Fog, Rain, LIDAR and Radar

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Fog and Lidar: Lidar

About 800-1000 nm wavelength (longer than red)

\[ d = \frac{c t}{2} \]

Wikipedia
Raindrop backscatter
Fog scattering

Source

Detector

FOG

Raindrop

Detector
What the sensor sees...

No fog

Extreme fog
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.
Fog
Rain
Very bright light

(a) VLS-128  (b) HDL-64S2  (c) HDL-32E

Carballo, 20
Fig. 9: “Rain pillars” as detected by a LiDAR.

- Qualitative effects
  - lost returns
  - fog torus
  - early returns
  - rain pillars
  - noise
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* $\equiv$ low, *cyan* $\equiv$ high, 3D bounding box annotation in *green*, ego vehicle dimensions in *gray*).
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.

Bansal et al 20
What the sensor sees...

Simulate this effect, with a form of point spread function

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

Hahner 21
Multi sensor methods

Image-only Detection

Lidar-only Detection

Proposed Fusion Architecture

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.

Bijelic et al 20
Gated cameras

From sensors unlimited website
Multi sensor bad weather data

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| Dataset Statistics | | | | | |
|---------------------| | | | | |
| Labeled Frames      | 15K         | 100k     | 198k       | 40K          | 13.5K |
| Labels              | 80k         | 1.4M     | 7.87M      | 1.4M         | 100K  |
| Scene Tags          | x           | ✓        | x          | ✓            | ✓     |
| Night Time          | x           | ✓        | ✓          | ✓            | ✓     |
| Light Weather       | x           | ✓        | x          | ✓            | ✓     |
| Heavy Weather       | x           | x        | x          | ✓            | ✓     |
| Fog Chamber         | x           | x        | x          | ✓            | ✓     |

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

Bijelic et al 20
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.
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).