GO: The Great Outdoors Multimodal Dataset

Peng Jiang[1], Kasi Viswanath[1], Akhil Nagariya[1], George Chustz[1], Maggie Wigness[2], Philip Osteen[2], Timothy Overbye[2], Christian Ellis[2], Long Quang[2], Srikanth Saripalli[1]

***Abstract*—The Great Outdoors (GO) dataset is a multi-modal annotated data resource aimed at advancing ground robotics research in unstructured environments. This dataset provides the most comprehensive set of data modalities and annotations compared to existing off-road datasets. In total, the GO dataset includes six unique sensor types with high-quality semantic annotations and GPS traces to support tasks such as semantic segmentation, object detection, and SLAM. The diverse environmental conditions represented in the dataset present significant real-world challenges that provide opportunities to develop more robust solutions to support the continued advancement of field robotics, autonomous exploration, and perception systems in natural environments. The dataset can be downloaded at: https://www.unmannedlab.org/the-great-outdoors-dataset/**

***Index Terms*—Off-road Robotics, Radar, Navigation, Semantic Segmentation**

I. Introduction

Research efforts supporting autonomous ground robot operation in unstructured environments are experiencing rapid growth, driven by the increasing demand for autonomous systems capable of navigating and perceiving complex terrains. Applications in agriculture, search and rescue, and environmental monitoring are fueling this expansion. The use of traditional ground robotics solutions that have primarily focused on urban operation, with well-defined roads, infrastructure, and structured cues, will be insufficient for the off-road domain. Unlike structured urban environments, natural terrains present unique challenges, including *unpredictable obstacles* (e.g., fallen trees, rocks, and wildlife), *varying surface types* (e.g., mud, sand, gravel, and vegetation), *dense vegetation* that obstructs visibility and hinders movement, *uneven topography* (e.g., steep slopes, cliffs, and ditches), and *degraded sensor data* (e.g., blurry images or missing LiDAR hits) stemming from the characteristics and complexity of the off-road environment. To achieve effective perception, localization, and planning in such environments, robots require diverse sensory inputs and comprehensive training data. This necessitates the curation of datasets that accurately represent the complexity of these natural settings.

The emergence of several multi-modal datasets to train and evaluate perception systems in off-road robotics supports the notion that diverse sensor inputs are critical to addressing the complex and variable nature of unstructured terrains. Early efforts such as RELLIS-3D [1] include LiDAR and RGB data, providing essential depth and visual information for off-road robotics. It also provides semantic annotations for LiDAR

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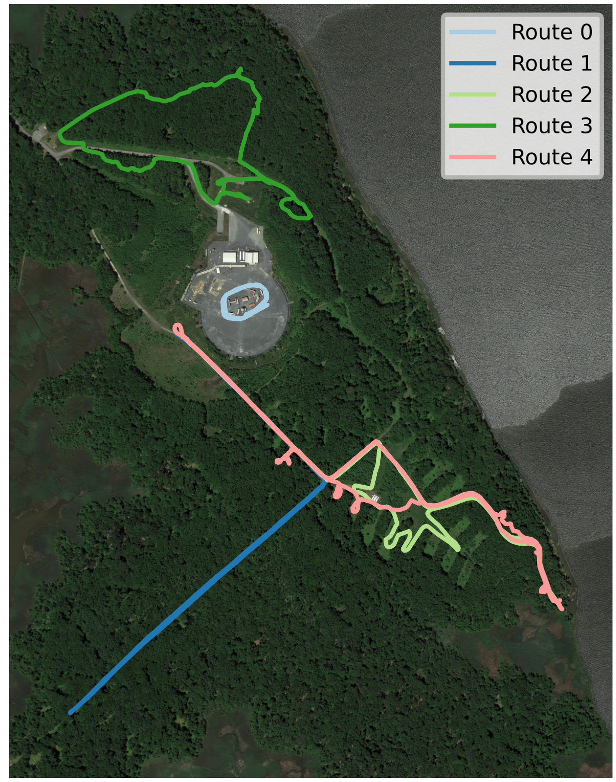


Fig. 1. The GO dataset comprises five routes, covering a cumulative distance of 10.26 km and a total duration of 98.60 minutes.

and camera data, focusing on unstructured environments, particularly rural and natural settings. The GOOSE dataset [2] and its extension GOOSE-Ex dataset [3] offers multi-platform data, including visual and LiDAR sensors, for semantic segmentation in challenging off-road conditions. TartanDrive 2.0 [4] is an enhanced version of the original TartanDrive [5], incorporating an expanded sensor suite that includes multiple LiDAR units alongside cameras and inertial sensors. It covers diverse off-road terrains, providing a comprehensive dataset for self-supervised learning in off-road conditions.

A shortcoming of the previously mentioned datasets is that exteroceptive sensors like LiDAR and RGB cameras are highly susceptible to interference from large particles like dust, rain, and snow due to their limited wavelength detection range (RGB camera: 400-700 nm; LiDAR: 750 nm to 1.5 µm). Thus, these sensors can be unreliable in degraded conditions such as low light, moonlight, darkness, dust (1-400 µm wavelength), smoke (0.1-2.5 µm), fog (10-50 µm), snow, and rain (2 mm). To better address operation in degraded conditions, sensors such as radar and NIR cameras have been explored in the off-road domain. OORD [6] provides radar

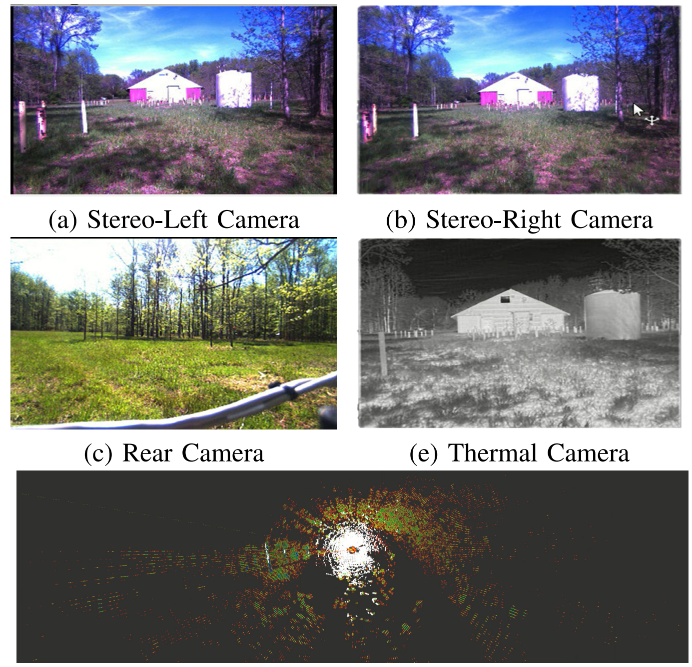
TABLE I
COMPARISON OF SEVERAL EXISTING OFF-ROAD MULTI-MODAL DATASETS

Dataset	Camera	Stereo	LIDAR	NIR	Radar	IMU	GPS	Labels
RELLIS-3D [1]	●	●	●	○	○	●	●	●
TartanDrive 2.0 [4]	●	●	●	●	○	●	●	○
OORD [6]	●	○	○	○	●	●	●	○
GOOSE-Ex [3]	●	●	●	●	○	●	●	●
FOMO [7]	●	●	●	○	●	●	●	○
TAS-NIR [8]	●	○	○	●	○	○	○	●
GO	●	●	●	●	●	●	●	●

data for place recognition in rugged, off-road environments, contributing significantly to radar research in unstructured settings. The FoMo dataset [7] provides LiDAR and radar data for navigation in boreal forests, emphasizing sensor fusion in complex natural environments. The TAS-NIR dataset [8] consists of paired visible and near-infrared (VIS+NIR) images, with fine-grained semantic segmentation of vegetation and ground surfaces in unstructured outdoor environments. For a comprehensive overview of existing off-road datasets, we refer the reader to the survey by Mortimer and Maehlisch [9], which highlights key limitations in these data. While many multi-modal off-road data resources are available, there is still a lack of data that encompass a comprehensive set of all previously mentioned sensing modalities that are well calibrated and accompanied by ground truth annotations for evaluation (see Table I).

To address the limitations of existing datasets and fill the gap in comprehensive multi-modal data for unstructured environments, we introduce the Great Outdoors (GO) dataset. This dataset provides a rich collection of sensor data and dense ground truth annotations for five long-distance, off-road routes that depict varying terrain and challenging unstructured conditions. Figure 1 shows an overhead view of these routes. In summary, the GO dataset offers several key contributions:

- **Comprehensive Sensor Suite:** Integrates a wide range of modalities, including monocular, stereo, and thermal imagery, LiDAR, radar, and inertial measurements, enabling sensor fusion research to support robust perception, localization, and planning in diverse conditions.
- **Inclusion of Thermal and Radar Data:** Enhances perception capabilities in degraded environmental conditions such as low light, dust, or smoke, where traditional sensors like cameras and LiDAR may be unreliable.
- **High-Quality Semantic Annotations:** Provides detailed semantic annotations for images, supporting tasks like semantic segmentation, object detection, and SLAM, crucial for scene understanding and navigation in unstructured terrains.
- **Precise Trajectory Ground Truth:** Includes centimeter-precision route traces derived from RTK GPS, which are valuable for the development and assessment of SLAM and odometry estimation algorithms.
- **Diverse Terrain Coverage:** Captures a variety of natural environments, including forests, rocky trails, open fields, and bodies of water, ensuring the dataset's applicability to a wide range of real-world off-road scenarios.



(a) Stereo-Left Camera (b) Stereo-Right Camera

(c) Rear Camera (e) Thermal Camera

(e)Lidar data (white) and Threshold filtered Radar data (color)

Fig. 2. Example of the raw perception sensor data from the GO Dataset. The figure shows (a) the left stereo camera view, (b) the right stereo camera view, (c) the rear camera view, (d) thermal camera imagery, and (e) a combined representation of LiDAR (white) and threshold-filtered radar data (color)

II. DATASET DESCRIPTIONS

A. Sensor Setup

We used a Clearpath Warthog mobile robot as our platform to gather data. The onboard sensor suite includes:

- 1 × Ouster OS1 LiDAR: 64 Channels, 2048 horizontal resolution, 10 Hz, 45° vertical field of view;
- 1 × RGB Camera: FLIR Blackfly S, Rear-mounted, running at 30 Hz;
- 1 × Stereo Camera: FLIR Blackfly S, Front-facing stereo configuration, 30 Hz;
- 1 × Thermal Camera: FLIR Boson 640, operating at 60 Hz;
- 1 × Inertial Navigation System (IMU/GPS): MicroStrain 3DM-GX5-AHRS, provides 200 Hz IMU data;
- 2D mmWave Radar: The Navtech CTS350-X functions at 4 Hz, offering 360° azimuth coverage with a 0.9° sampling interval, and has a range capacity of 270 meters along with 400 input rotations per cycle
- RTK GPS: The Sparkfun RTK Facet provides a maximum accuracy of 1.4 cm and operates at a frequency of 4 Hz.

B. Sensor Calibration and Synchronization

To ensure accurate sensor synchronization across the computer and sensor network, we utilize Precision Time Protocol (PTP) for radar, LiDAR, and monocular and stereo cameras. A high-precision clock serves as the authoritative time source that synchronizes sensors and computers via PTP. The thermal camera and GNSS/IMU rely on ROS timestamps for synchronization.

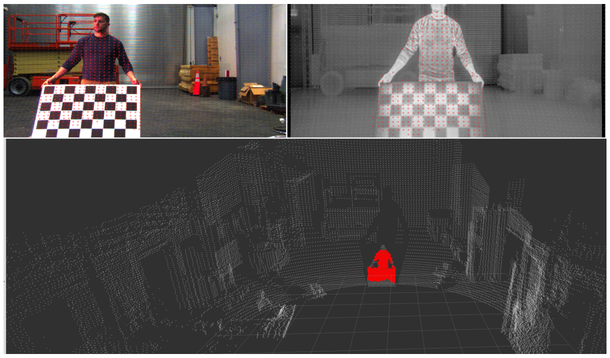


Fig. 3. Qualitative visualization of the LiDAR-Camera calibration.

TABLE II
DETAILS OF THE FIVE ROUTES OF THE GO DATASET

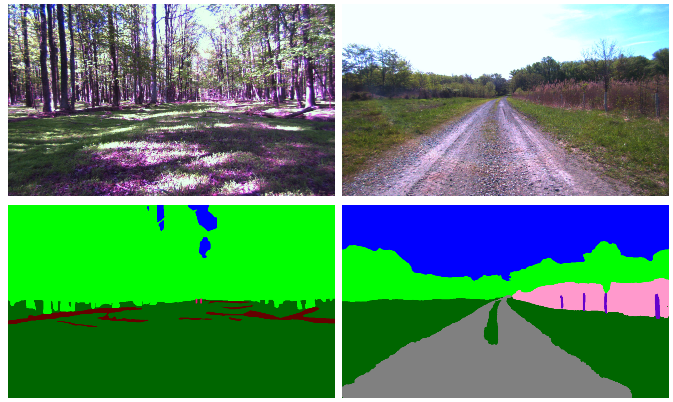
Route	t(min)	d(km)	v_{max}(m/s)	v_{avg}(m/s)	Environment
0	3.43	0.58	4.00	2.91	paved area
1	13.02	2.35	3.98	3.15	trails
2	33.40	1.82	3.18	0.98	trails, forest
3	17.90	2.79	4.06	2.80	trails, forest
4	30.85	2.72	3.96	1.59	trails, forest

For calibration, we employ the MSG-Cal method [10], using a planar board to align the LiDAR and RGB/Thermal camera sensors, as shown in Fig. 3. The radar's transformation with respect to other sensors is calibrated using a 3D model to align the radar data with the 3D scanned point cloud accurately.

C. Route Information

Data acquisition was conducted over a two-day period in May at the DEVCOM Army Research Laboratory's Robotics Research Collaboration Campus (R2C2). The dataset comprises a teleoperated collection of five distinct routes (as seen in Fig. 1), collectively spanning 10.26 km of unstructured terrain with a combined total operation time of 98.60 minutes. A summary of the time, distance, velocity, and environment type for each route is presented in Table II. The driving environment is broadly categorized into two types: *Forest Area* and *Trails*, which can be seen in Fig. 4 (a) and (b), respectively.

- *Route 0* serves as a test route where the robot travels at high speed in a minimally featured paved area, covering 0.58 km in 3.43 minutes, with a peak speed of 4.00 m/s.
- *Route 1* features a loop on a gravel roadway, spanning 2.35 km in 13.02 minutes and an average speed of 3.15 m/s.
- *Route 2* is the most intricate route among the five, integrating both gravel trails and forest regions, resulting in an average speed of just 0.98 m/s due to difficult terrain.
- *Route 3* was recorded on a trail with multiple instances of the robot deviating into off-road areas before returning to the main path, achieving an average speed of 2.80 m/s.
- *Route 4* followed the same trail as *Route 3* but on a different day, and deviated into different off-road areas, resulting in an average speed of 1.59 m/s.



(a) Forest Area (b) Trail

Fig. 4. Example images and semantic segmentation labels from the GO Dataset. The figure shows (a) a forest area and (b) a trail, along with their respective semantic segmentation results.

D. Semantic Annotations:

1) Ontology: The GO dataset provides detailed pixel-wise semantic annotations (see Fig. 4) to support enhanced autonomous off-road navigation. By integrating the ontological frameworks of the RELLIS-3D dataset [1] alongside the RUGD dataset [11], we constructed a comprehensive ontology of terrain and object categories tailored for our GO dataset. In total, the dataset includes 22 distinct classes, covering categories including trees, grass, dirt, sky, gravel, bush, mulch, water, poles, fences, persons, buildings, objects, vehicles, barriers, mud, concrete, puddles, rubble, asphalt, and a void class.

2) Annotation process: The annotation process was semi-automated: we selected keyframes and used the Segment Anything Model (SAM) [12] and OffSeg model [13] to provide initial segmentation labels. These initial labels were then refined by human annotators who manually assigned semantic labels, adjusted boundaries, and corrected errors. We also provide labels to thermal image data by utilizing the calibration between RGB camera and thermal cameras.

3) Class Distribution: The semantic class distribution for the GO dataset can be seen in Fig. 5 and reveals that vegetation-related classes, such as trees and grass, are highly represented, while man-made structures like fences, vehicle, and building are less frequent. This imbalance highlights the dataset's emphasis on natural terrains, making it well-suited for off-road robotics, but also presents challenges for training balanced perception models across all classes.

III. RESEARCH DIRECTIONS AND OPEN QUESTIONS

The GO dataset can be used in the following research areas:

- **Robust Localization:** The dataset provides accurate GPS ground truth trajectories synchronized with LiDAR, visual, radar, and NIR sensor data. This enables the development and evaluation of robust odometry, SLAM, and place recognition algorithms, particularly those leveraging novel modalities like radar and NIR or exploring advanced sensor fusion techniques for improved accuracy in off-road environments.

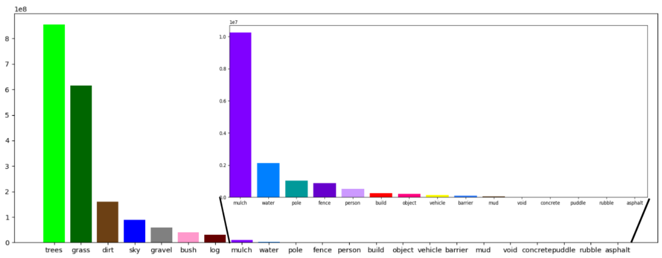


Fig. 5. Image Label distribution. The tree, grass, dirt and sky constitute the major classes.

- **Advanced Perception:** High-quality semantic annotations facilitate the development and evaluation of perception models for tasks such as semantic segmentation, object detection, and terrain classification. This rich labeled data enables the development of autonomous systems capable of robustly understanding and interpreting complex outdoor scenes.
- **Reliable Navigation:** The dataset includes diverse routes with loops, varying speeds, and challenging terrains, providing a realistic testbed for evaluating and improving vision-based navigation models like ViNT [14]. The multi-modal data enables these models to learn robust features and generalize effectively to complex off-road environments.

While the GO dataset offers a valuable resource for off-road robotics research, it also presents several challenges and open questions that warrant further investigation:

- **Generalization to Unseen Environments**: How well do models trained on the GO dataset generalize to new and unseen off-road environments with different terrain types, vegetation, weather conditions, and object distributions?
- **Effective Multi-modal Fusion**: How can data from different sensor modalities (e.g., LiDAR, visual, radar, thermal, etc.) be effectively fused to achieve robust and accurate perception, localization, and navigation in challenging off-road settings?
- **Robustness to Degraded Features**: How can algorithms be made robust to degraded or missing sensor data caused by factors like dust, fog, rain, snow, or low-light conditions common in off-road environments?
- **Developing Standardized Evaluation Metrics**: What are the most appropriate metrics for evaluating the performance of different algorithms on the GO dataset, considering the specific challenges and requirements of off-road robotics tasks?

IV. Conclusion

This paper introduces the Great Outdoors (GO) dataset, a comprehensive resource designed to advance robotics research in unstructured environments. The GO dataset features a diverse range of sensor modalities, detailed semantic annotations and GPS traces, and challenging off-road scenarios. The novel characteristics of the GO dataset allows it to serve as a catalyst for developing more capable and adaptable autonomous systems for a variety of real-world applications in challenging outdoor settings. Future datasets aim to increase diversity across seasons, weather, and times of day, while simultaneously traversing more complex terrains beyond off-road trail.

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V. Biography Section

Peng Jiang is a Postdoctoral Researcher in the Mike Walker '66 Department of Mechanical Engineering at Texas A&M University. He earned his B.S. degree in Mechanical Engineering from the University of Electronic Science and Technology of China in 2014, followed by a M.S. degree in Mechanical Engineering from Shanghai Jiao Tong University in 2017. He obtained his Ph.D. degree in Mechanical Engineering from Texas A&M University. His research interests include scene understanding, sensor calibration and multi-modal data fusion.

Kasi Viswanath is a PhD student in the Mike Walker '66 Department of Mechanical Engineering at Texas A&M University. He received in BSMS degree in Physics from Indian Institute of Science Education and Research Bhopal.

Akhil Nagariya is a Senior Research Engineer in the Department of Mechanical Engineering at Texas A&M University, College Station. He is working on collaborative air-ground simulation and learning-based planning algorithms for autonomous driving. He completed his Ph.D. at Texas A&M University, where he worked on reinforcement learning-based trajectory tracking controllers for various types of off-road vehicles. Before joining Texas A&M, he worked for UUrmi Systems, where he led the teams working on navigation and localization subsystems for self-driving cars. Before joining Uurmi Systems, he worked on the human intent prediction module of the navigation subsystem of indoor robots.

George Chustz is a PhD student in the Mike Walker '66 Department of Mechanical Engineering at Texas A& M University. He earned his B.S. degree in Mechanical Engineering from the Mike Walker '66 Department of Mechanical Engineering at Texas A& M University.

Maggie Wigness is a senior computer scientist in the Intelligence for Robotics branch at the DEVCOM Army Research Laboratory. She earned her PhD in Computer Science from Colorado State University in 2015. Maggie leads research efforts focused on autonomous mobility for ground vehicles in unstructured environments, and has led and shaped research directions in many Army collaborative research alliances. She helped enable the advancement of ML-based approaches to support off-road mobility by spearheading some of the initial large-scale off-road benchmark datasets that are used extensively by the robotics research community.

Philip Osteen is a roboticist in the Autonomous Systems branch at the DEVCOM Army Research Laboratory. He received his B.S. degree in Aerospace Engineering from the University of Florida in 2007, and his M.S. degree in Mechanical Engineering from the University of Florida in 2009, where he participated in the 2007 DARPA Urban Challenge. He subsequently worked at the Robotics, Vision, and Control Group at the University of Seville, before beginning his current position in 2010. His research interests include label efficient deployment of machine learning algorithms, multi-modal data fusion, and representations for autonomy in unstructured environments.

Timothy Overbye is a postdoctoral researcher in the Intelligence for Robotics branch at the DEVCOM Army Research Laboratory. He received his B.S degree in Mechanical Engineering at the University of Illinois Urbana-Champaign in 2017 and his PhD in Mechanical Engineering from Texas A&M University in 2023. His research interests include perception, mapping, and path planning in unstructured environments.

Christian Ellis is a joint postdoctoral researcher at the DEVCOM Army Research Laboratory and the University of Texas Austin Center for Autonomy focused on building safe and robust algorithms for autonomous systems which can operate in environments beyond where they were trained. His research interests include safe inverse reinforcement learning, environmental uncertainty quantification, open world learning, test and evaluation, and formal verification. Resulting publications provide applied solutions to real world autonomous systems. Christian received a Ph.D. in Electrical and Computer Engineering in 2024 for his dissertation titled, "Terrain Aware Autonomous Ground Navigation in Unstructured Environments Informed by Human Demonstrations," and a B.S. in Computer Science: Software Engineering in 2019 from the University of Massachusetts, Dartmouth.

Long Quang acquired a Bachelor of Science in Electrical Engineering at the University of Texas at Dallas. He is currently an electronics engineer in the Intelligence for Robotics branch at the DEVCOM Army Research Laboratory, where he actively facilitates robotics research and systems integration.

Srikanth Saripalli is a Professor in the Mechanical Engineering department and the Director of the Center for Autonomous Vehicles and Sensor Systems (CANVASS) at Texas A&M University. He holds the J. Mike Walker '66 Professorship. His research focuses on robotic systems, particularly in air, water, and ground vehicles, and the necessary foundations in perception, planning, control, and system integration for this domain. He is currently leading several efforts in off-road autonomous ground vehicles funded by DARPA and the Army. He has also led several long-term ($>$ 6 months) on-road deployments of autonomous 18-wheeler trucks and shuttles in Texas. He is also interested in developing autonomous vehicles for warehouses, mobility challenges, and paratransit applications.