# Fog, Rain, LIDAR and Radar

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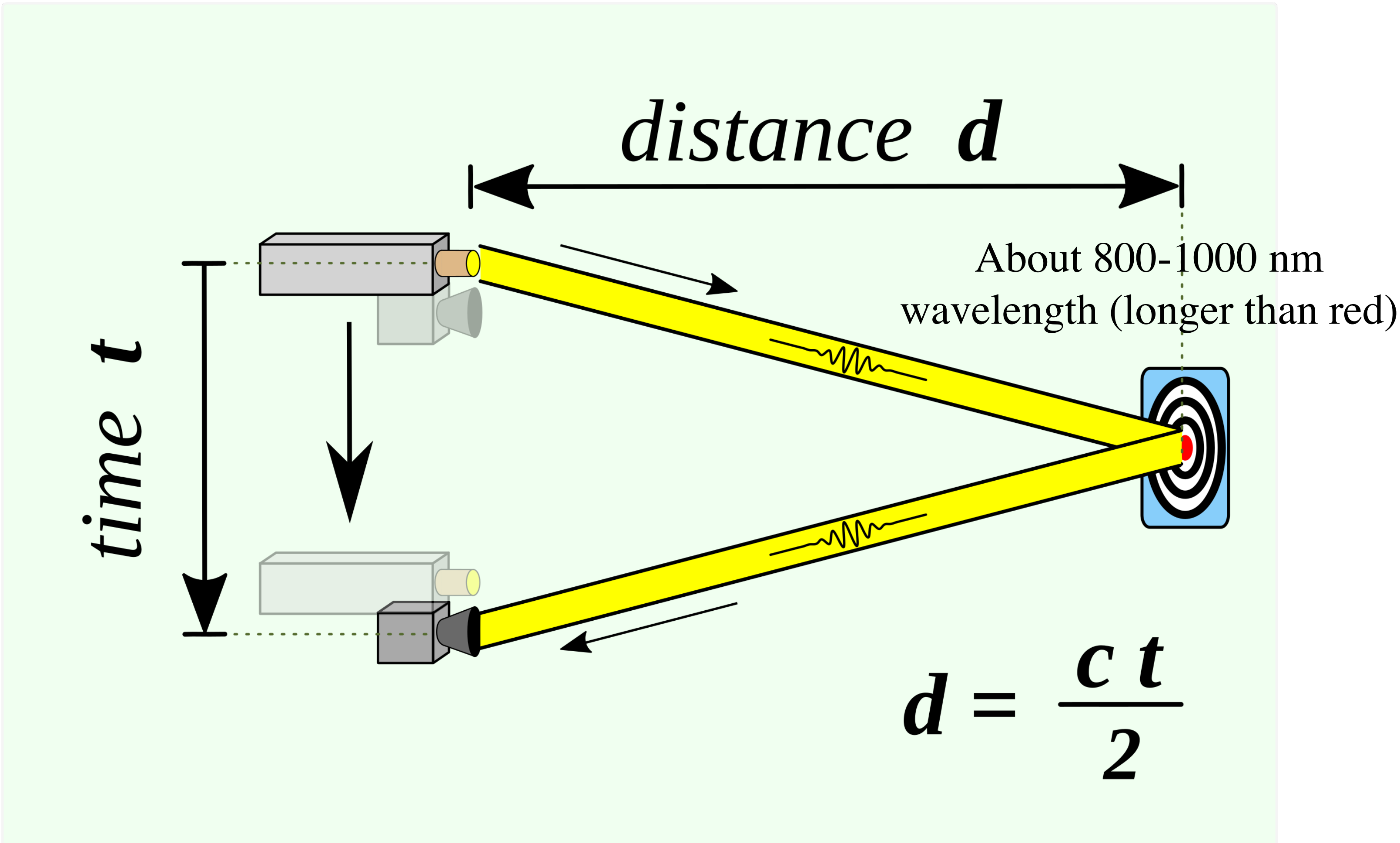
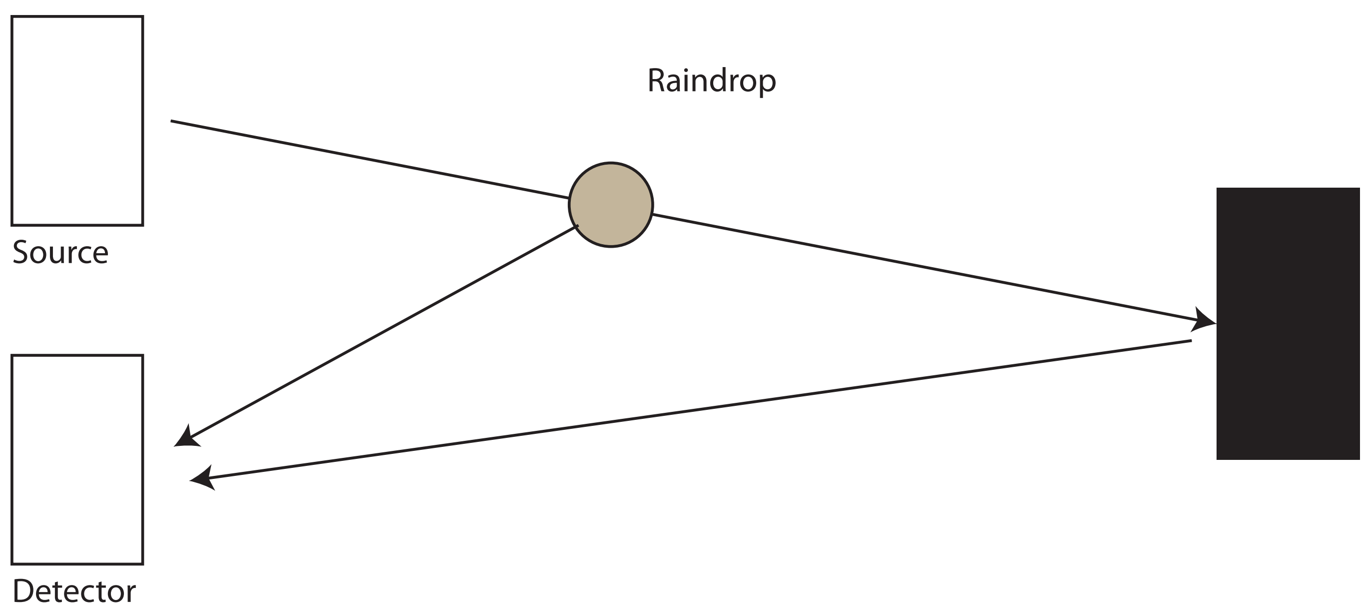
UIUC

# Fog and Lidar: Lidar

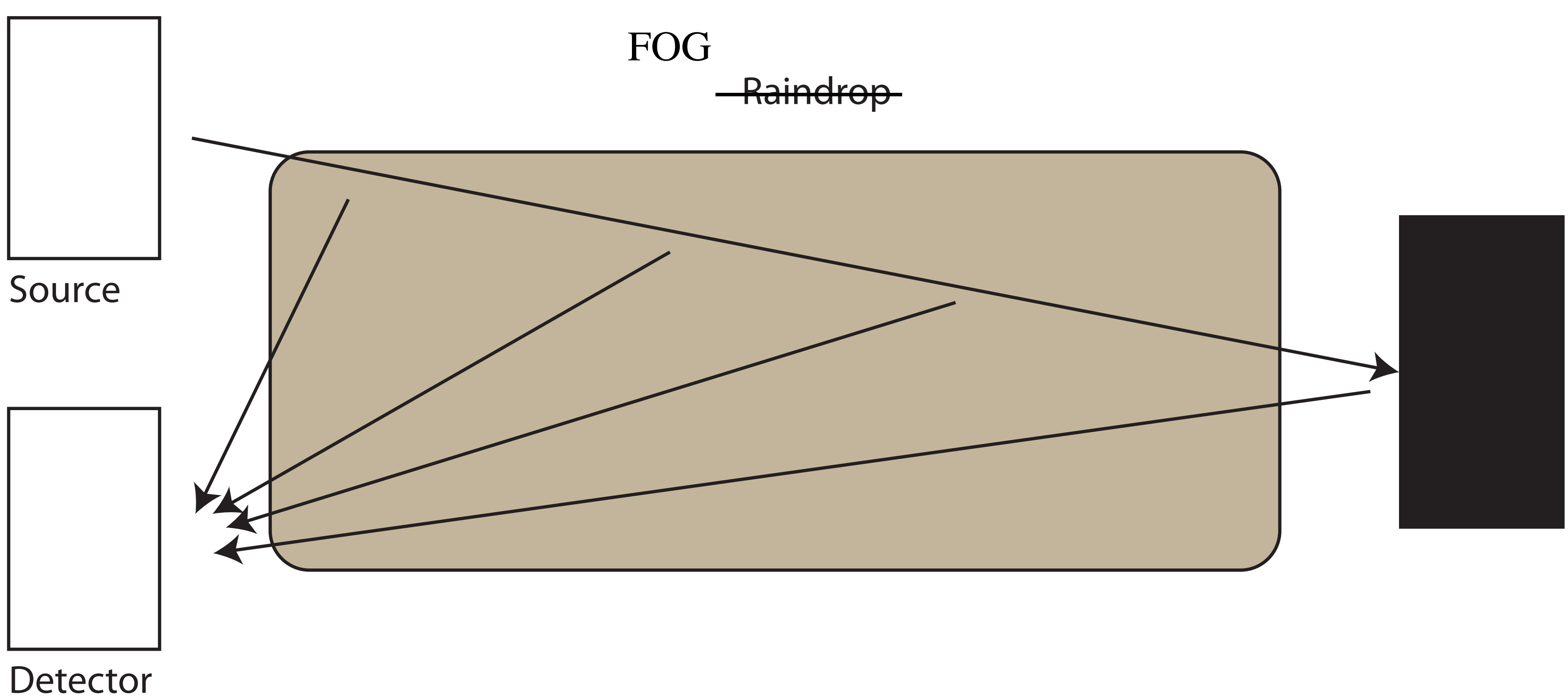



Wikipedia

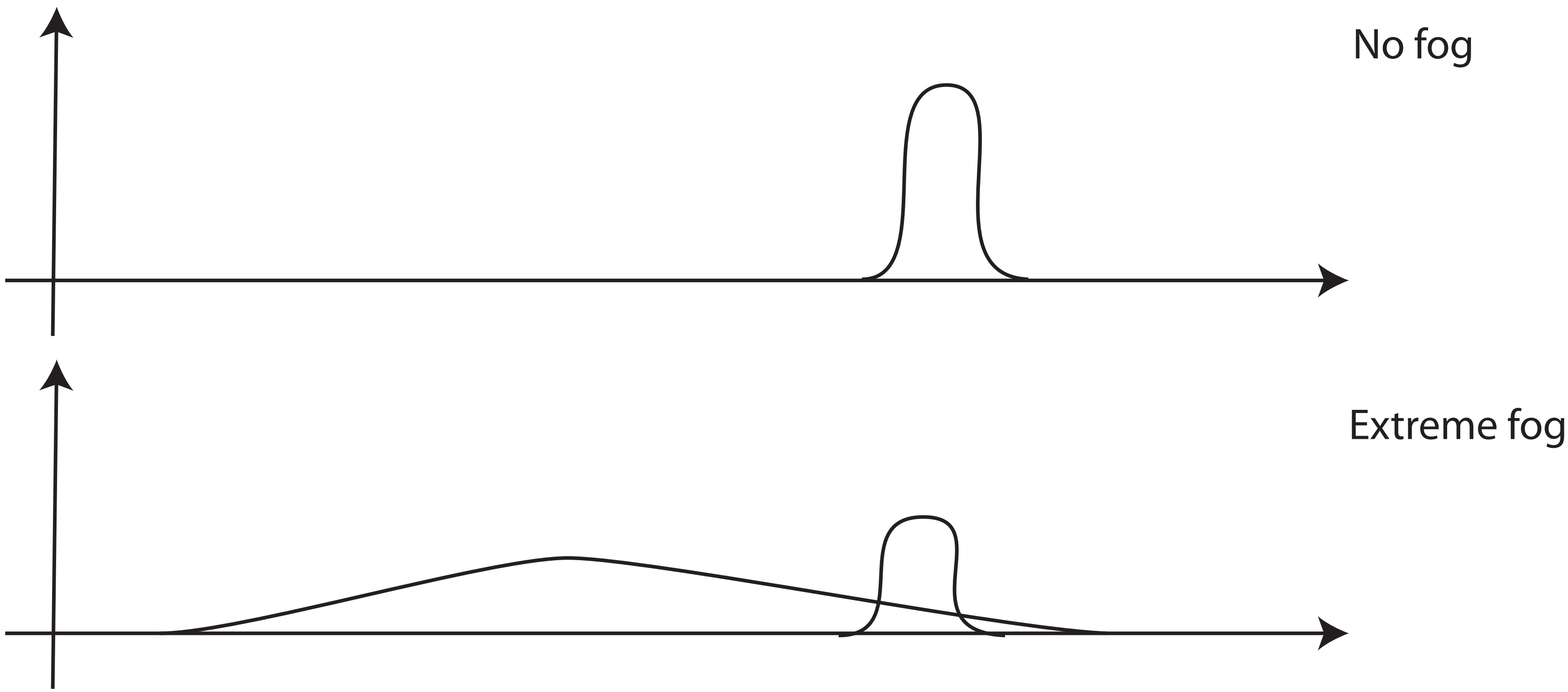
# Raindrop backscatter



# Fog scattering



# What the sensor sees…



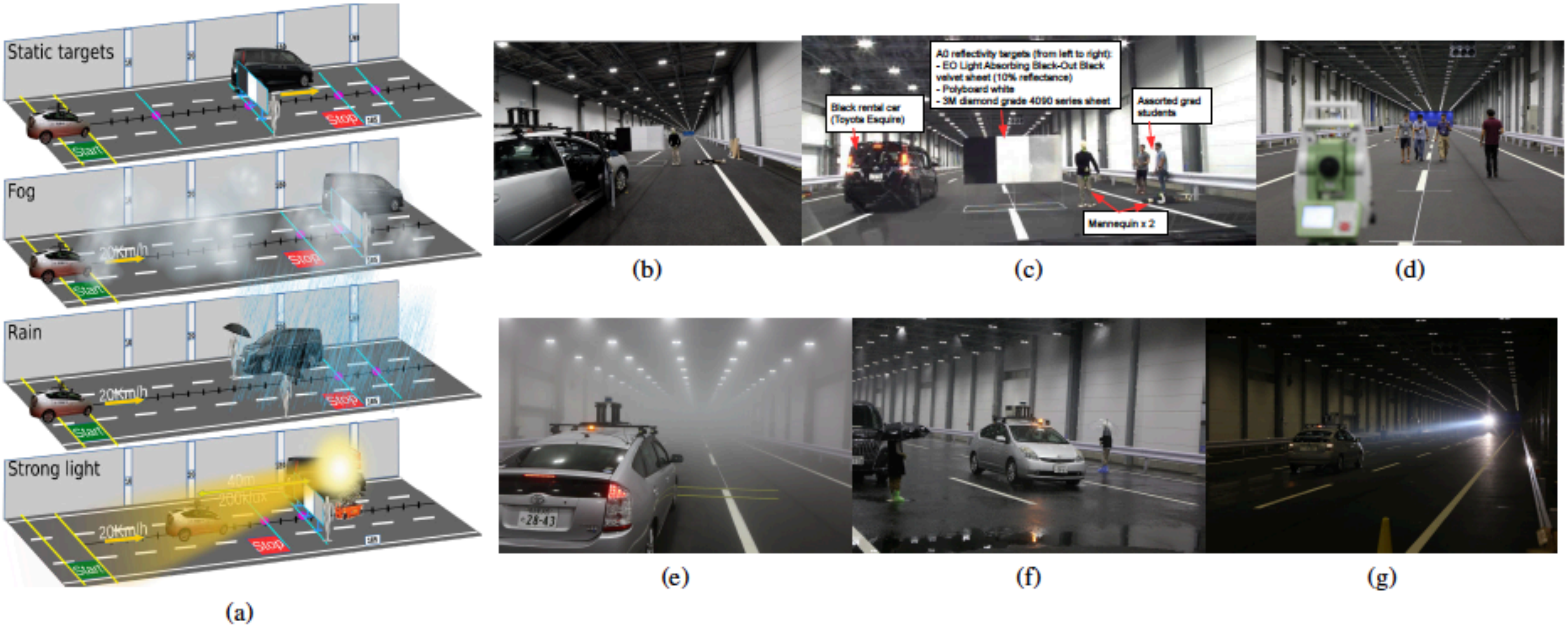
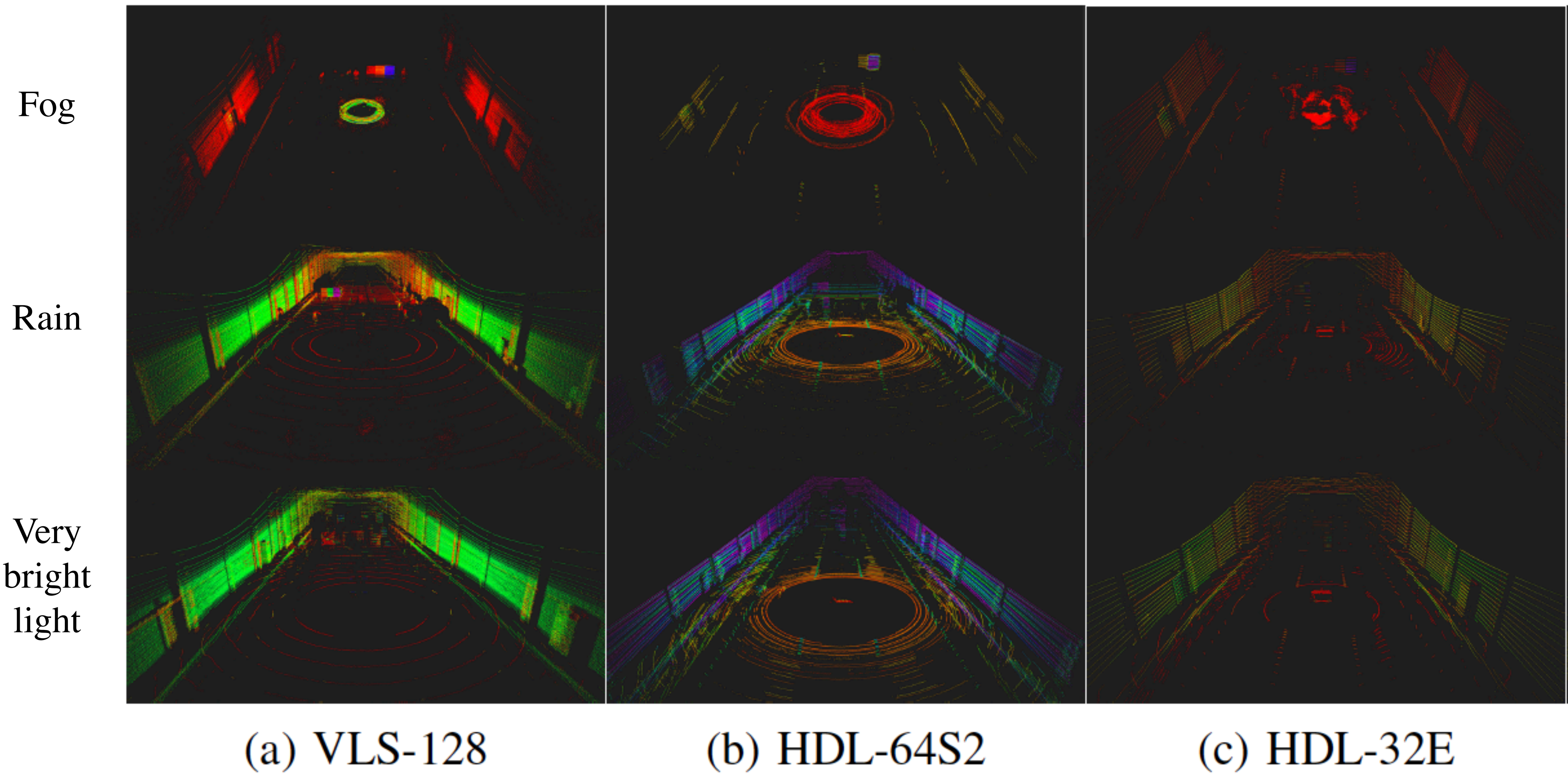



Fig. 5: Static targets and adverse weather experiments at JARI's weather chamber: (a) configuration of the different scenarios, (b) and (c) measurement, (e) to (g) sample adverse weather scenes, (d) setting up ground truth.

Carballo, 20




Carballo, 20

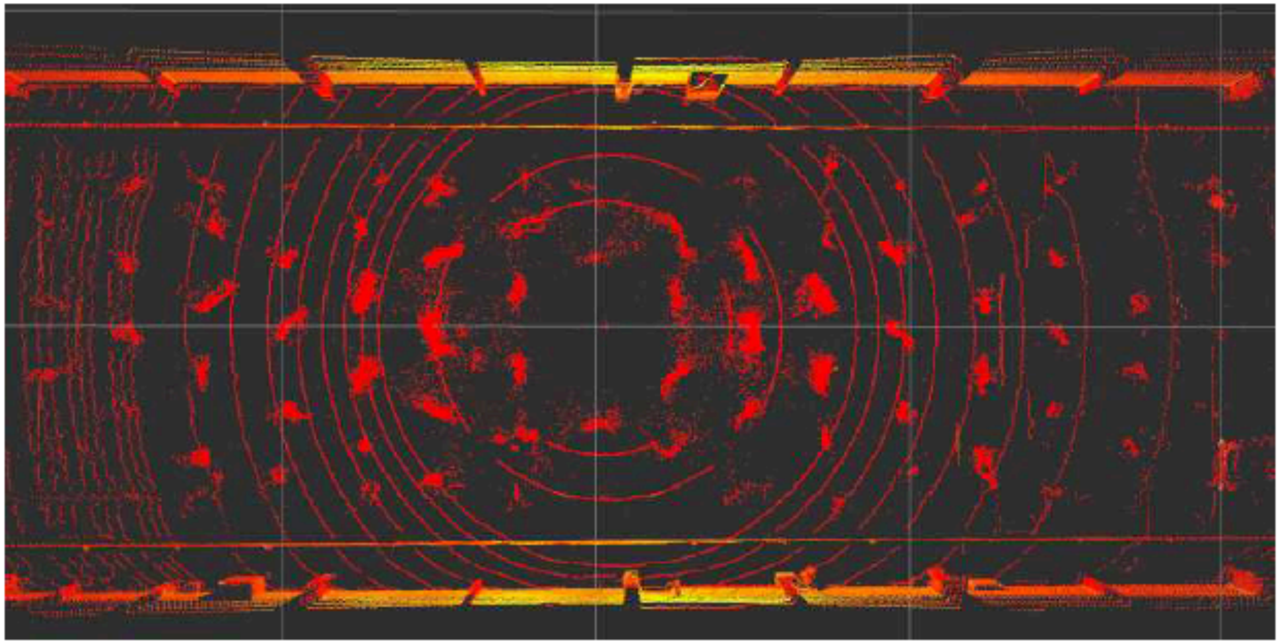
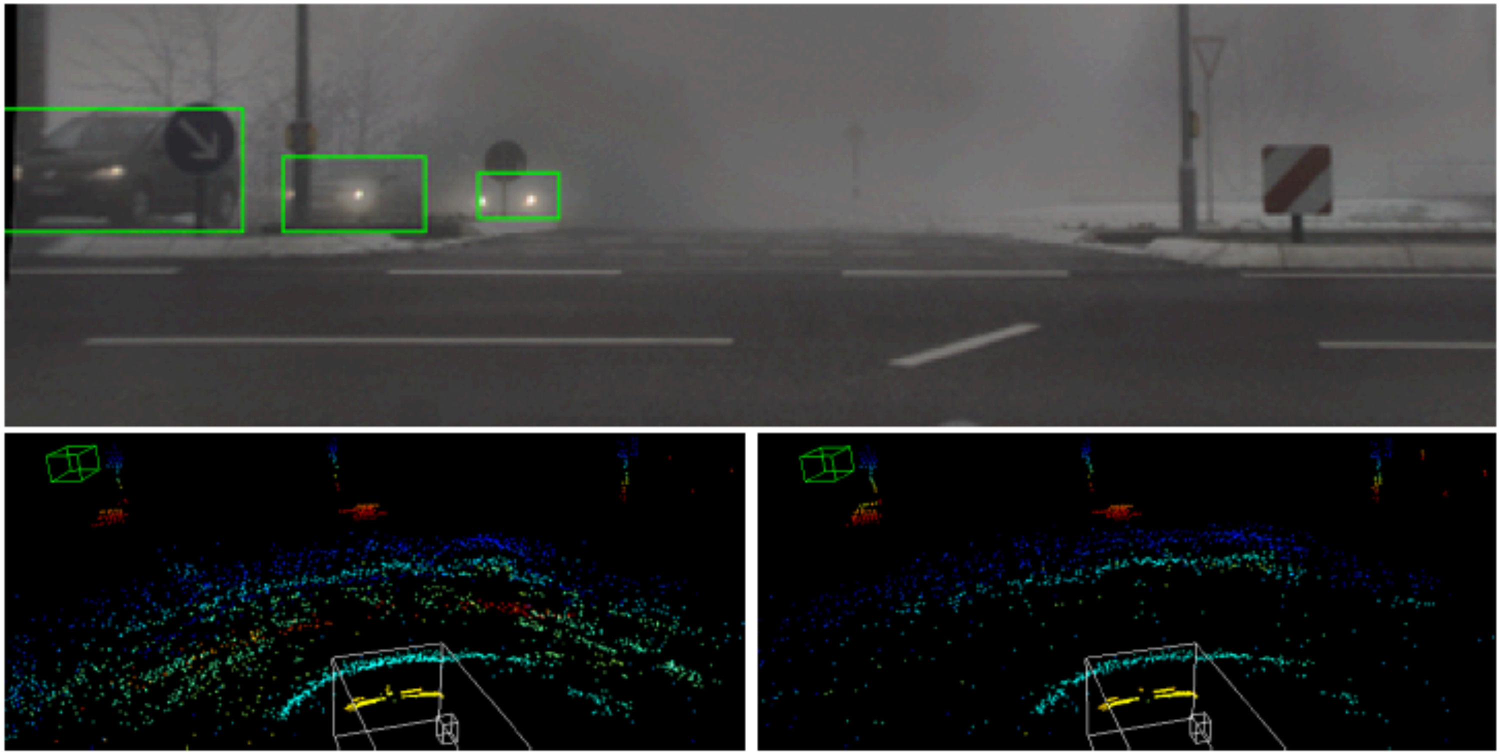


Fig. 9: “Rain pillars” as detected by a LiDAR.

- Qualitative effects
  - lost returns
  - fog torus
  - early returns
  - rain pillars
  - noise

Carballo, 20



(a) *strongest* returns (b) *last* returns

Figure 1: LiDAR returns caused by fog in the (top) scene. (a) shows the *strongest* returns and (b) the *last* returns, color coded by the LiDAR *channel*. The returns of the ground are removed for better visibility of the points introduced by fog. Best viewed in color (red $\widehat{=}$ low, cyan $\widehat{=}$ high, 3D bounding box annotation in green, ego vehicle dimensions in gray).

Hahner 21

# Radar is unaffected

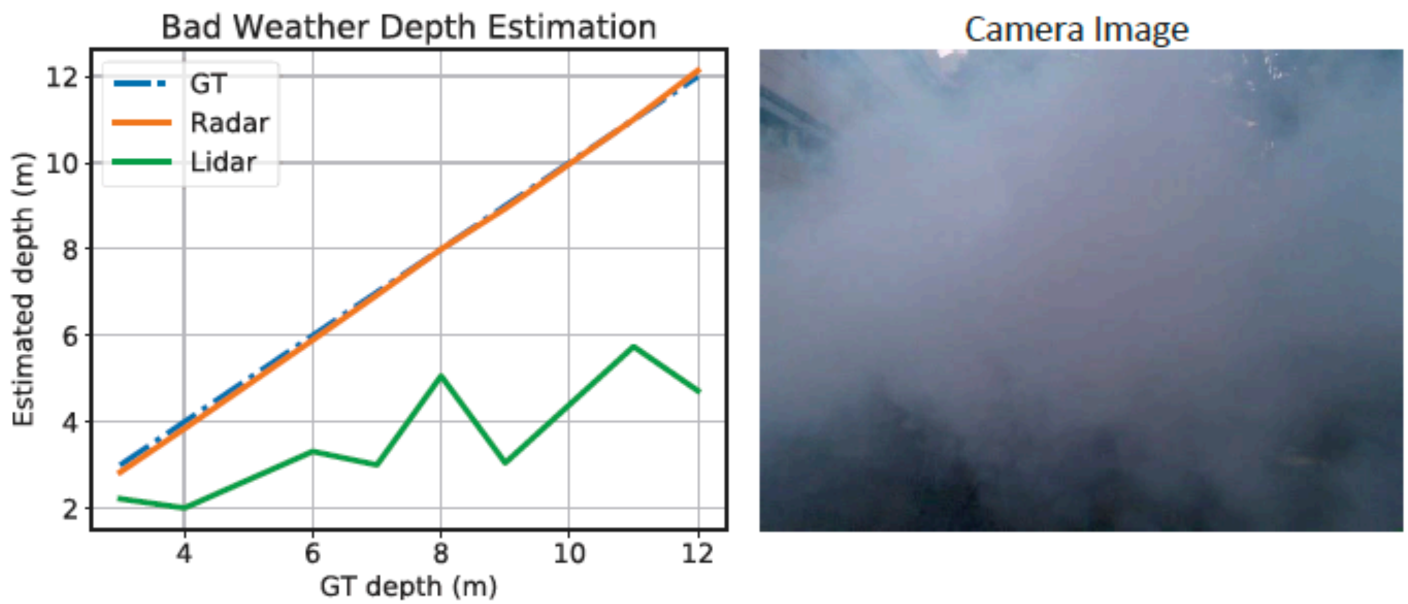



**Figure 16:** *Performance comparison of different sensors in the presence of adverse conditions. The left plot shows the depth estimation performance of Radar and LiDAR for an object directly in front of the sensor in the presence of fog. The right figure shows the camera image for the experiment.*

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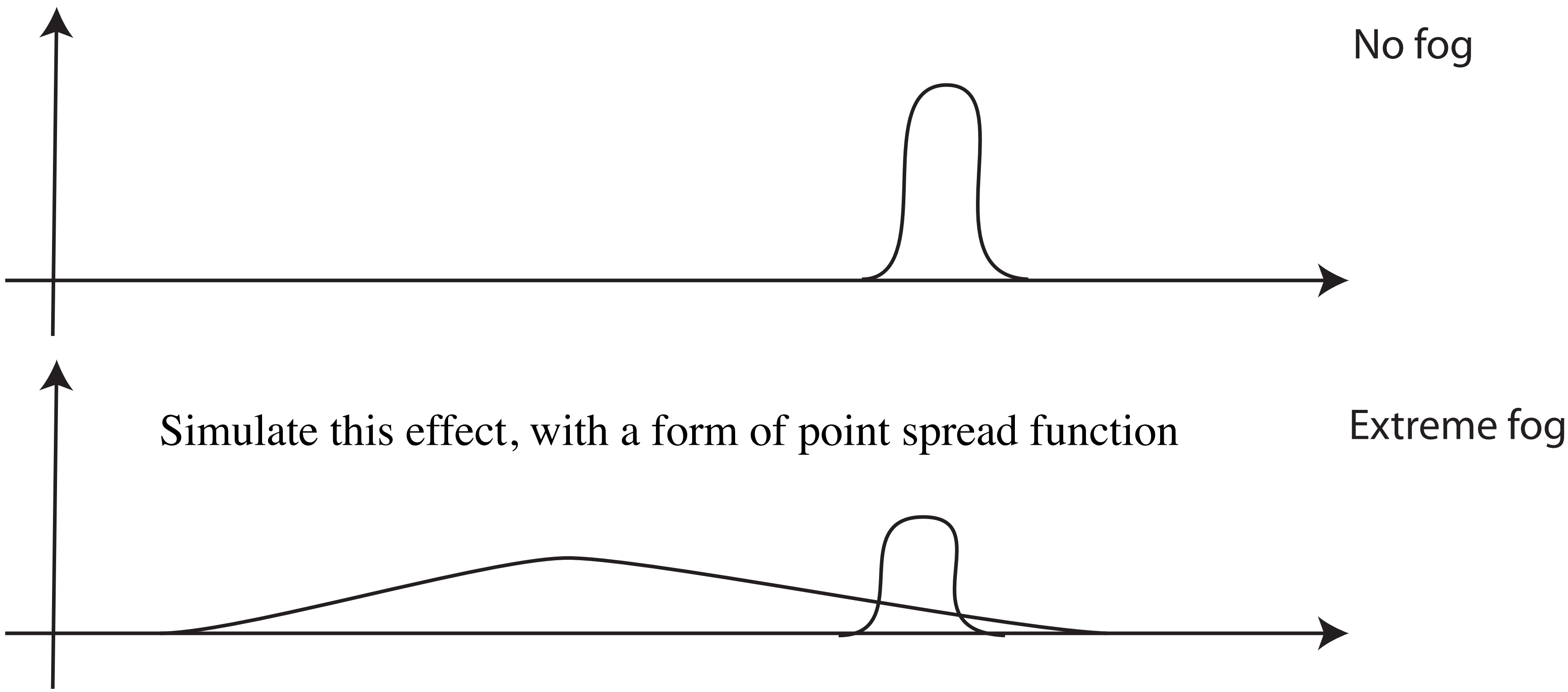
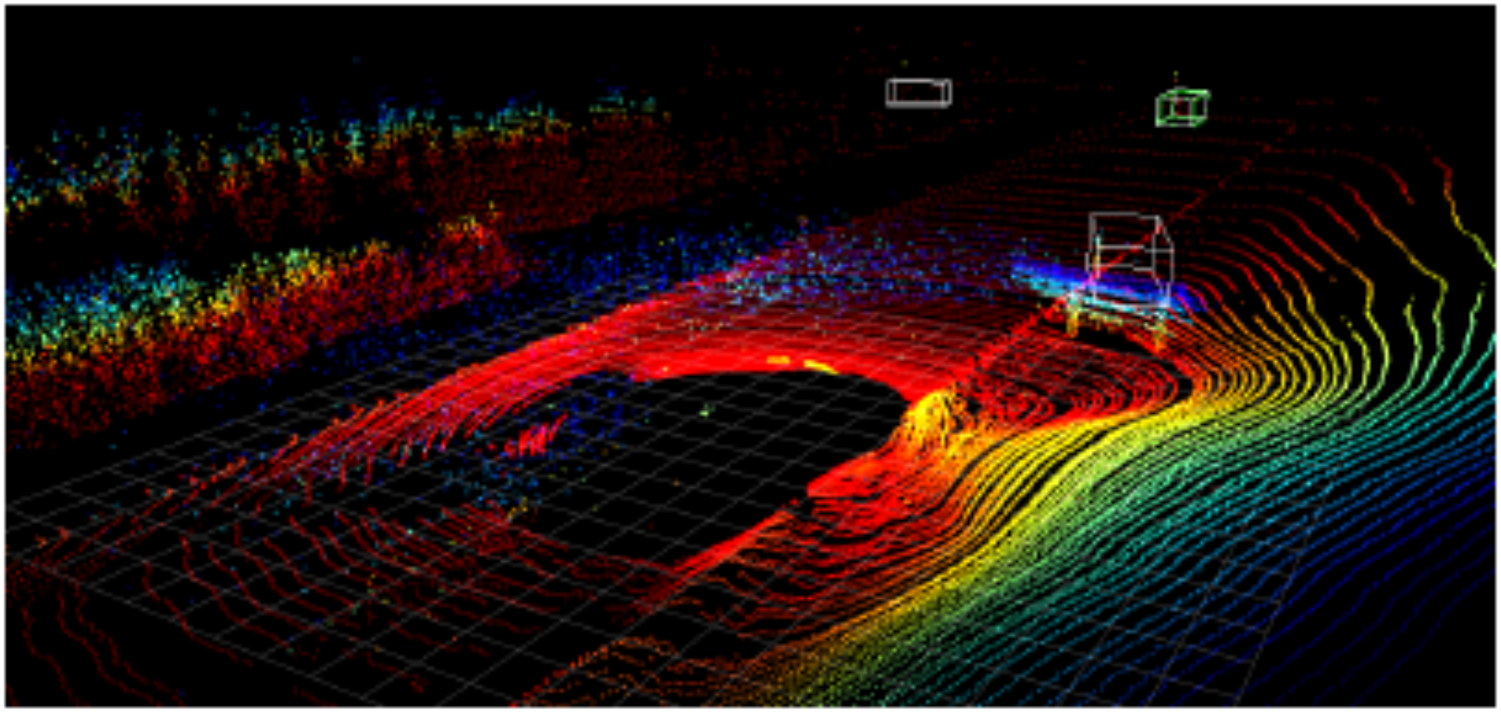
# What the sensor sees…

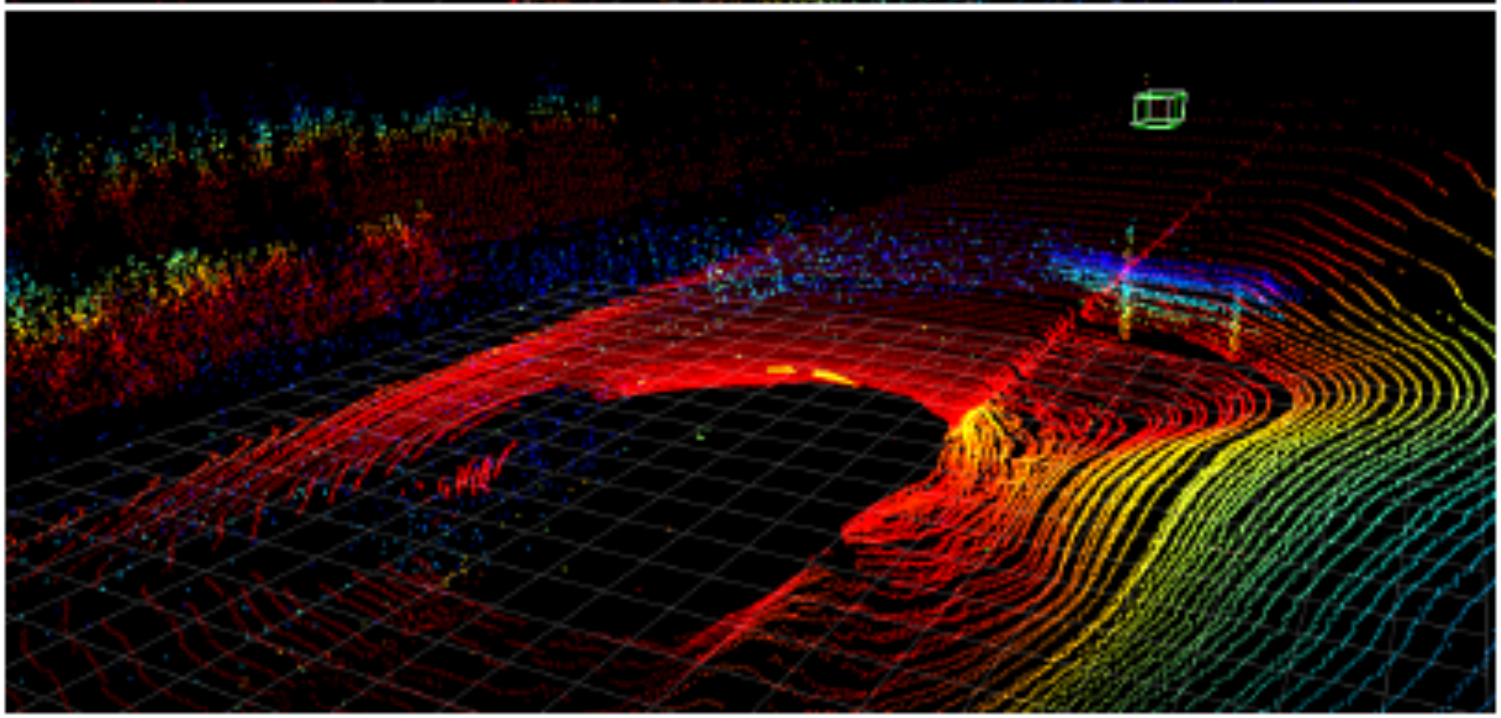



Hahner 21



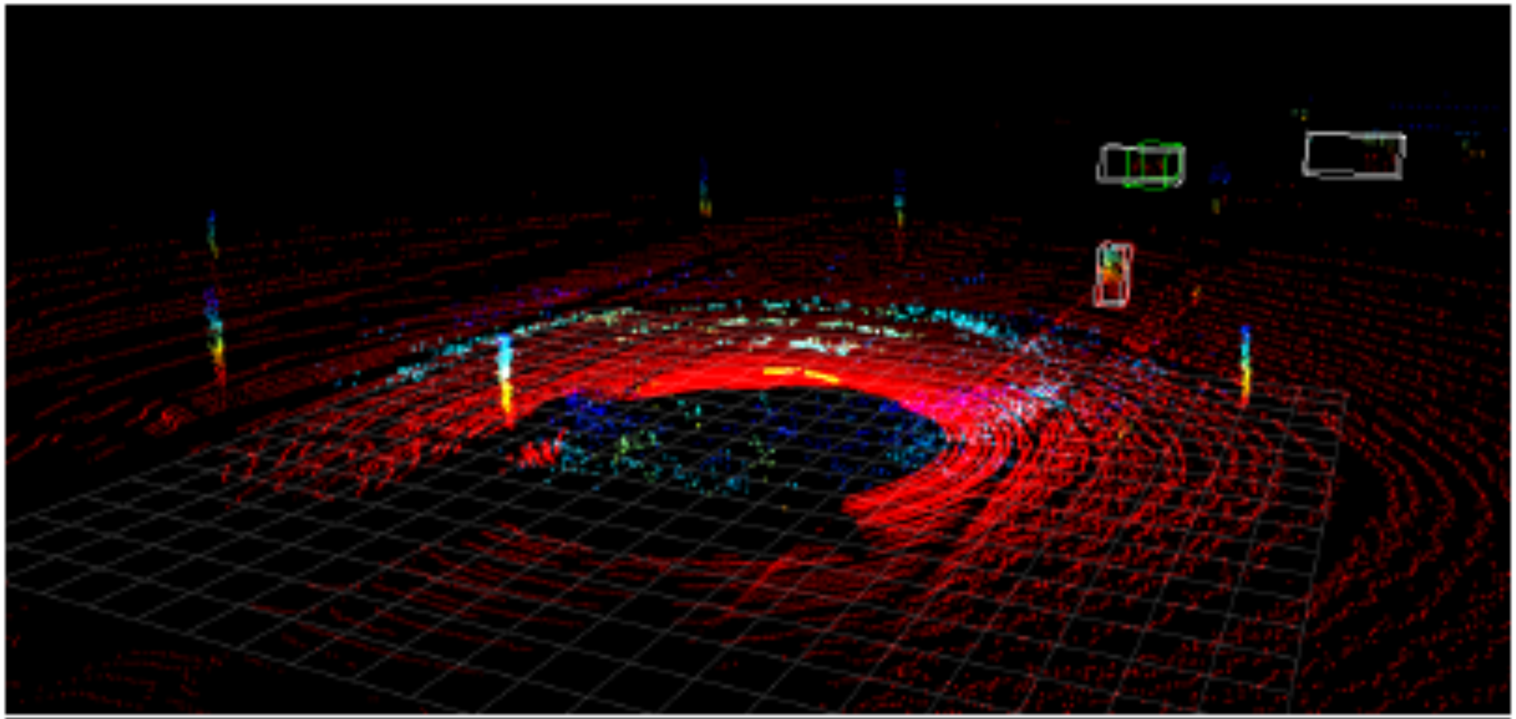
PV RCNN trained on
good weather lidar returns
only

Lidar captured in dense fog



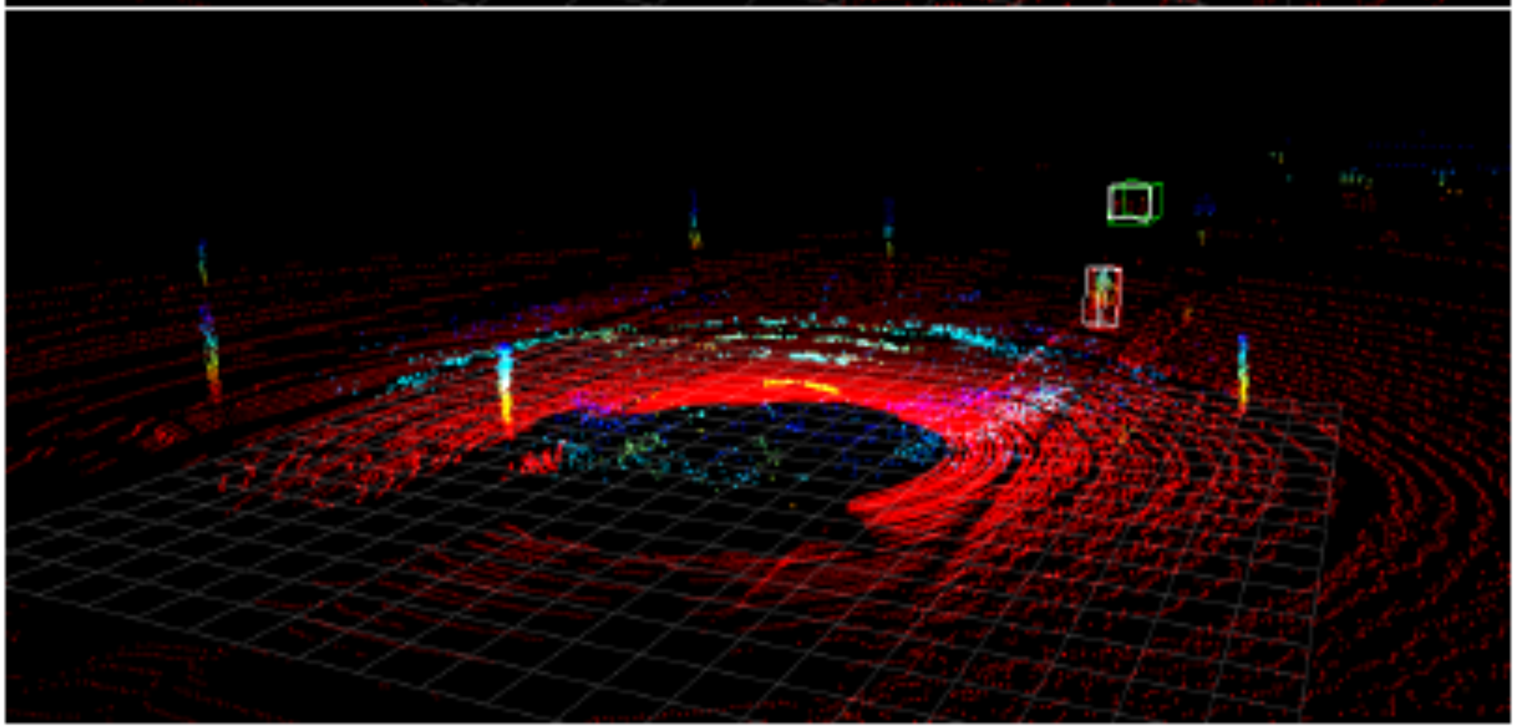
PV RCNN trained on
good and simulated bad
weather lidar returns
only

Hahner 21



PV RCNN trained on good weather lidar returns only

Lidar captured in dense fog



PV RCNN trained on good and simulated bad weather lidar returns only

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# Multi sensor methods

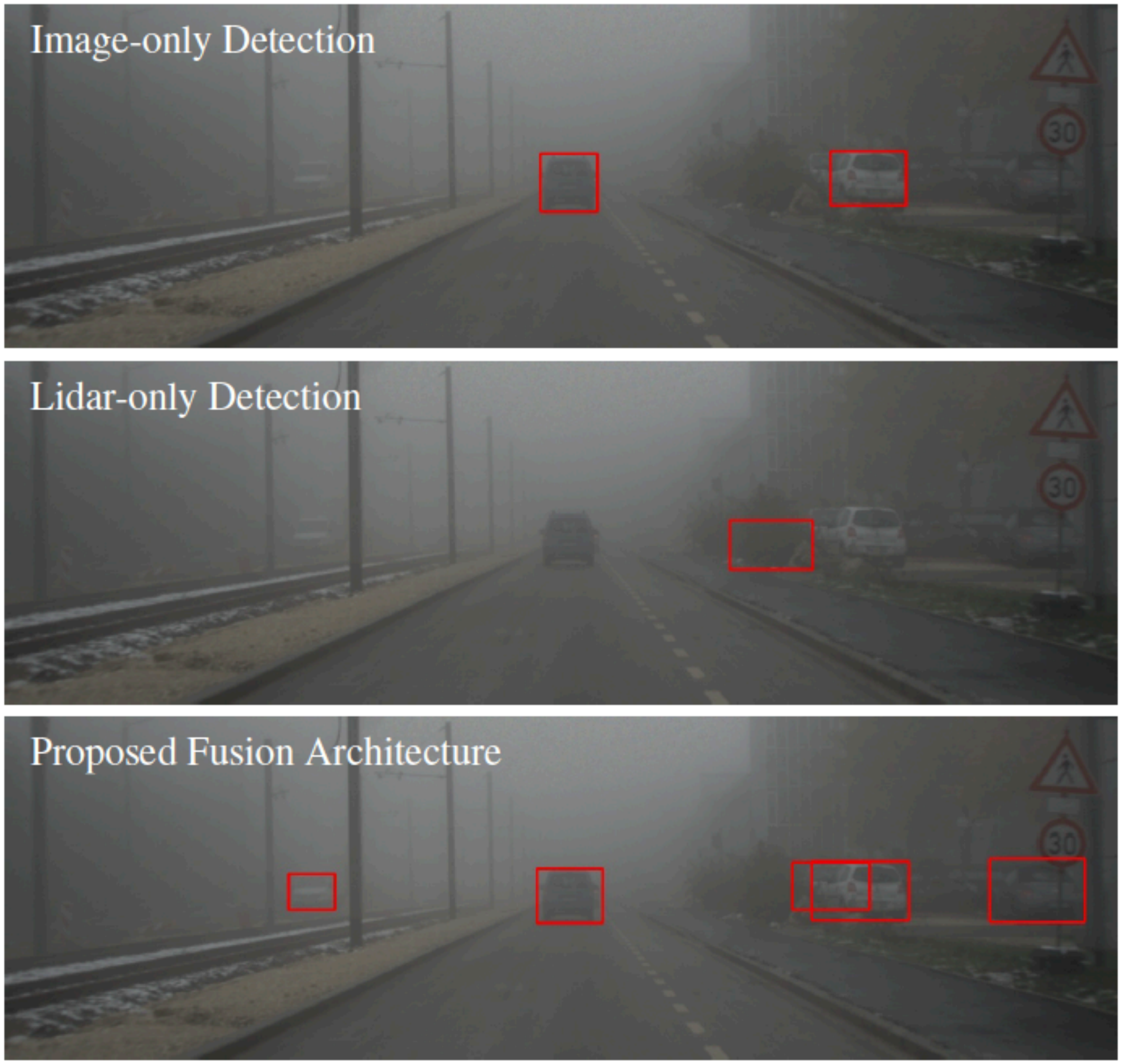


Figure 1: Existing object detection methods, including efficient Single-Shot detectors (SSD) [41], are trained on automotive datasets that are biased towards good weather conditions. While these methods work well in good conditions [19, 59], they fail in rare weather events (top). Lidar-only detectors, such as the same SSD model trained on projected lidar depth, might be distorted due to severe backscatter in fog or snow (center). These asymmetric distortions are a challenge for fusion methods, that rely on redundant information. The proposed method (bottom) learns to tackle unseen (potentially asymmetric) distortions in multimodal data without seeing training data of these rare scenarios.

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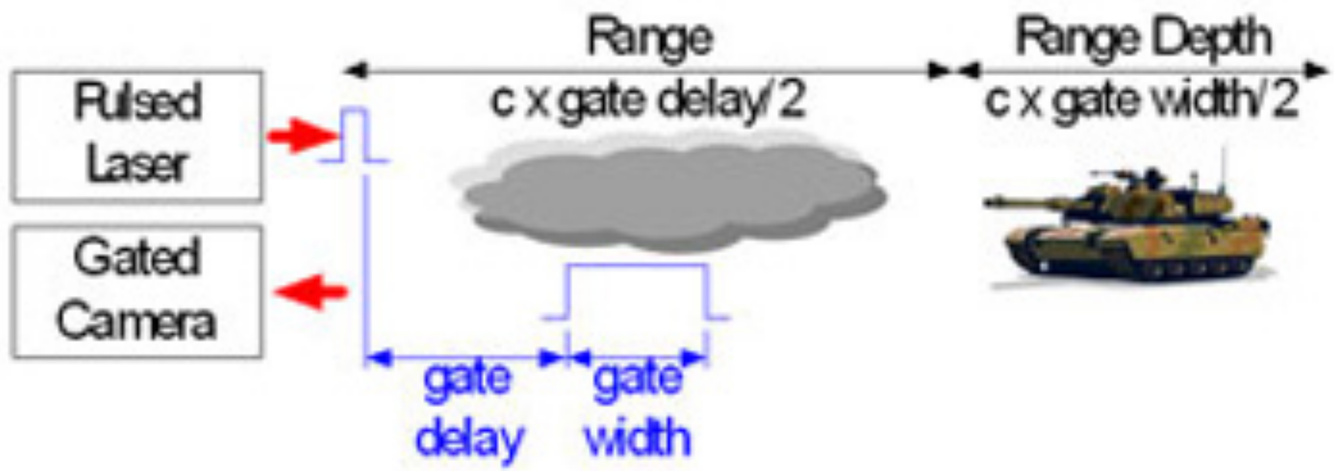
# Gated cameras




From sensors unlimited website

# Multi sensor bad weather data

| DATASET<br>SENSOR SETUP | KITTI [19] | BDD [69] | Waymo [59] | NuScenes [6] | Ours |
|---|---|---|---|---|---|
| RGB CAMERAS | 2 | 1 | 5 | 6 | 2 |
| RGB RESOLUTION | 1242×372 | 1280×720 | 1920×1080 | 1600x900 | 1920x1024 |
| LIDAR SENSORS | 1 | ✗ | 5 | 1 | 2 |
| LIDAR RESOLUTION | 64 | 0 | 64 | 32 | 64 |
| RADAR SENSOR | ✗ | ✗ | ✗ | 4 | 1 |
| GATED CAMERA | ✗ | ✗ | ✗ | ✗ | 1 |
| FIR CAMERA | ✗ | ✗ | ✗ | ✗ | 1 |
| FRAME RATE | 10 Hz | 30 Hz | 10 Hz | 1 Hz/10 Hz | 10 Hz |
| DATASET STATISTICS | | | | | |
| LABELED FRAMES | 15K | 100k | 198k | 40K | 13.5K |
| LABELS | 80k | 1.47M | 7.87M | 1.4M | 100K |
| SCENE TAGS | ✗ | ✓ | ✗ | ✓ | ✓ |
| NIGHT TIME | ✗ | ✓ | ✓ | ✓ | ✓ |
| LIGHT WEATHER | ✗ | ✓ | ✗ | ✓ | ✓ |
| HEAVY WEATHER | ✗ | ✗ | ✗ | ✗ | ✓ |
| FOG CHAMBER | ✗ | ✗ | ✗ | ✗ | ✓ |

Table 1: Comparison of the proposed multimodal adverse weather dataset to existing automotive detection datasets.

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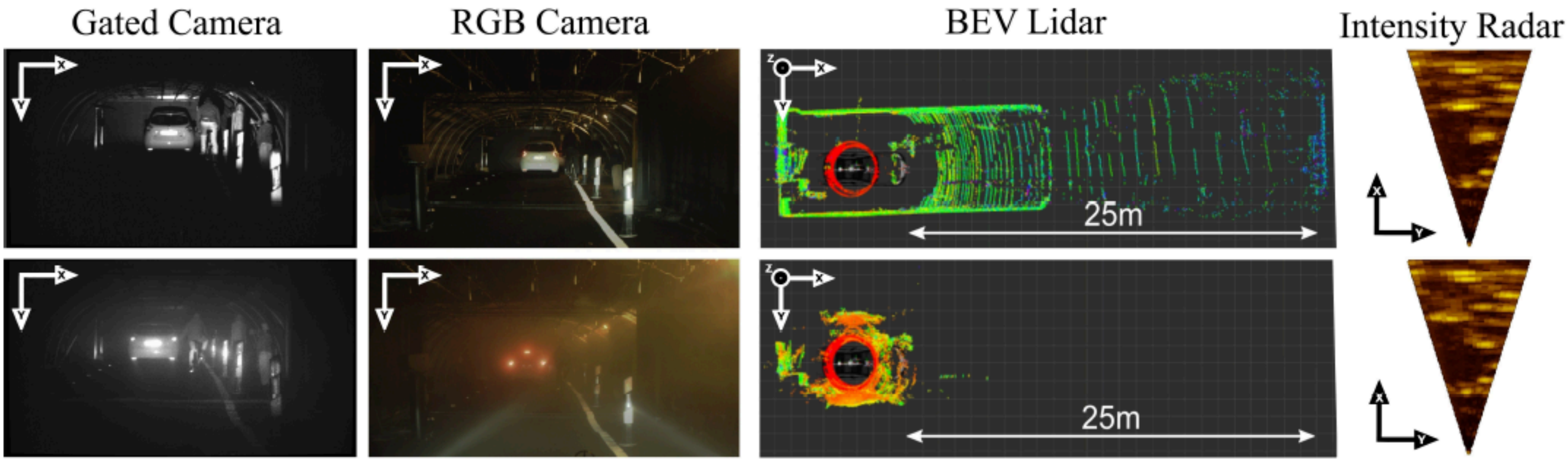


Figure 3: Multimodal sensor response of RGB camera, scanning lidar, gated camera, and radar in a fog chamber with dense fog. Reference recordings under clear conditions are shown in the first row, recordings in fog with visibility of 23 m are shown in the second row.

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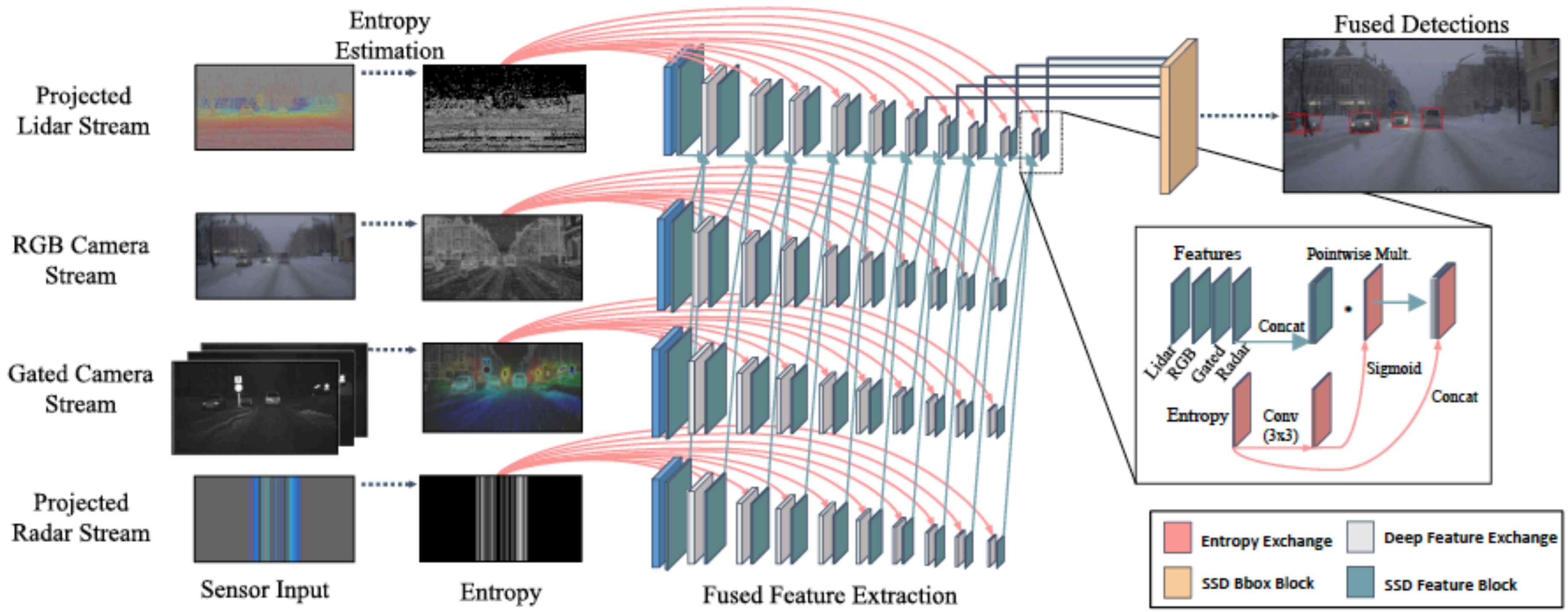


Figure 4: Overview of our architecture consisting of four single-shot detector branches with deep feature exchange and adaptive fusion of lidar, RGB camera, gated camera, and radar. All sensory data is projected into the camera coordinate system following Sec. 4.1. To steer fusion in-between sensors, the model relies on sensor entropy, which is provided to each feature exchange block *(red)*. The deep feature exchange blocks *(white)* interchange information *(blue)* with parallel feature extraction blocks. The fused feature maps are analyzed by SSD blocks *(orange)*.

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