A Real-World Perception Dataset with Complex Adverse Traffic Scenarios

Hangyu Li
Department of Civil and Environmental Engineering,
University of Wisconsin-Madison,
Madison, United States
Email: hli939@wisc.edu

Bofeng Cao
Department of Electrical and Computer Engineering,
University of Wisconsin-Madison,
Madison, United States

Zhaohui Liang, Ph.D.
Department of Civil and Environmental Engineering,
University of Wisconsin-Madison,
Madison, United States

Wuzhen Li
Department of Electrical and Computer Engineering,
University of Wisconsin-Madison,
Madison, United States

Chengyuan Ma, Ph.D., Shixiao Liang, Hang Zhou, Jiaxi Liu
Department of Civil and Environmental Engineering,
University of Wisconsin-Madison,
Madison, United States

Hongkai Yu, Ph.D.
Department of Electrical and Computer Engineering,
Cleveland State University,
Cleveland, United States

Xiaopeng Li, Ph.D., Corresponding Author
Department of Civil and Environmental Engineering,
University of Wisconsin-Madison,
Madison, United States
Email: xli2458@wisc.edu

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Statement of Significance
Complex Adverse Traffic Scenarios (CATS), such as severe weather, low visibility, and dynamically changing work zones, remain among the most challenging conditions for current autonomous driving systems. Progress in these scenarios is fundamentally constrained by the lack of high-quality real-world datasets that capture the adverse environmental, lighting, and operational conditions. To address this gap, we present a comprehensive real-world dataset collected across four seasons with diverse adverse weather, complex roadway environments, and richly annotated dynamic and static traffic elements. This dataset aims to support future research on robust autonomous driving and help accelerate progress toward safe operation in the most challenging real-world environments.

Author Contribution Statement
The authors confirm contribution to the paper as follows: study conception and design: H. Li, B. Cao, H. Yu, X. Li; vehicle configuration: H. Li, B. Cao, Z. Liang; data collection: H. Li, B. Cao, Z. Liang, W. Li, C. Ma, S. Liang, H. Zhou, J. Liu; data processing: H. Li, B. Cao, W. Li; draft manuscript preparation: H. Li, B. Cao, H. Yu, X. Li. All authors reviewed the results and approved the final version of the manuscript.

INTRODUCTION

The evolution of ego-vehicle perception systems has been a pivotal force in enabling production-grade L2$^+$ autonomous driving. Modern systems leverage tightly integrated multi-modal sensor suites, such as cameras, LiDAR, and radar, to capture heterogeneous sensory signals from complex road environments. Unified representation paradigms, including Bird's-Eye-View (BEV) (*1, 2*) and 3D Occupancy Grids (OCC) (*3–5*) have significantly advanced feature integration, supporting robust scene understanding at scale. The emergence of Vision-Language Models (VLMs) (*6, 7*) further equips perception systems with human-like reasoning capabilities, enabling adaptive interpretation in open-world conditions.

Despite this progress, the inherent limitations of on-board sensors such as occlusion, measurement noise, adverse environmental effects, and restricted fields of view remain critical bottlenecks preventing reliable operation at higher levels of autonomy (e.g., L3 and above), especially in Complex Adverse Traffic Scenarios (CATS) (*8, 9*). Severe variations in weather and lighting conditions introduce substantial sensing degradation, reducing detection reliability and propagating uncertainty into downstream planning and control modules (*10–12*).

While numerous real-world datasets such as KITTI (*13*), Waymo (*14*), and nuScenes (*15*) have played a transformative role in advancing autonomous driving perception, they primarily capture conventional road, weather, and lighting conditions. Due to the stringent and unpredictable data collection requirements, datasets covering CATS remain scarce, and research in these scenarios has often had to rely on digital simulations (*16, 17*) or controlled indoor environments (*12*), which cannot fully replicate real-world variability and sensor behavior.

To fill this gap, we introduce a comprehensive real-world dataset specifically designed to capture the challenges of autonomous driving under Complex Adverse Traffic Scenarios. This dataset was collected across four seasons with diverse adverse weather (rain, snow, fog), varied lighting (direct sunlight, low-light, nighttime), and dynamically evolving roadway environments, including irregular work zones and snow-covered roads. It includes synchronized 10 Hz LiDAR, 30 Hz multi-view cameras, and 125 Hz GNSS/IMU measurements.

DATASET

In this section, we introduce our vehicle configurations, data acquisition, and annotations.

Vehicle configurations

We used a Lincoln MKZ sedan to collect data, with the main sensors installed on an aluminum frame, as shown in Figure 1.

Sensors setup

The vehicle is equipped with a 128 beam mechanical spinning LiDAR, seven automotive grade GMSL2 cameras, and one high-precision INS. The LiDAR is installed in the upper middle position to cover the widest 360 degree viewing angle. Seven cameras include two front-view (wide-angle and telephoto) cameras, one rear-view camera, and four side-view cameras.

Speifically, we use 10 Hz RoboSense Ruby Plus 128-beam LiDAR, with dual return mode, 250m range, and angle resolution 0.2°. Cameras are 30 Hz OMNIVISION OX08B40, YUV422 8bit, 3840×2160, 140dB HDR, LFM for front and rear ones. On the other hand, we use OMNIVISION OX03C10, YUV422 8bit, 1920×1080, 140dB HDR, LFM for side ones. In addition, one deeply coupled GPS/INS integration with Epson G320 IMU, 0.5°/h bias instability is employed.

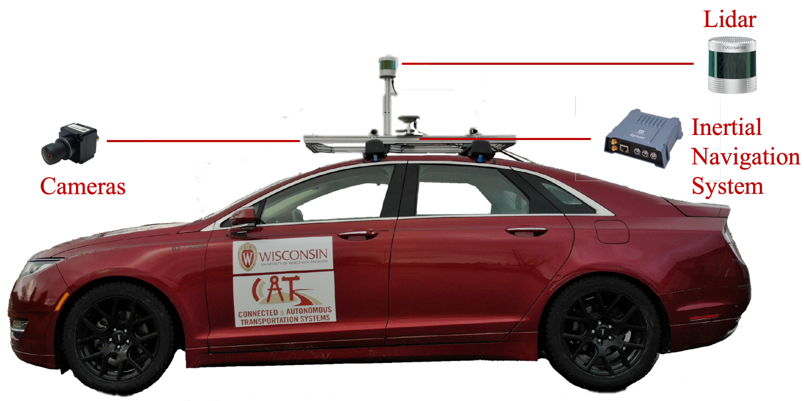


FIGURE 1 Sensor configurations of our data-collecting vehicle.

Data acquisition

We collected data in different seasons, weather, and lighting conditions (see Figure 2), and collected the raw data of ROS2 bags through multiple hard drives stored simultaneously. The cameras, LiDARs, and INSs all publish hardware timestamps. Finally, the point clouds and uncompressed camera images were unpacked from the recorded raw data bags.

For camera calibration, we used the original factory internal parameters provided by the suppliers. We referred Koide et al. (18) to the calibration of camera and LiDAR extrinsic parameters. The calibration from LiDAR to IMU was carried out with reference to Lv et al. (19).

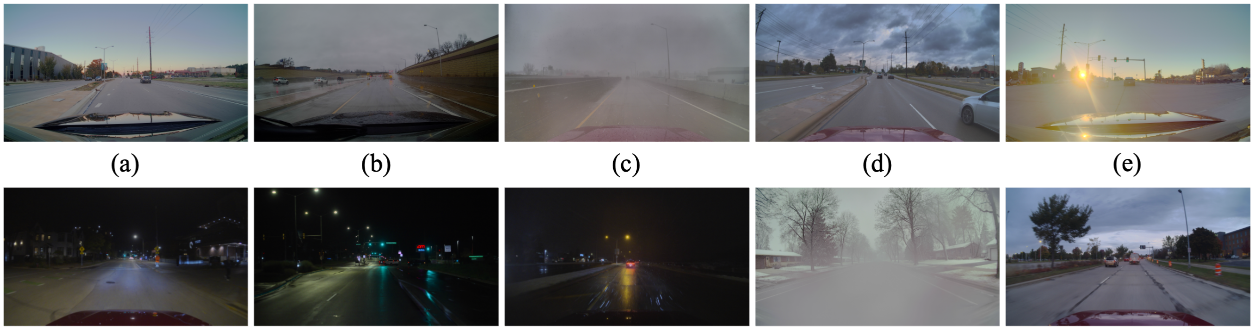
During our collection, we ensured that our INSs were always in a fixed status to get the most precise global localization. This information is then used to derive our initial guess for the poses of sensor frames in each time stamp. Finally, the fine-tuning is conducted through GICP (*20*) for point clouds registration, which ultimately transformed to obtain our ground truth localization and pose of each frame.

Data annotation

We provide precise 4D annotation, including 3D bounding boxes and time-consistent IDs, as well as time-consistent dimensions for rigid objects. Annotation is achieved through the fusion of images and point clouds, and we provide detailed annotations for any object that can only be recognized in an image or a point cloud. Meanwhile, each object has a globally independent ID to assist in cross-frame re-recognition.

Two major categories of vehicles and vulnerable road users (VRU) are set for dynamic objects. In the category of vehicles, we further distinguish them with six subclasses: Car, Van, Truck, Trailer, Bus, and Others. Among them, due to the potential impact on traffic behavior and subsequent tracking tasks, we set an emergency attribute for them to distinguish between police cars, fire trucks, and ambulances on duty. For the VRU class, our subclasses include Pedestrian, Scooter, Bicycle, and Motorcycle.

In addition, a virtual link could be given through an ID pair, indicating the physical connection between the two. For example, a link between one Car object and one Trailer object may together indicate a pickup truck towing a trailer.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

FIGURE 2 Ten typical complex and adverse scenarios.

CONCLUSION

In this work, we present a perception dataset with **A**dverse **T**raffic **S**cenarios (**CATS-V2V**). It is a large-scale real-world dataset collected on various adverse weather, lighting, and road conditions, including rain, snow, direct sunlight, nighttime, urban intersections, and roads in rural and campus areas. Specifically, the dataset provides anonymized point clouds and images from one LiDAR and seven cameras of the vehicle, as well as 4D bounding box annotations (3D + time) and HD Maps. Future plans include combining multiple vehicles, collaborating with roadside infrastructure, and including diverse emerging automotive sensors to provide a richer dataset covering various corner cases, and developing tools for converting it to motion datasets and realistic digital twins. We hope the dataset will promote research in the community.

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