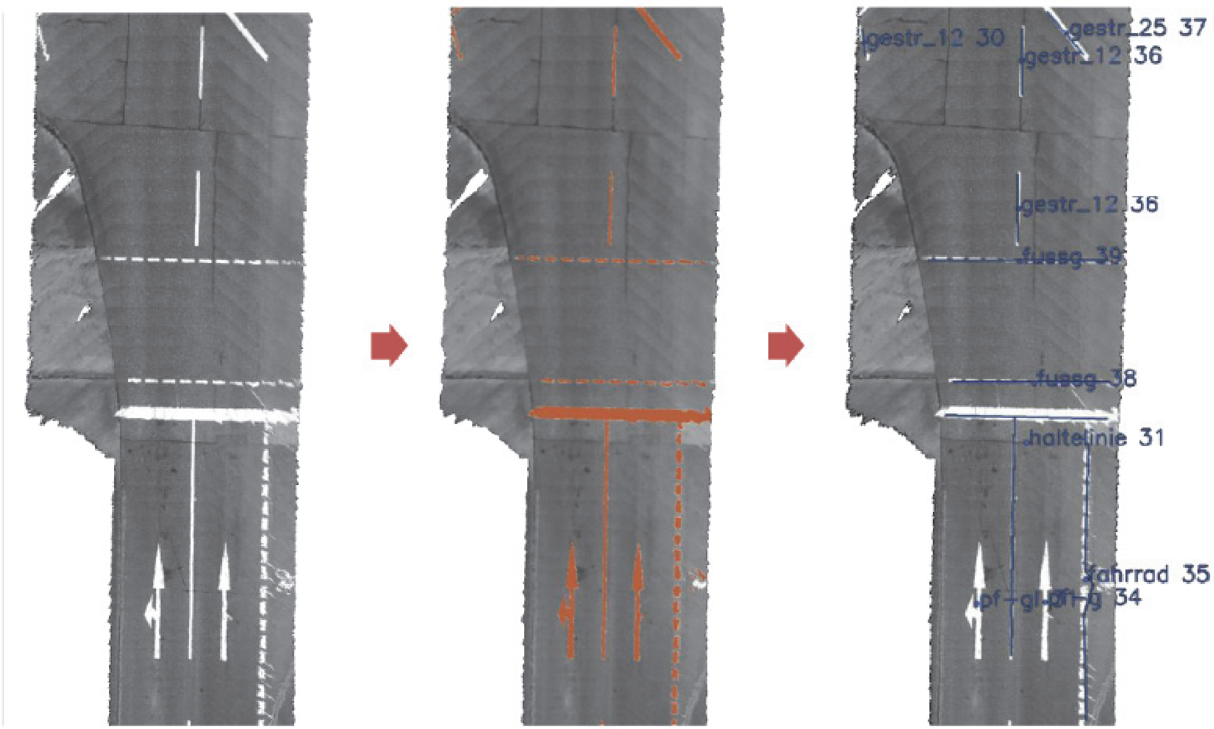
# Mapping Today @ HERE

- Mapping of the world with LiDAR and camera setups combined with RTK GPS
- Data mining and Deep Learning algorithms extract significant objects (lanes, speed limits, localization objects, …) from raw data in post processing
- GPS for precise geolocation of all map attributes



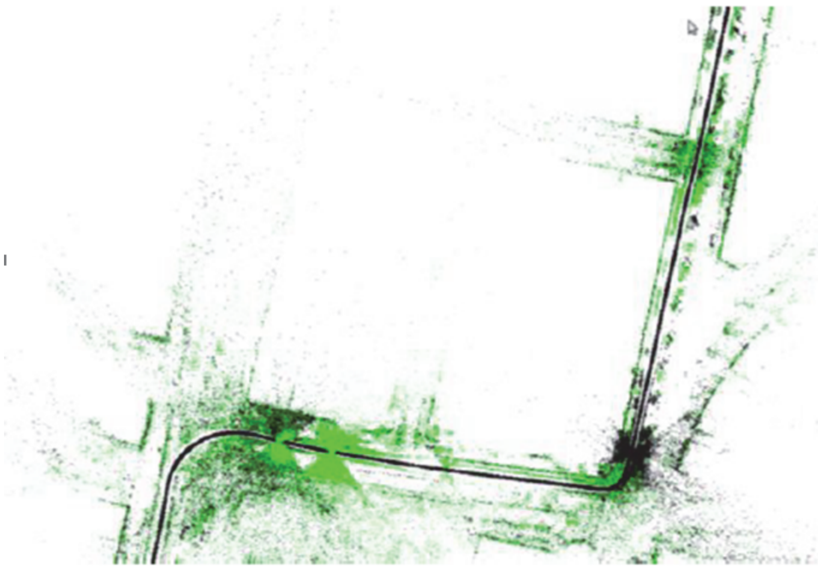

Fusion
FeatureLoc
LaneLoc
DGPS

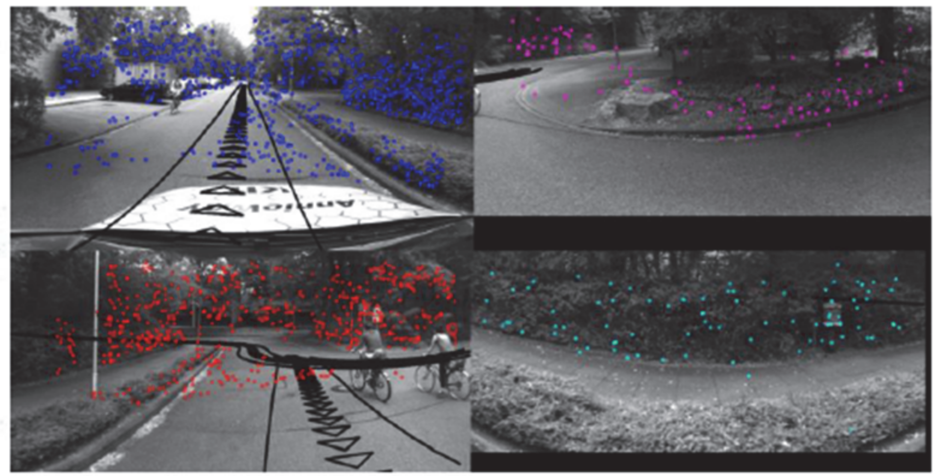
# Increasing the Robustness of the Mapping Process - Automation




Courtesy FZI@KIT (C. Stiller)

# Increasing the Robustness of the Mapping Process – Sensor Setup

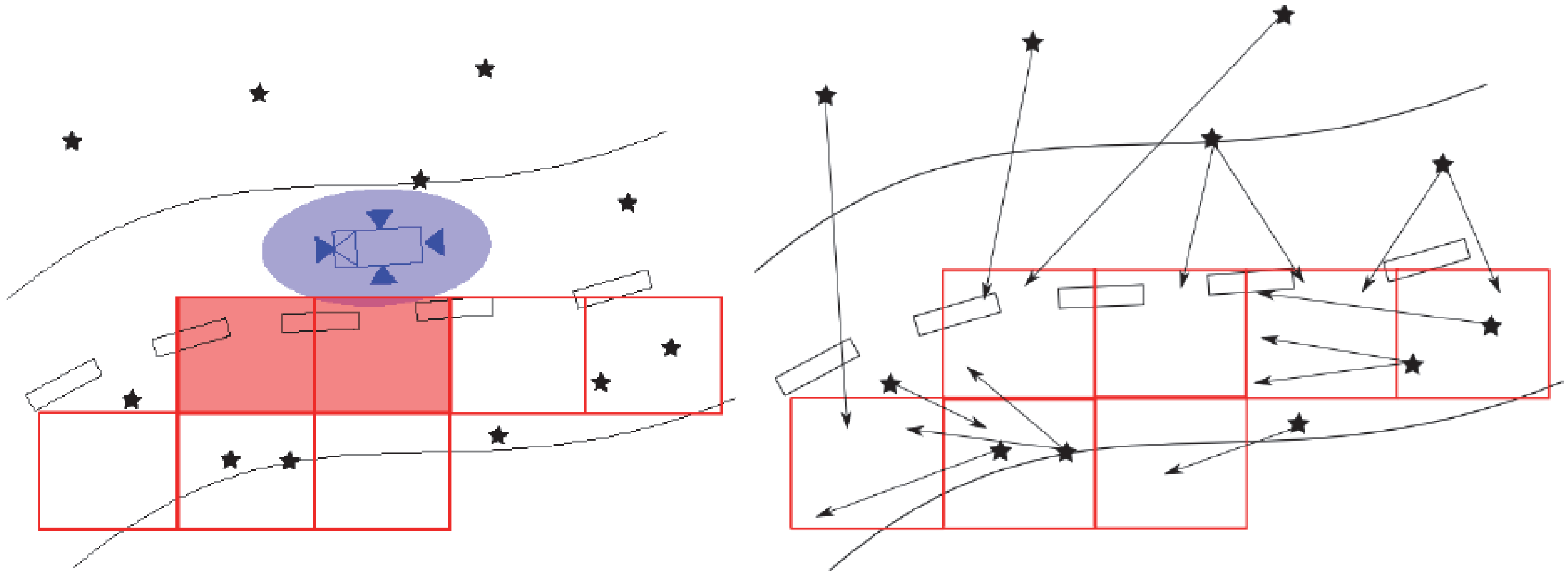




mapped in front camera
mapped in rear camera
mapped in left camera
mapped in right camera

Courtesy FZI@KIT (C. Stiller)

# Increasing the Robustness of the Mapping Process – Data Representation



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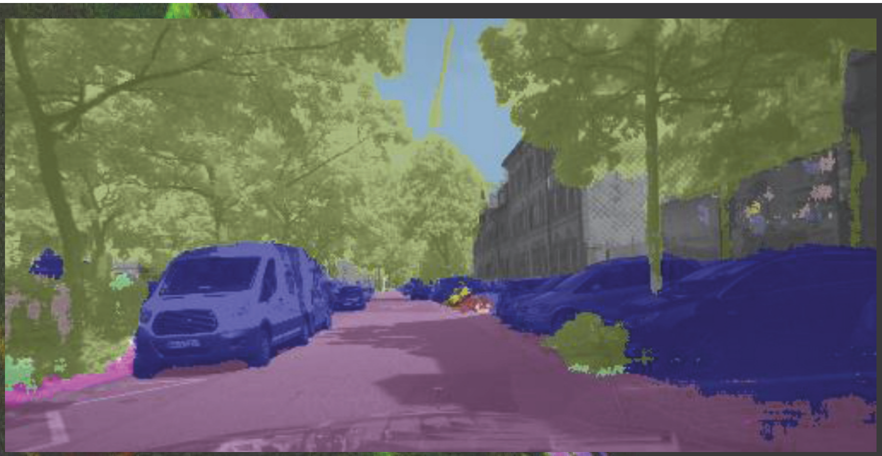
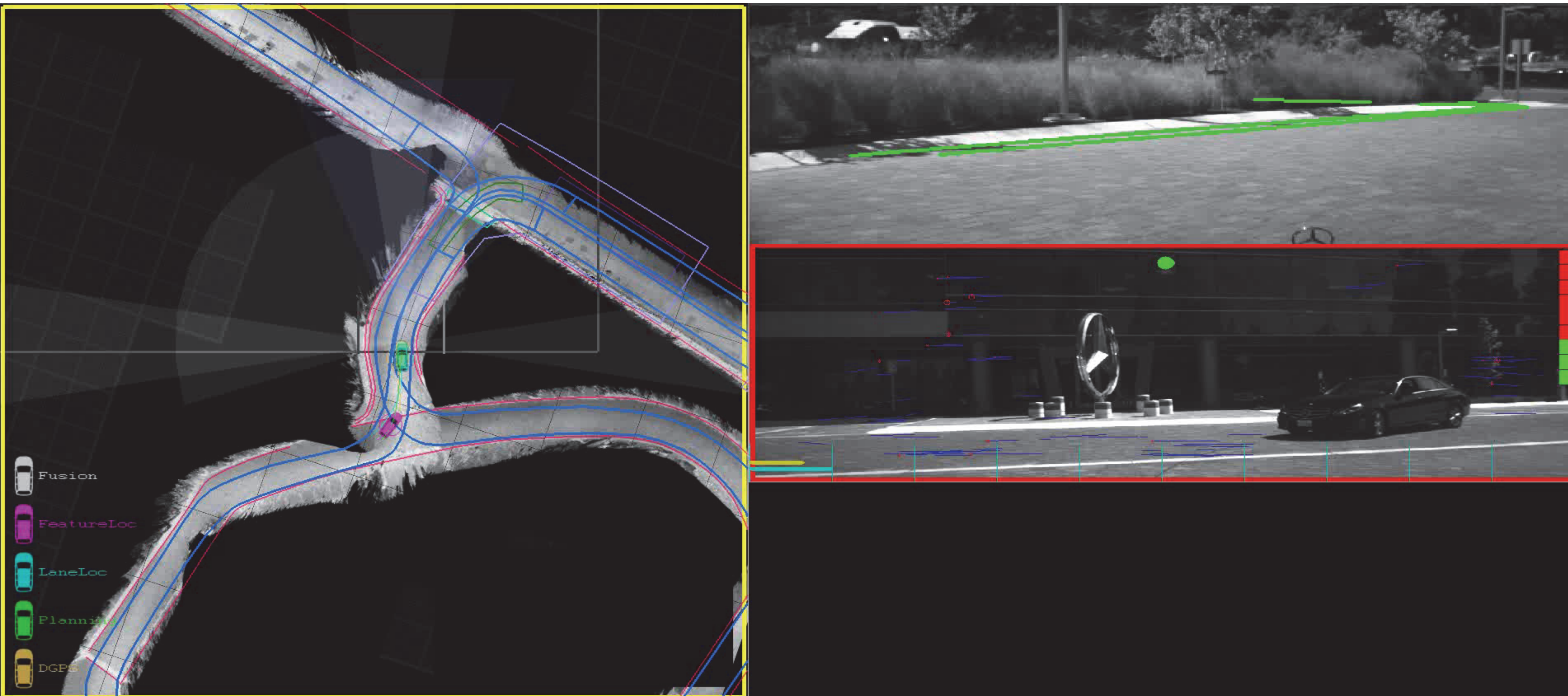
# Industrialization

- Minimal set of specifiable landmarks
- Simple representation
- Robust object classes that are detectable by automotive grade sensors

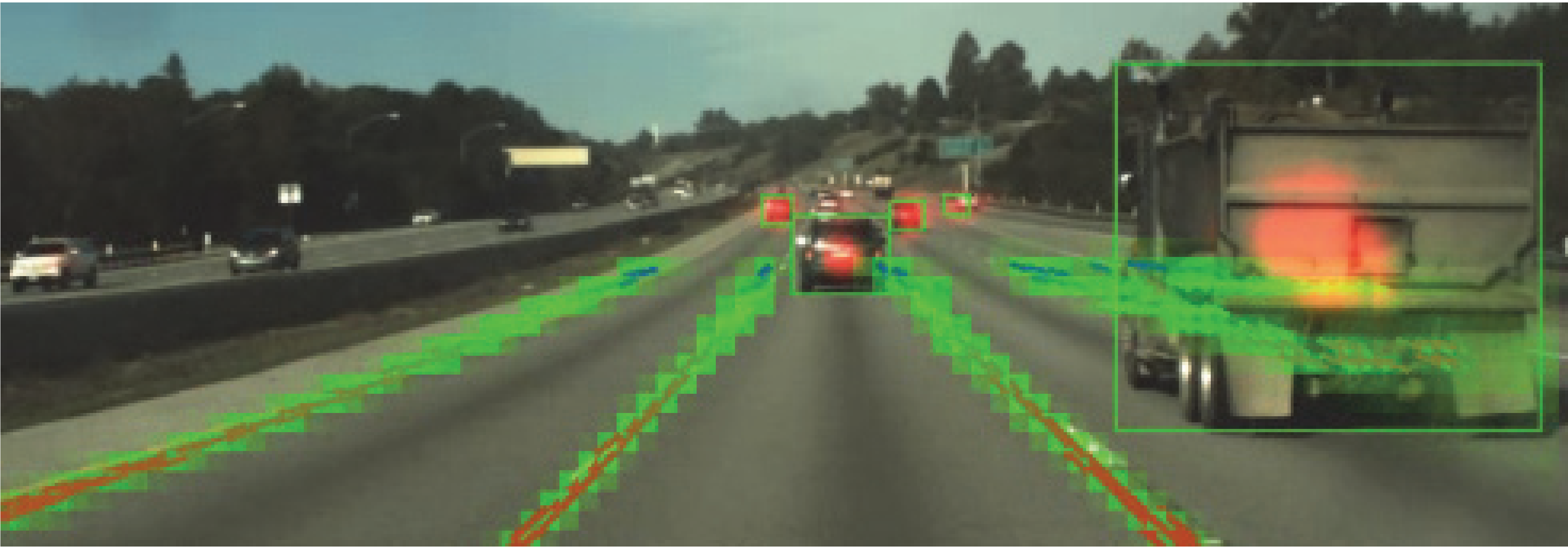


# Mapping Algorithms – Grid

# Mapping Algorithms - Features



# Mapping Algorithms - Context



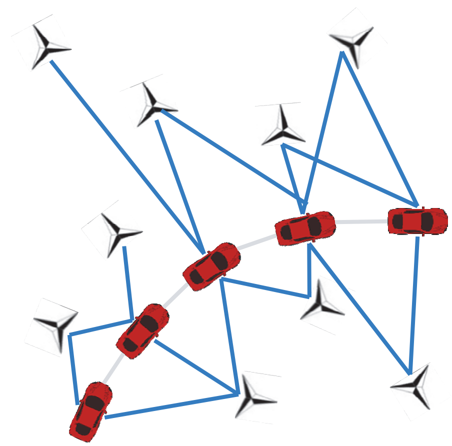
Need a more high level representation of the world to achive both scalability, accuracy and integrity requirements.

Source: An Empirical Evaluation of Deep Learning on Highway Driving, 04/2015, Standford University, Brody Huval et al.

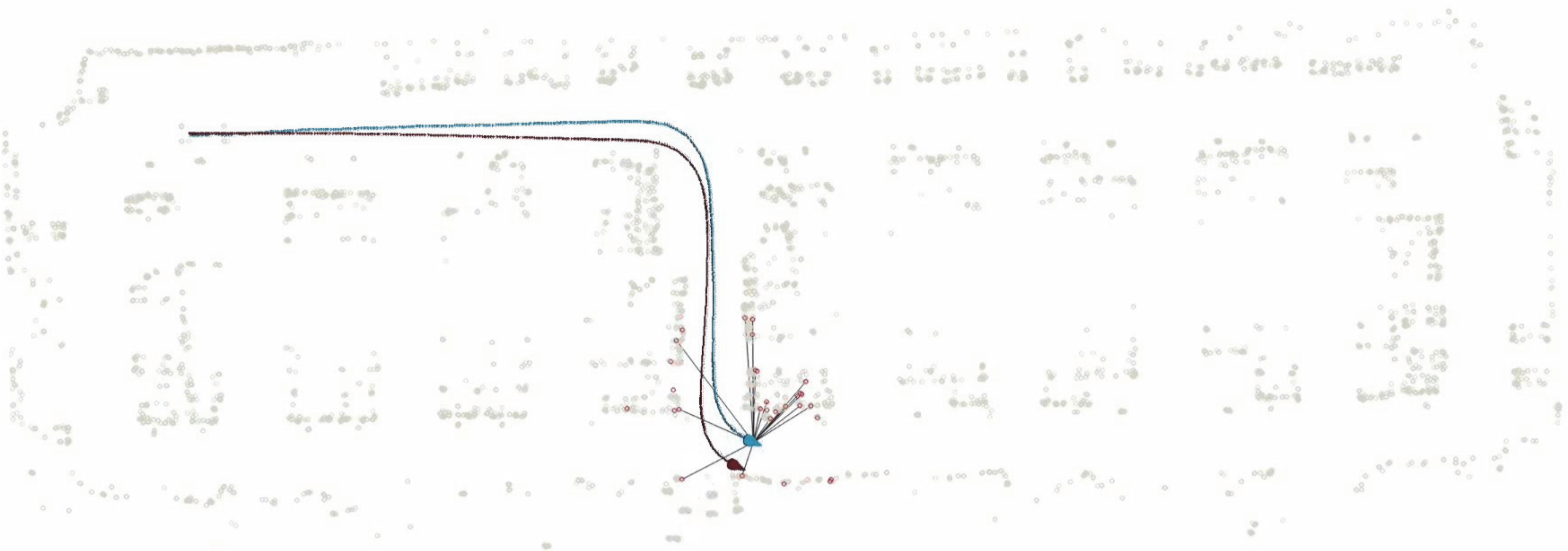
# Scalability: Exploration of new Areas
# Initial Map

- Constraints forming graph map
  $J_0 = j_{initial} + j_p + j_{lm}$
  - Solve GraphSLAM problem by graph optimization $\min_{p,lm} J_0$
- Result:
  - optimized mapping trajectory ($p$)
  - Optimized radar landmarks ($lm$)

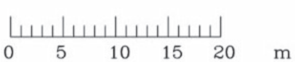
=> Optimized landmark positions $lm$ used for localization



# Localization



estimated pose · odometry



# Scalability: Exploration of new Areas
# Fully performing map

- Constraints forming graph map

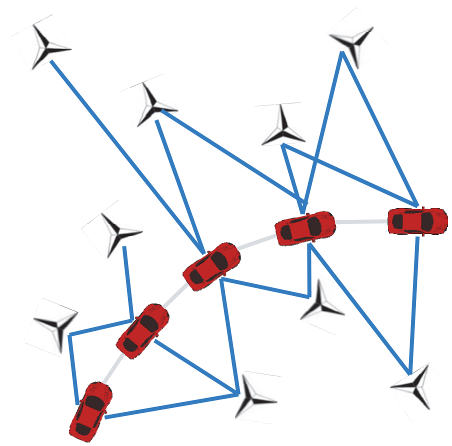
  $J_0 = j_{initial} + j_p + j_{lm}$

  - Solve GraphSLAM problem by graph optimization $\min\limits_{p,lm} J_0$

- Now: Consider $J_0 \dots J_{n-1}$ graph maps

  - Then we can find an overall cost function

=> Optimizing $J_{tot}$ yields $p$ and $lm$ for all trajectories



$$J_{tot} = \sum_{i=0}^{n-1} J_i + \sum_{i=0,j=0}^{n-1} J_{ij}$$

Cost of all maps by themselves

Cost of interactions between maps


0 5 10 15 20 m

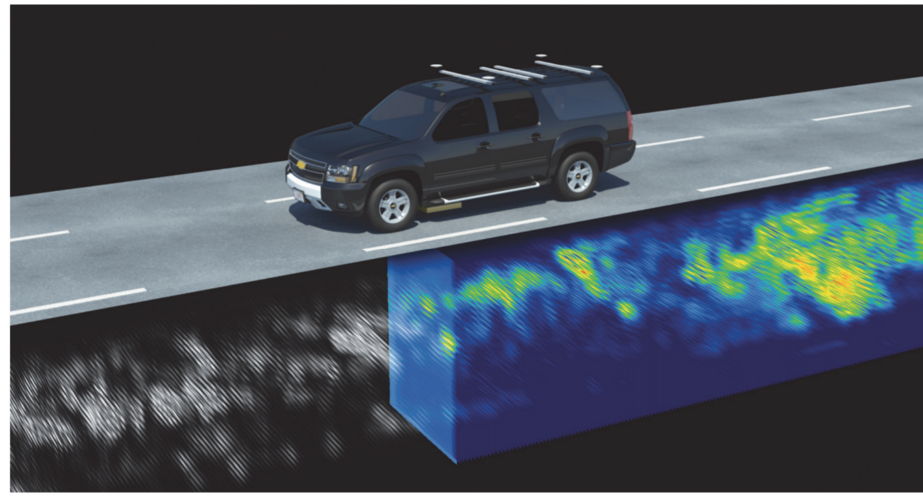
# Collective Mapping – Startups show the way

Startups like Mapillary

- #CompleteTheMap - A challenge to map your city
- Mapping large areas with deep learning from dash cam images mostly
- Semantic labelling provides planning information (lane markings, traffic lighs) and localization objects

# Radar – Ground Facing

- Ground facing radar used for mapping of the density distribution below the road surface
- Highly robust towards changing weather and driving conditions (rain, snow, off-road…)
- Centimeter level accuracy and high availability



The Localizing Ground-Penetrating Radar (LGPR), courtesy MIT
https://www.ll.mit.edu/publications/technotes/TechNote_LGPR.pdf

- However radar array requires a lot of power, not applicable in production vehicles today. However automotive radars can be used.

# Scalability: Scene Understanding

- High Level features enable map updates on a large scale
- But reliable detection and classification  more difficult than ever
- Cityscapes Dataset (Vision)
    - Semantic, instance wise and dense pixel annotations
    - 30 Classes (dynamic and static)
    - 50 Cities over several months

“The Cityscapes Dataset for Semantic Urban Scene Understanding”, M. Cordts et al.

www.cityscapes-dataset.net

# Summary

- Need robust localization for path planning in autonomous driving applications
  - Localization pinpoints location in map to interpret map data correctly
- Feature Maps use sparse representations of the world, but are usually proprietary to the sensor setup and algorithms
- Goal: High Level classified feature maps that can be shared among a fleet of cars from different OEMs

# Conclusion - So, how can we measure the world?

- Using a sparse, high level description of the world
- By interpreting semantic information about the world
- By having every car with sensors contribute in map updates