Automotive Sensor Performance in Adverse Weather

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Abstract

Vision in all seasons is one of the key components enabling the perception for autonomous driving in various difficult weather situations aside sunny California. Towards achieving this ultimate goal, different kind of problems have to be faced. Adverse weather noise is complex, it can have multiple appearances and disturbs each sensor technology differently. This can be circumvented by enhanced and robust sensor technologies, where the performance is increased and robust downstream algorithms can interpret the perceived sensor signals. To assess both enhancement directions novel evaluation metrics as well as dataset baselines are necessary.

1. Introduction

Improved vision and environment interpretation under adverse weather conditions plays a crucial role in the expansion of robotics and autonomous driving technologies into many parts of the world and in our every day use. Especially for the automotive sector an increase in environment perception is important. For example in the US, between 2007 to 2016, an average of 21 % of all crashes per year have been caused due to adverse weather conditions. In those incidents 5,376 persons were killed and 418,005 have been injured annually. One of the main reason is the visibility reduction for human drivers and the disturbed perception. Due to its high visibility reduction, fog has caused 3 % of all weather related accidents and has been furthermore responsible for about 9 % of all weather related fatalities [1], even though being one of the rarest weather phenomena [18].

Just like humans, the assistance systems that are available on the market are disturbed by adverse weather conditions [2]. To increase general performance, different automotive and robotics companies rely on a large number of different sensors such as RGB-camera, radar and lidar. In clear weather conditions, these sensors usually provide reliable sensor streams that can be fed into intelligent algorithms for object detection, depth estimation or semantic scene understanding. However, in real world scenarios including fog, haze, snow and rain, the performance of these sensors drops significantly. While in camera images contrast degenerates, lidar pointclouds lose points and get dispersed due to atmospheric attenuation and scattering [7, 6, 16, 17].

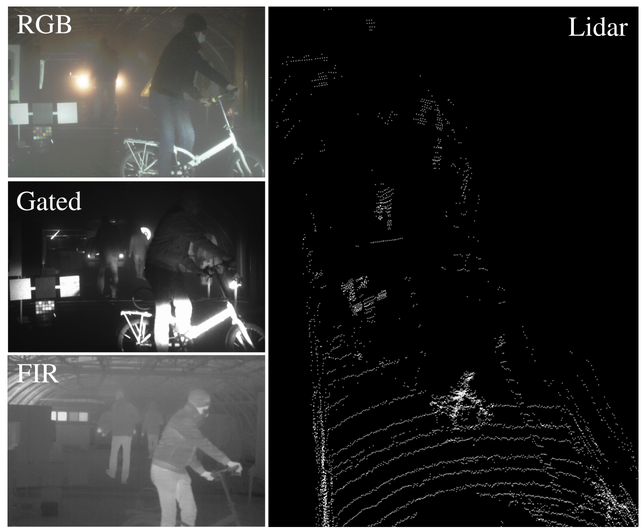

Figure 1: Qualitative RGB (aptina ar0230), gated (BWV gated cam), FIR (Axis Q1922) images and lidar (Velodyne HDL-64S2) pointcloud in fog with a visibility of approximately 50 m and an oncoming car. All sensors get massively disturbed hindering a reliable environment perception. Note the third vulnerable road user next to the oncoming car. He disappears in the standard RGB image and lidar pointcloud.

Given the sensor development, the distortions can be minimized, but as physical laws cannot be overcome, there will be always disturbances in sensor data. Therefore, the collection of sensory data in such conditions is crucial to evaluate sensor performance and create appropriate evaluation techniques. Furthermore, such data can be used to evaluate the downstream perception pipeline. Consequently, this extended abstract covers the difficulties in sensor performance assessment and data collection.

2. Data Collection Campaigns

Current automotive benchmarking datasets that evaluate depth estimation, object detection or segmentation tasks [9, 11, 15, 12, 29] are biased towards good weather sce-

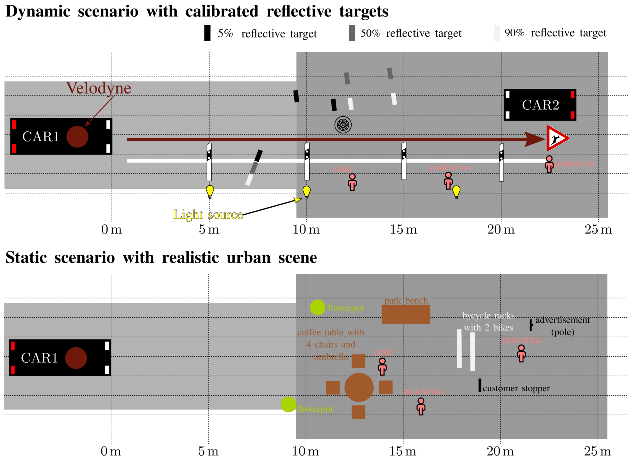

Figure 2: Exemplary scene setup for the evaluation of enhancement methods [8].

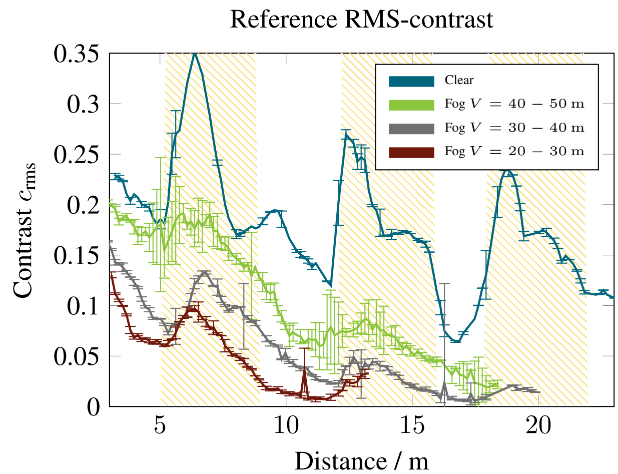

Figure 3: Reference contrast without enhancement for different fog densities shown from clear to increased fog levels. The regions of the chamber illuminated by light sources are highlighted in yellow [8].

narios. Real world adverse data is for example provided in [3, 5, 26]. Those datasets offer a good evaluation opportunity but are rather small and are lacking the multi modality that is needed for safe autonomous driving. Due to the lack of large scale, real world, adverse weather data, methods have been developed augmenting such data towards natural scenes, e.g. fog [26, 28], night [27, 22], blurred [20] or rainy scenes [14, 31, 25, 30]. For creating synthetic foggy images many existing methods are based on the well-known physical model of Koschmieder [19]. Those simulation methods have been applied to enhance the downstream object detection [20], semantic scene segmentation [26] or to provide a high resolution undisturbed image to a human observer [4, 23, 13, 24, 21].

In order to increase the simulation performance and detection methods, real data is crucial. Therefore, we have conducted a large scale data collection campaign in a fog chamber in [10]. An exemplary experiment setup for the evaluation of enhancement methods is shown in Figure 2. To validate it with real world scenes we undertook a test drive in northern Europe. This enabled the evaluation of current sensor performance. Paving the way for a reliable performance evaluation in such conditions, different challenges had to be circumvented. It starts with trivial problems as sensor cleaning systems and ends at low ambient temperatures in Northern Scandinavia leading to further weather phenomena as drifting snow that disturbs sensory data differently.

3. Challenges and Conclusion

The main challenges were the asymmetrically failing sensors and finding appropriate metrics for assessing the sensor specific performance. In Figure 1, a qualitative comparison between FIR-, RGB-, gated-camera and lidar is shown. Quantitatively it was found that the maximal viewing distance for current state of the art lidar systems is limited to 25 m given a fog visibility of smaller than 50 m. Different techniques such as multiple echos enhanced the maximal perception depth only slightly [6]. Besides lidar systems also the rapid contrast degeneration of RGB-cameras has been measured. Figure 3 shows the contrast degeneration of the complex scene in Figure 2. The contrast is measured in terms of the RMS contrast between three well defined reflective targets with reflectivity I_x and $x = 5\,\%,\ 50\,\%$ and $90\,\%$.

$$c_{rms} = \sqrt{\frac{(I_{90} - I_{50})}{2} + \frac{(I_{50} - I_5)}{2}} \tag{1}$$

Especially in regions without illumination the contrast drops significantly and therefore hinders perception. Another interesting event are oncoming cars as shown in Figure 1. Due to the introduced light cone by the oncoming car, potential vulnerable road users next to the oncoming car are covered and not recognizable in the RGB-camera. This can be circumvented by other sensor technologies as gated imaging [7] or suitable enhancement methods which have been quantitatively investigated in [8].

4. Acknowledgements

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