Machine Learning Radar Perception for Autonomous Vehicles

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Agenda

- RadarNet Overview
- RadarNet Dynamic Obstacle Heads
- RadarNet Occupancy & Segmentation Heads
- Demo Videos

Radar Detector (NVIDIA RadarNet)

Data
- Global, multi-sensor, large volume
- Lidar-based ground truth

Input
- Point accumulation over a time window + ego motion compensation (increase density of sparse data)
- BEV projection of radar detections of surround radars
  - All radars to one image (computationally efficient)
- Multiple features (like an RBG stack)

Model (real-time emphasis)
- INT8 (QAT training)
- Few ms runtime on DRIVE Orin GPU / DLA

Output
- Obstacles (vehicle, pedestrian, motorcycle/cyclist)
  - Class head
  - Regression head
- Occupancy
  - Existence & visibility
  - Segmentation

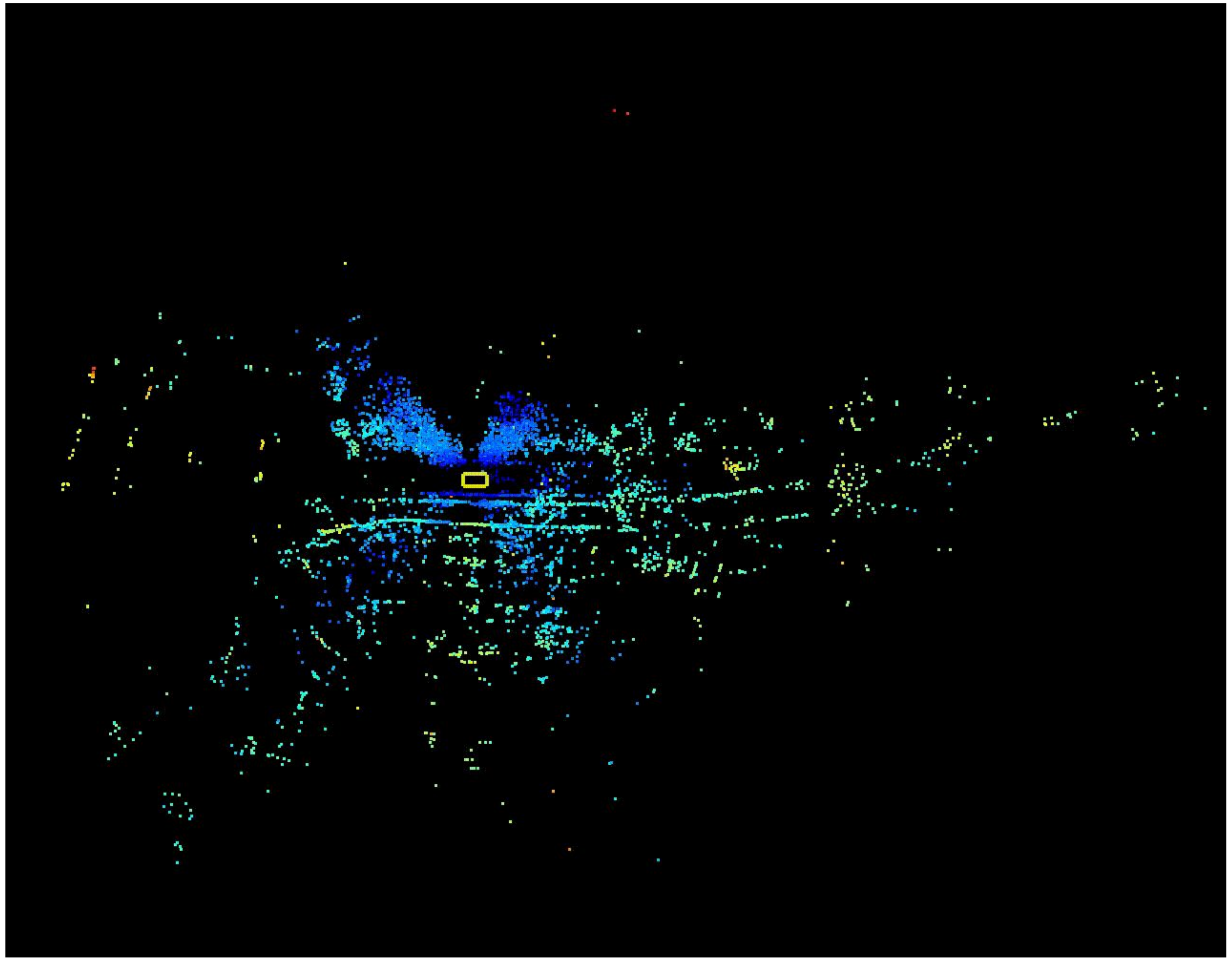


Figure: accumulated radar point cloud toggling through multiple features

Dynamic Obstacle Heads

Clustered classification & bounding box parameter regression

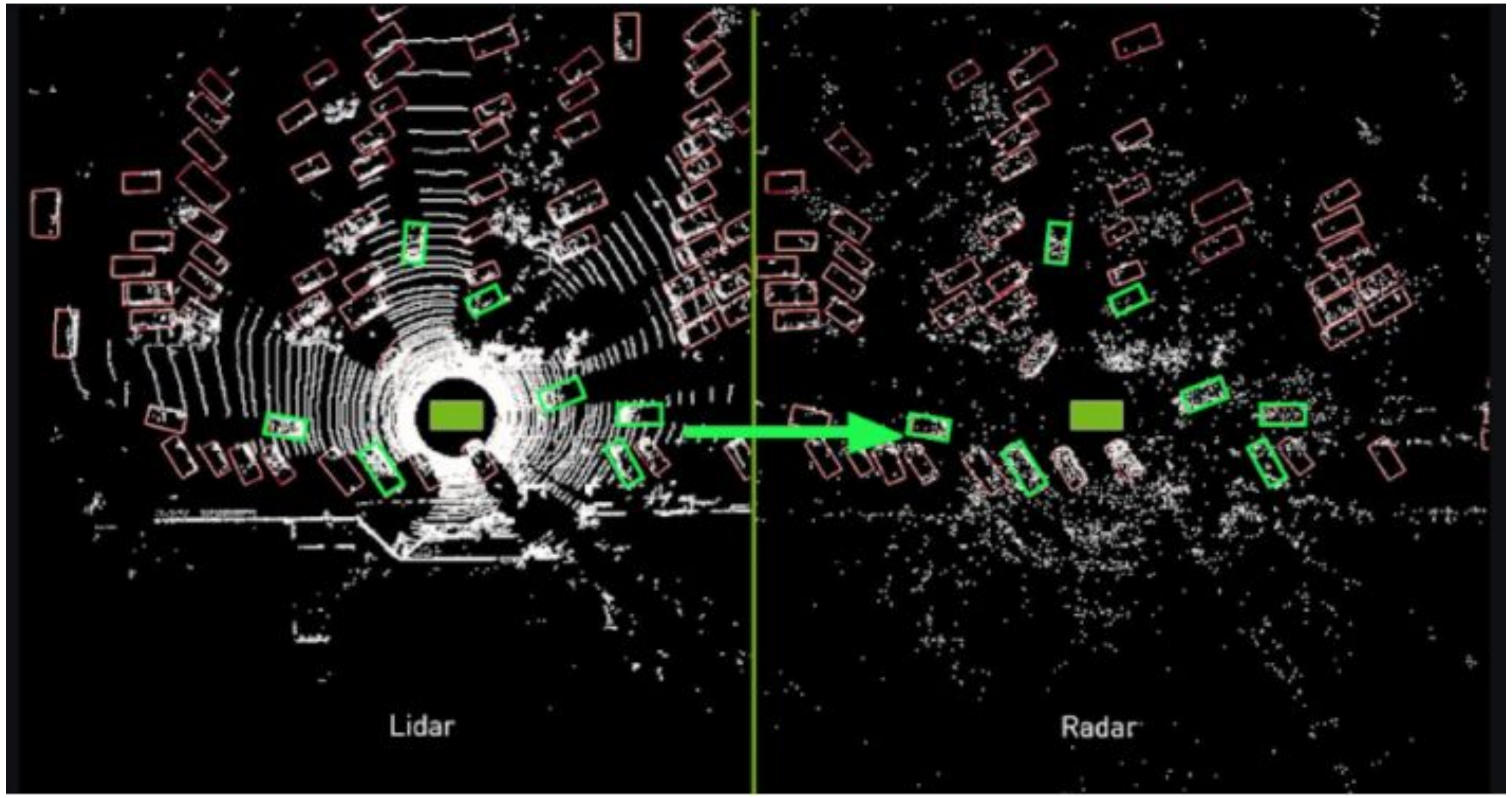
- 3D Ground Truth manually labeled on lidar spins is projected into radar domain (BEV)
- Classification with 4 classes (vehicle, pedestrian, bicycle, background)
  - DNN predicts a single bounding box per object (OneNet) → No NMS needed
- Regression of multiple box parameters, such as width, length, orientation, and center offset

Figure: radar points overlaid with inference results from obstacle and free space detections

Ground Truth Generation for Dynamic Obstacles

2021: AI improves autonomous vehicles

- Radar is difficult for humans to label (especially for non-experts, and at scale)
- Labeling based on lidar and camera must therefore be propagated into the radar domain
- This leads to challenges, such as multi-sensor synchronization



Occupancy & Segmentation Heads

2023: Detecting obstacles and drivable free space with RadarNet

- RadarNet predicts dense occupancy and semantic segmentation
- General static obstacle detection
  - Covers road hazards, barriers, trees, bridges, and other ill-defined static objects
- Drivable free space can be extracted in post-processing if required

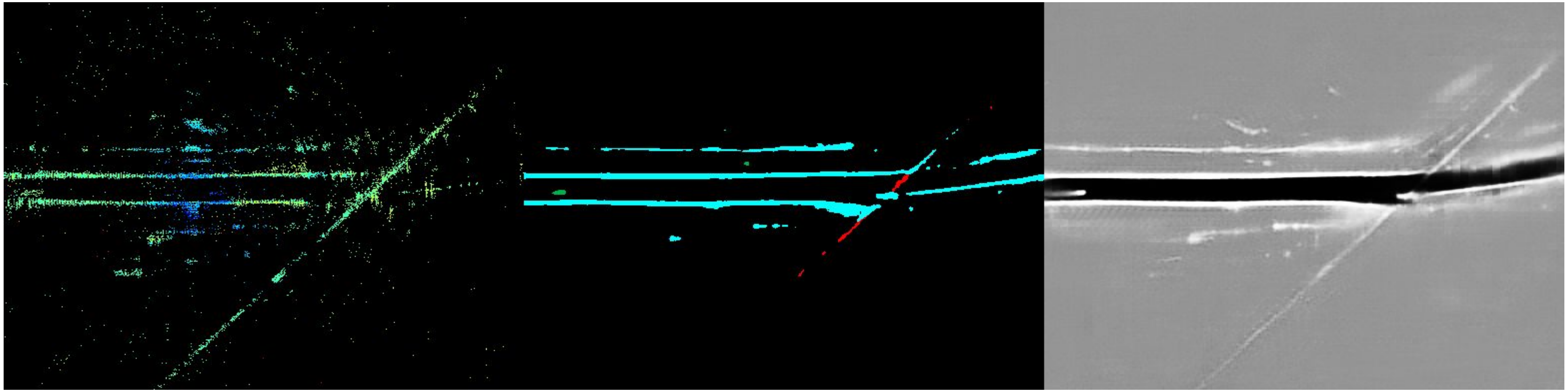


Figure: radar input accumulated point cloud (left), segmentation result (center), occupancy result (right)

GT and Inference for Occupancy

2023: Detecting obstacles and drivable free space with RadarNet

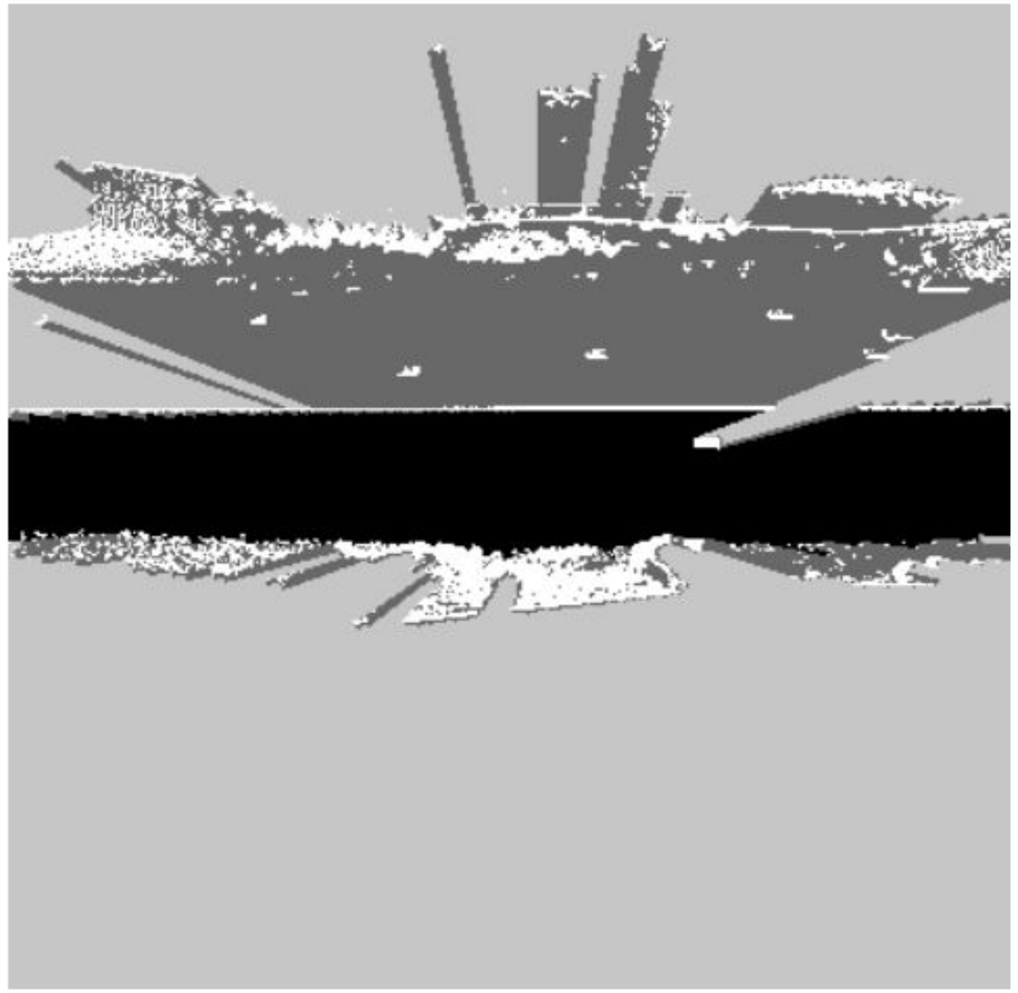


Figure: Visual representation of a semi-automatically generated occupancy training label, including observed and free areas (black), observed and occupied areas (white), unobserved areas (light gray), and partially observed areas (dark gray)

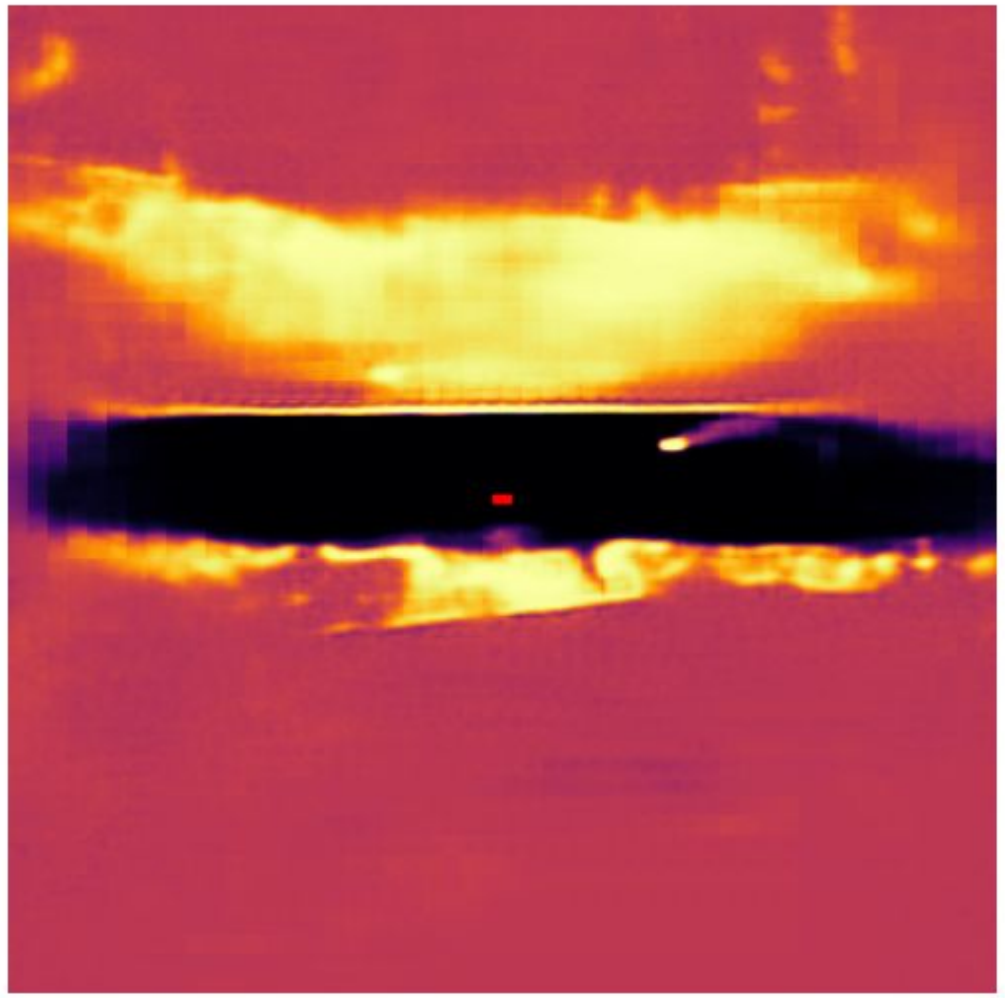


Figure: Inferred dense occupancy probability map, dark areas showing low probability (directly, free of any obstacles), bright areas showing high probability (observed directly, occupied), and red areas showing uncertain probability (unobserved)

Inference for Segmentation

2023: Detecting obstacles and drivable free space with RadarNet

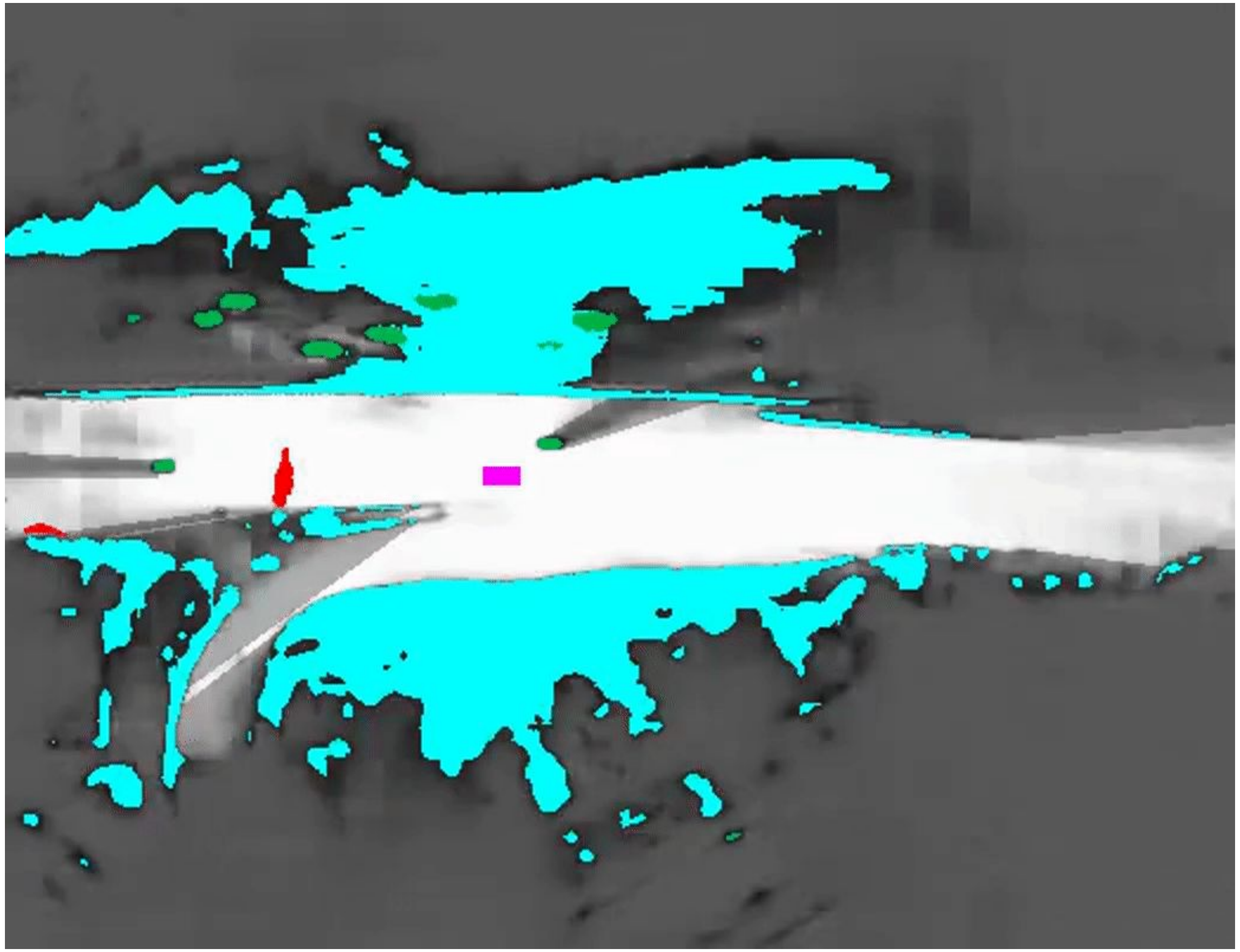


Figure: Occupancy probability map overlaid with fine-grained semantic segmentation showing the ego vehicle (purple), other vehicles (green), general obstacles (blue), and elevated obstacles (red)

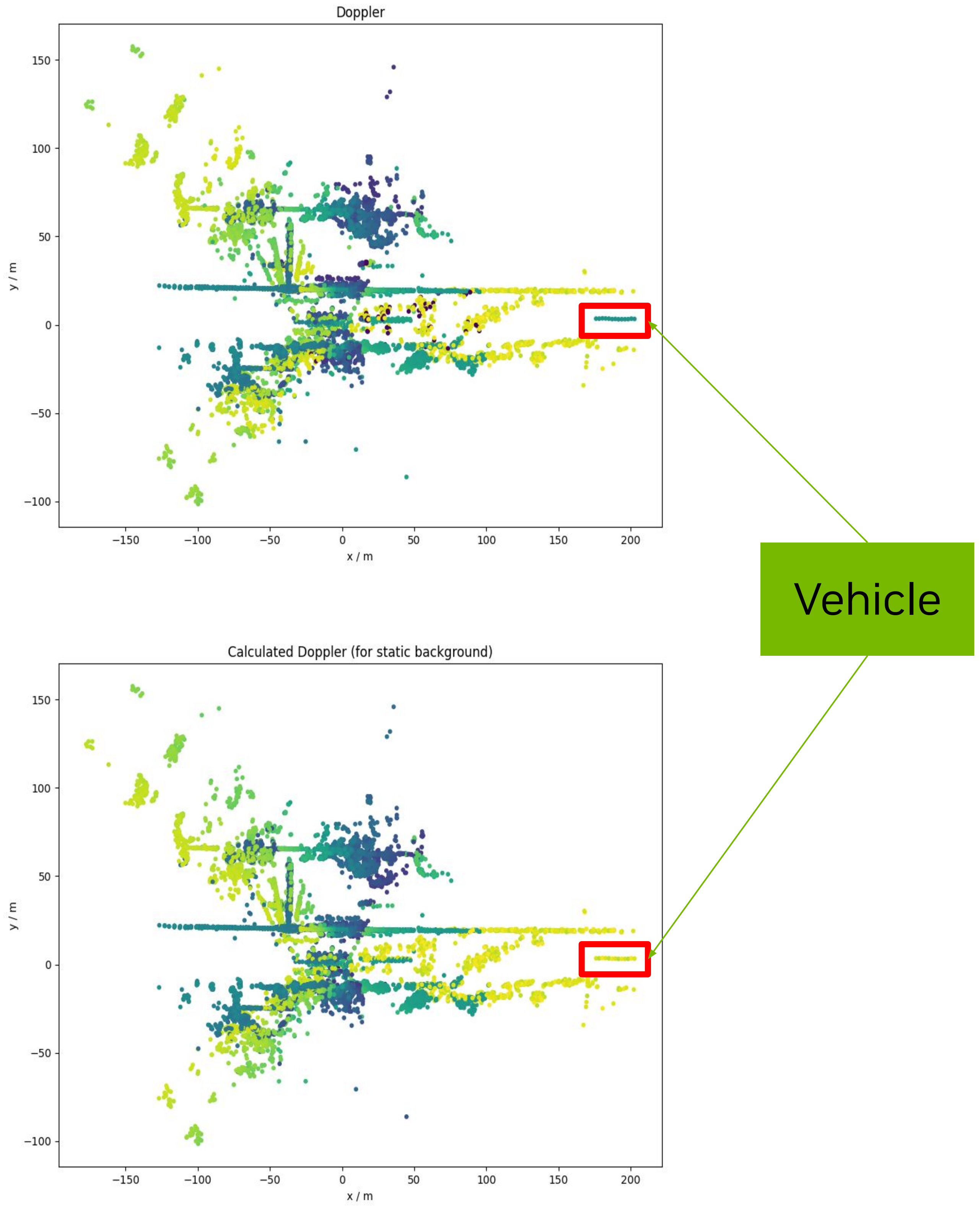
Self-Supervised Doppler Loss

Learned velocity without explicit labels

Question
- Can we learn 2D BEV velocity using self-supervision?

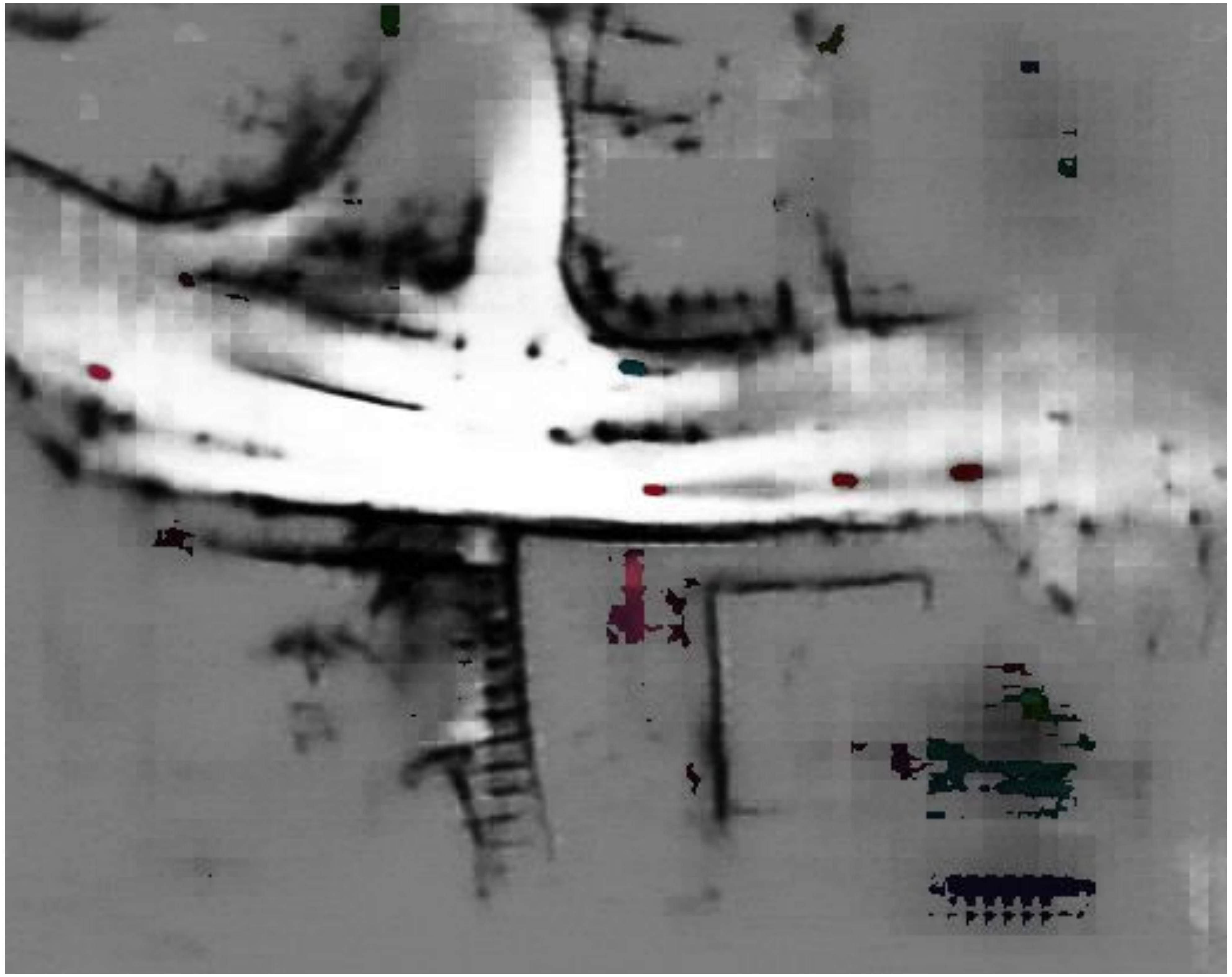
Solution
- Define loss function in terms of expected per-scan doppler

Implementation Challenges
- Our input image is ego-motion compensated, which smears moving objects over a large region of the image



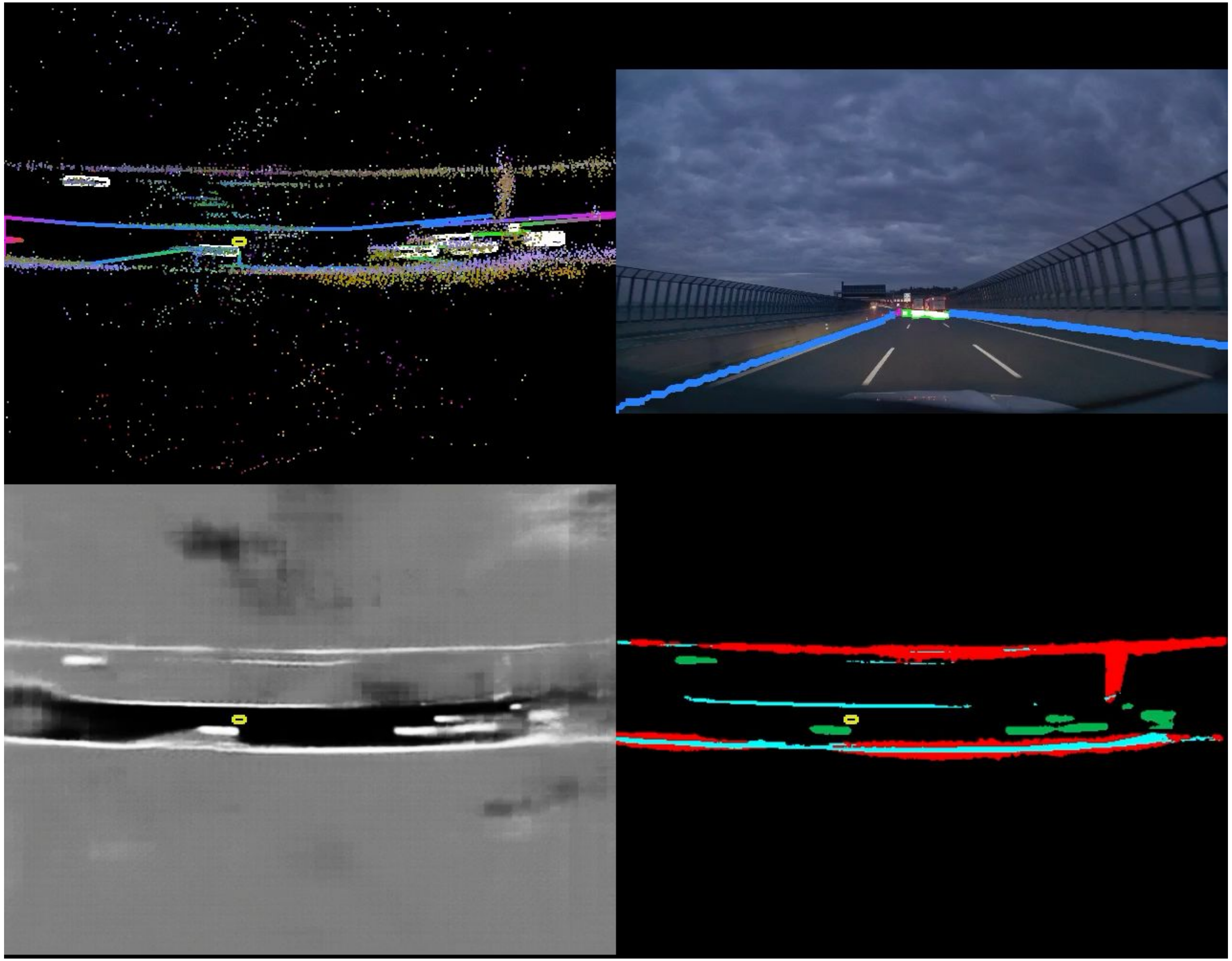
Dynamic Occupancy

Based on self-supervised velocity



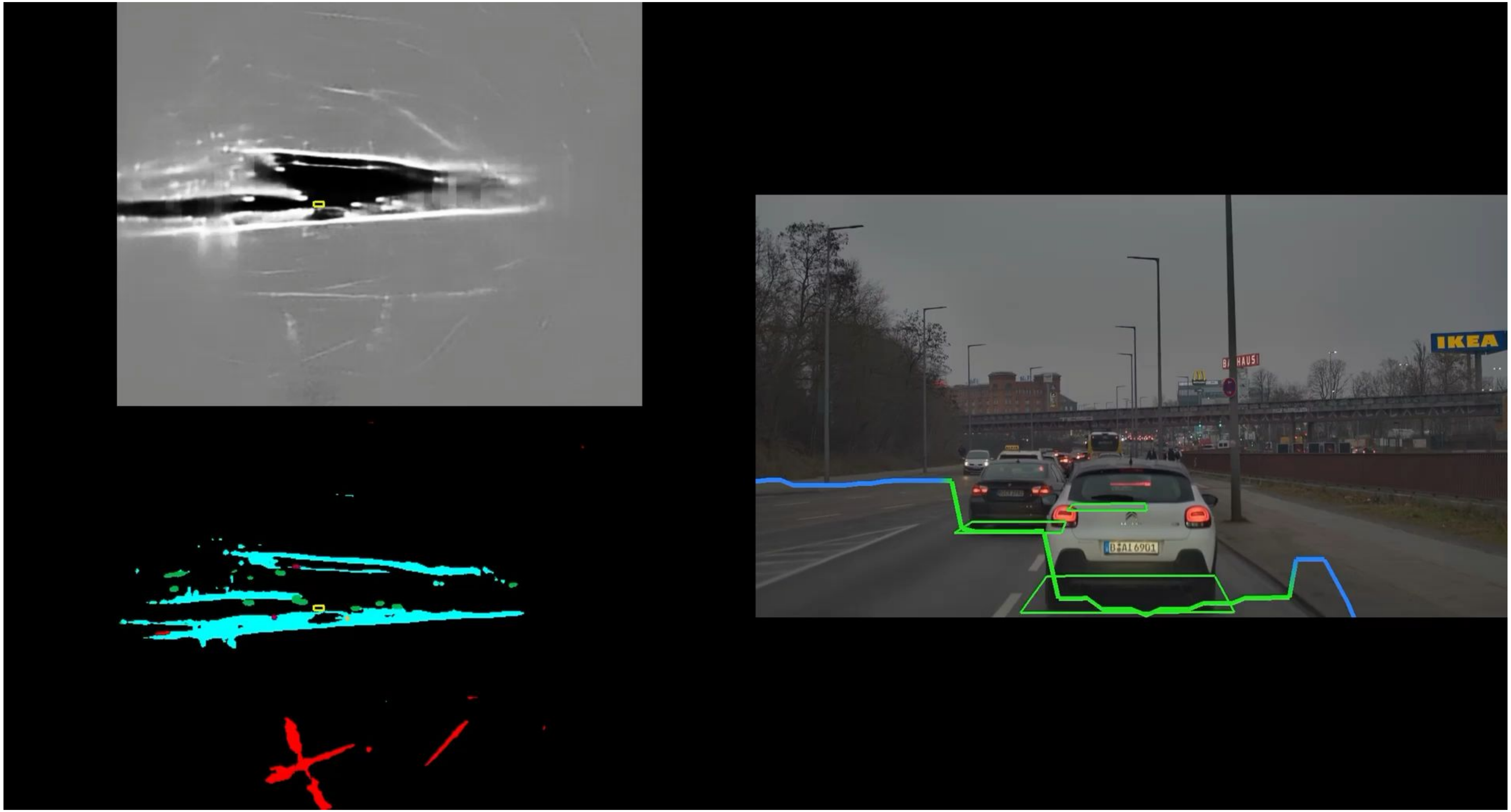
Demo Videos

Tunnel - classical failure mode for radars with no elevation resolution



Demo Videos

Urban driving #1: busy street, pedestrians and cyclist on sidewalk



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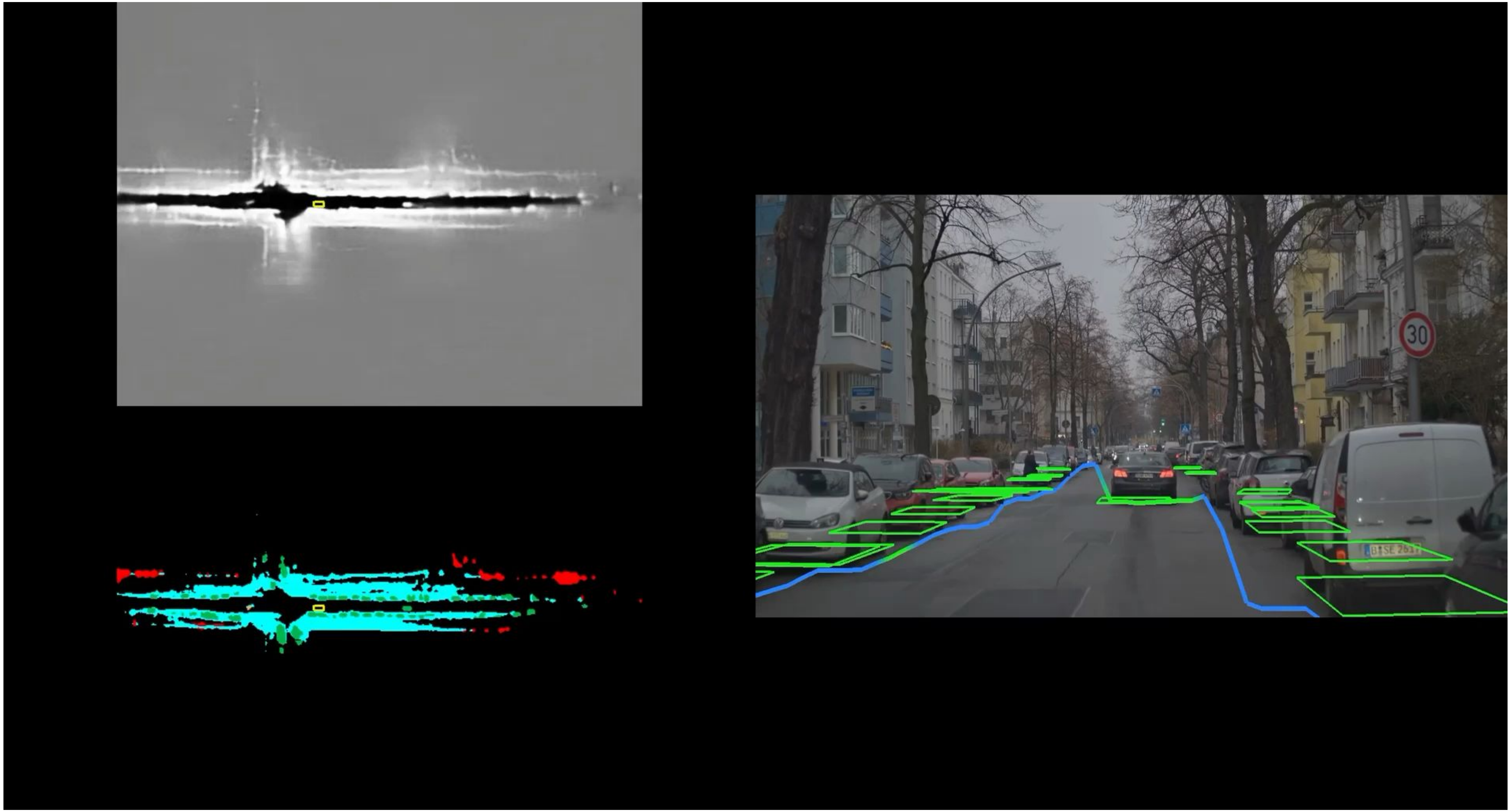
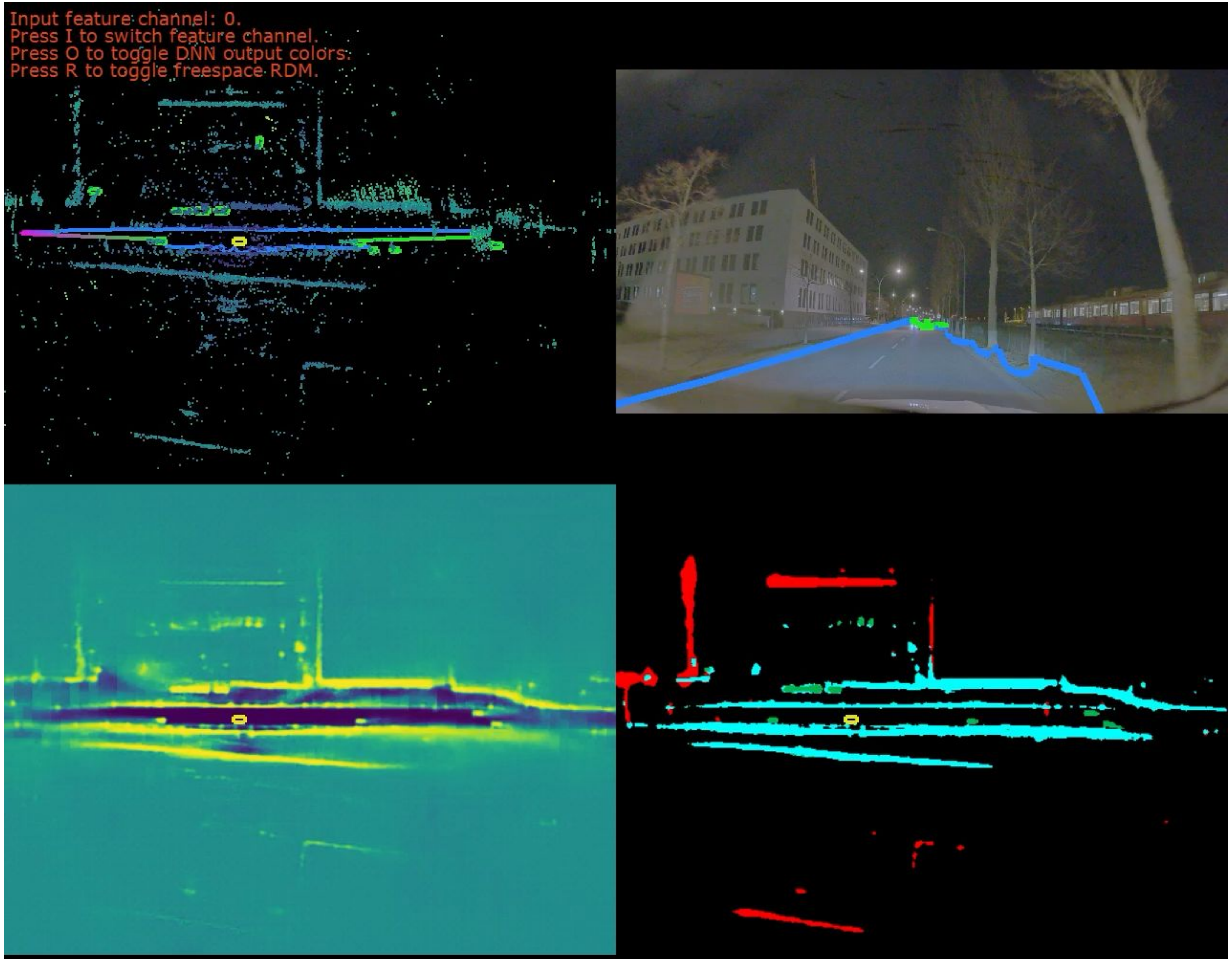
Demo Videos

Urban driving #2: dense parked cars and pedestrian crossing



Demo Videos

Urban driving #3: nighttime driving



Thank you!

For more information, visit:

- https://developer.nvidia.com/blog
- https://www.nvidia.com/en-us/self-driving-cars/drive-videos/