ARL-MR-1129 ● JUNE 2025

Distributed Autonomous Robotic Experiments and Simulations (DARES): Program Review

by Srikanth Saripalli, Susan Toth, and Kristin E. Schaefer

NOTICES

Disclaimers

ARL-MR-1129 ● JUNE 2025

Distributed Autonomous Robotic Experiments and Simulations (DARES): Program Review

Srikanth Saripalli
Texas A&M University

Susan Toth and Kristin E. Schaefer
DEVCOM Army Research Laboratory

REPORT DOCUMENTATION PAGE

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED START DATE	3. DATES COVERED END DATE
June 2025	Memorandum Report	25 April 2025	16 June 2025

4. TITLE AND SUBTITLE
Distributed Autonomous Robotic Experiments and Simulations (DARES): Program Review

5a. CONTRACT NUMBER	5b. GRANT NUMBER	5c. PROGRAM ELEMENT NUMBER
W911NF-21-2-0064		
5d. PROJECT NUMBER	**5e. TASK NUMBER**	**5f. WORK UNIT NUMBER**

6. AUTHOR(S)
Srikanth Saripalli, Susan Toth, and Kristin E. Schaefer

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)	8. PERFORMING ORGANIZATION REPORT NUMBER
DEVCOM Army Research Laboratory ATTN: FCDD-RLA-IA Aberdeen Proving Ground, MD 21005	ARL-MR-1129

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRIBUTION STATEMENT A. Approved for public release: distribution unlimited.

13. SUPPLEMENTARY NOTES
ORCID: Kristin Schaefer, 0000-0002-1342-3446

14. ABSTRACT
The Distributed Autonomous Robotic Experiments and Simulation (DARES) cooperative agreement (CA) has completed its first three option years and is set to enter the final option year in October 2025. The DARES CA focused on six research areas covering the linking of proving grounds, semantic representations of environments, autonomy and perception, distributed and collaborative autonomous systems, and artificial intelligence algorithms. This report provides an overview of the programs and critical outcomes from the first three option years, followed by an initial proposal for the last year.

15. SUBJECT TERMS
Army, artificial intelligence, autonomy, robotics, simulation, Texas A&M University, Military Information Sciences

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	C. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED	UU	46

19a. NAME OF RESPONSIBLE PERSON	19b. PHONE NUMBER *(Include area code)*
Kristin E. Schaefer-Lay	(520) 691-4801

STANDARD FORM 298 (REV. 5/2020)
Prescribed by ANSI Std. Z39.18

Contents

List of Figures

1. Introduction

The Distributed Autonomous Robotic Experiments and Simulations (DARES) cooperative agreement (CA) was initiated to advance foundational science in the areas of distributed autonomy, robotics, and simulation. Three main technical areas were selected:

- Technical Area 1: Develop and demonstrate the remote operation and real-time control of multiple autonomous agents operating in a synthetic environment that is synergistically shared with the Robotics Research Collaboration Campus (R2C2) facility in Maryland and the Texas A&M University (TAMU) RELLIS* Starlab Facility in College Station, Texas.
- Technical Area 2: Develop a user-friendly methodology to seamlessly parameterize lower-fidelity, computationally efficient physics-based dynamics models from currently available (but computationally intensive) medium-fidelity and ultra-high-fidelity models. Evaluate them in the synthetic environment developed in Technical Area 1.
- Technical Area 4†: Develop robust object detection and tracking algorithms under foggy, rainy, and other degraded visual environments; develop algorithms to plan optimal trajectories for an air vehicle with motion, fuel, and resource constraints; develop threat/anomaly detection algorithms and define evaluation criteria for concept demonstration of developed algorithms in further years.

Within this agreement, the U.S. Army Combat Capabilities Development Command Army Research Laboratory provided expertise and recommended collaborators in associated technologies including artificial intelligence, cybersecurity, synthetic environments, sensors, embedded systems, and positioning, navigation, and timing. Together TAMU and the DEVCOM Army Research Laboratory continuously evaluated research priorities and requirements to assess if additional technology areas need to be explored to fully accomplish the research goals and collaborated to plan, organize, conduct, and assess all aspects of the research effort.

---

*RELLIS is an innovation and technology campus. Its name stands for Texas A&M's core values: Respect, Excellence, Leadership, Loyalty, Integrity, and Selfless Service.
†Technical Area 3 was not selected for funding.

2. Initial Program Goals and Outcomes

Under the selected technical areas, there were specific research goals and deliverables, which are discussed below.

2.1 Technical Area 1: Distributed and Virtual Proving Grounds

This area had two main deliverables: initial simulation setup and connection between RELLIS Starlab and R2C2; and algorithms and middleware support for integrating simulated, emulated, and real components over a lossy network.

2.1.1 Deliverable 1: Initial Simulation Environment Setup in Starlab and Connection with R2C2

The principal investigators (PIs) for this deliverable were Drs. Hubbard, Saripalli, Hasnain, and Walsh. The ARL point of contact (POC) on this work was Dr. Kristin E. Schaefer-Lay. The goal of this deliverable was a demonstration of robotic platforms operating in shared, augmented-reality scale environments produced using ARL's Unity simulation with ARL's Ground Autonomy Stack. The initial plan was to have live robots operating at R2C2 where their behavior could be observed using a virtual reality setup that projects the actual vehicle dynamics and motion measured at RELLIS Starlab. Due to network and cyber requirements, this deliverable was demonstrated in the opposite manner, where researchers at R2C2 were able to control and interact with live robots at RELLIS Starlab.

2.1.1.1 Task 1: Integration of the Unity Simulation and ARL Ground Autonomy Stack with RELLIS Starlab Motion Capture System

The high-fidelity motion capture facilities of RELLIS Starlab were integrated with a Robot Operating System (ROS) platform. This enabled precision state estimation of the autonomous agents that will be needed for operating in scaled environments.

2.1.1.2 Task 2: Develop Architecture for Synchronizing Environments between RELLIS Starlab and R2C2

A custom plug-in was designed for ARL's Ground Autonomy Stack, which allowed for seamless communication of environments over standard internet networks between the two locations. This communication architecture was responsible for transmitting information about the environment from the host (where the environment is created) to the client (remote location where operations are performed).

2.1.2 Deliverable 2: Algorithms and Middleware Support for Integrating Simulated, Emulated, and Real Components over a Lossy Network

The PIs for this deliverable were Drs. Kumar and Shakkottai. The ARL POC was Dr. Ananthram Swami. TAMU developed a base implementation of an in-house sensor network architecture that can support simulated, emulated, and real sensors over a given communication network. The architecture is based on automatons called "components" that are named, possess state, contain algorithms, and can be composed into data generation, processing, and consumption chains. This deliverable involved the development of algorithms for maximizing the utility of information developed in a network. This included algorithms for ensuring a high value of information while minimizing network load via rate selection of information generation.

2.1.2.1 Task 1: Optimization of Sensor Network

The goal of this task was to optimize the sensor network to maximize the utility of the system by choosing the sensor transmission resolution and rates according to the available network resources. On the algorithmic side, TAMU designed a distributed algorithm that can tune the sensing resolution and frequency using a utility gradient-based feedback control scheme. The systems side included the development of application programming interfaces to enable a feedback control loop between sensors and recipients. Gradient-based algorithms were instantiated over the feedback control loop using video resolution and frame rate as the dimensions of control to ensure high utility across recipients.

2.1.2.2 Task 2: Maximize Utility of Information

The goal of this task was to develop algorithms that would transmit high-value information at the appropriate rates to ensure accurate computed functions. With the goal of ensuring highly accurate function computation using multiple sources of information, TAMU developed algorithms that determine the correct rate of transmission for different classes of functions in a distributed manner. Next, TAMU developed value-aware components capable of determining the tradeoff between the quality of information and transmission rate to send the correct feedback to the sensing nodes to minimize the network load while ensuring highly accurate function computation.

2.2 Technical Area 2: Semantic Representation and Modeling

This area had two main deliverables related to physics-based dynamic models and semantic perception models.

2.2.1 Deliverable 1: Parameterization of Lower-fidelity, Physics-based Dynamics Models

The PIs for this deliverable were Drs. Reddy, Srinivasa, and Wilkerson. The DEVCOM Ground Vehicle Systems Center (GVSC) POC was Dr. Paramsothy Jaykumar. The goal of this deliverable was to develop an automated, user-friendly methodology to seamlessly parameterize lower-fidelity, physics-based dynamics from currently available medium-fidelity or high-fidelity models.

2.2.1.1 Task 1: Viscoelastic-ribbon or Narrow Shell Model for Deformation of Multi-material Tires and Terrain Surfaces

The central idea behind the model was that the tire is treated as a "supported ribbon or narrow ring shell" subject to longitudinal and lateral shear, bending and twisting relative to the rigid hub. In a similar vein, the ground surface is also modeled as a thin strip surface layer supported by a rigid underlying terrain. In addition, the slip between the road and terrain can be modeled using a local friction circle or ellipse model that needs to be separately calibrating (including the effect of tire tread). TAMU's homogenized inelastic narrow shell model for multi-material tires was validated against high-fidelity finite element analysis (FEA) calculations of a strip of tire subject to axial torsional, shear, and bending loads. We aim to demonstrate a greater than 95% agreement between our plate theory and the FEA for axial displacement and curvature.

2.2.1.2 Task 2: Near Real-time Simulation of Terrain, Contact Patch, and Contact Traction Distribution

TAMU proposed to develop an in-house medium-fidelity finite element model (MF-FEM) of the tire that makes use of only two layers of shell elements contacting a terrain strip model. The outer layer of shell elements captures the inelastic behavior of the tread. A suite of MF-FEM calculations was carried out for various mesh resolutions to determine the coarsest mesh resolution that results in adequate (>85%) agreement between the MF-FEM and a high-fidelity finite element model (HF-FEM). The FEM simulations consisted of tire contact at a prescribed normal force using various substrates modeling. Additionally, a few simulations were conducted to assess the MF-FEM predictions in challenging 3D geometries (e.g., a tire climbing an irregularly shaped boulder). A benchmarking database was developed that documents the single-processor run time of each MF-FEM simulation as well as its associated deviation from HF-FEM predictions.

2.2.2 Deliverable 2: Initial Semantic Models from LiDAR and Imagery Data

The PIs for this deliverable were Drs. Hasnain and Krishnamurthy. The ARL POC was Dr. John Fossaceca. The goal of this deliverable was to develop the initial semantic models from LiDAR and imagery data, and to validate them using data collected at RELLIS Starlab.

2.2.2.1 Task 1: Canonical Representation of Annotated Semantic Model of Environments

The goal of this task was to reduce large-scale labelled environmental datasets into compressed format for transmission, and recover and reproduce the environment on the client end with enough fidelity to support fully autonomous and efficient operations of robotic platforms irrespective of network quality. A sample labeled dataset of the RELLIS campus, RELLIS-3D was processed and converted to the reduced form. Transmission of this dataset over standard internet connection was performed in support of a mission in which a vehicular platform would autonomously navigate a set of waypoints in an environment with obstacles.

2.2.2.2 Task 2: Multi-level-of-detail (M-LOD) Geometric Modeling of Natural Scenes

The objective of this task was to determine a geometric representation of the environment that (1) is compressible for transmission over lossy networks, (2) represents different objects in a scene at different levels of detail, and (3) respects temporal variations in the scene as the vehicle moves. TAMU used the RELLIS-3D dataset to develop our M-LOD modeling framework. The approach was based on the observation that the red–green–blue (RGB) and LiDAR representations in a multimodal dataset offer different types of information. TAMU used an *ontology-aware topological representation* for M-LOD modeling of natural scenes. Based on user input, the proposed method was able to generate a specific level of detail for identified semantic labels in a scene.

2.3 Research Outcomes: Option Years 1–3

2.3.1 Robotics Research Collaboration Campus Digital Twin

The TAMU team developed a comprehensive high-fidelity virtual model of ARL's R2C2 Military Operations on Urban Terrain site. This approach combined LiDAR scans, photogrammetry, and geospatial data into a unified real-time simulation supporting visualization and robotics testing in Unreal Engine. Currently, 200 acres have been covered where all directly scanned areas have a digital twin placement of trees and terrain features (Figure 1).

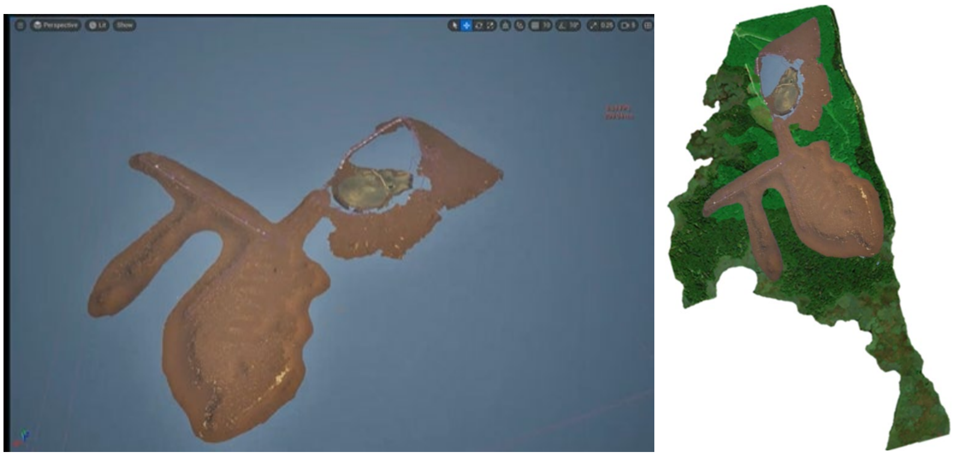

Figure 1. R2C2 areas modeled with high-fidelity LiDAR and photogrammetry. The left figure is the virtual area. The right figure is the virtual area overlaid on the full R2C2 peninsula.

A combination of the LiDAR and photogrammetry processes along with Gaussian splats provides a very high-fidelity virtual environment of R2C2 (Figure 2). Terrain graphics, such as tree species, do not identically match the tree species in Maryland. Available models of European trees were leveraged at this time. For the areas scanned, placement of real-world trees were identified and integrated. The areas outside the current scan scope were procedurally generated. The current model is in winter.

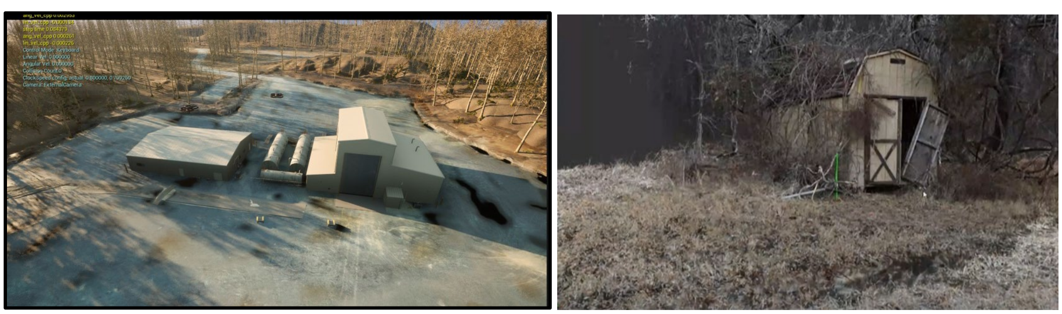

Figure 2. Visual depictions of the high-fidelity virtual environment in Unreal 5.4. The figure on the left was created using the LiDAR and photogrammetry procedures while the picture on the right uses Gaussian splats.

The underlying assets maintain compatibility with the Unity Game Engine, Omniverse, and other digital simulation platforms, establishing a scalable foundation for future site modeling (Figure 2). The R2C2 environment in the Unreal Engine has been integrated into ARL’s Live, Virtual, Constructive Toolkit and is currently in testing for a plug-in into GVSC’s ProjectGL Unreal autonomy simulation. In addition to using this environment for in-house ARL research, the

Unreal R2C2 Environment is being leveraged by ARL-NVIDIA collaborations for autonomy research, the Defense Advanced Research Projects Agency (DARPA) TIAMAT program exploring the Sim-2-Real gap (including MITRE; University of Texas at Austin; GE Aerospace; University of Pennsylvania; University of Washington; University of California, Berkeley; University at Buffalo; Duke University; and Carnegie Mellon University), and an international partnership agreement with Singapore for disaster relief research.

2.3.2 RELLIS-3D Multimodal Off-road Dataset

In collaboration with Dr. Maggie Wigness and Mr. Phil Osteen (ARL), the DARES team developed RELLIS-3D, the first and most comprehensive multimodal dataset for off-road autonomous navigation, addressing a critical gap in existing autonomy datasets that primarily represent urban environments.[1–4] This groundbreaking dataset includes annotations for 13,556 LiDAR scans and 6,235 images, along with full-stack sensor data in ROS bag format containing RGB camera images, LiDAR point clouds, stereo image pairs, high-precision GPS measurements, and inertial measurement unit data. RELLIS-3D has become an essential resource for researchers developing advanced algorithms to enhance autonomous navigation in challenging off-road environments. RELLIS-3D[*] is the only densely annotated multimodal off-road dataset for autonomous navigation, including annotations of 2D images and corresponding 3D point clouds. The public release of RELLIS-3D has filled a gap in the autonomy research community, who previously relied on datasets that are heavily focused on urban environments or lack dense multimodal annotations.

RELLIS-3D has been featured on the Army's home page and has garnered interest in the wider research community, with over 200 citations, and 317 stars and 51 forks on GitHub. Since it became available for open-source access on 4 March 2021, the dataset has resulted in 256 articles including 201 peer-reviewed articles, two master's theses, and seven dissertations. Publications, as documented in the Appendix, have leveraged the dataset for their research endeavors making it an internationally used dataset aligned to critical research advancements with LiDAR, perception, semantic segmentation, or off-road driving autonomy.

In 2022 and 2023, this dataset was leveraged by ARL as a foundation for the DoD-wide Deep Green Autonomous All-Terrain Model Challenge. This DoD-wide challenge is considered the premier Army data science competition. The competition structure forces algorithms to exhibit adaptive properties which are critical for Army systems operating in unstructured environments, tasking DoD

[*]https://github.com/unmannedlab/RELLIS-3D

teams with developing perception algorithms that perform pixel-level classification on data taken from new, undisclosed environments using image and depth information. The outcomes from this event resulted in a novel evaluation framework for comparing perception algorithms, evaluating over 100 candidate algorithms. In addition, the widespread adoption and utility of RELLIS-3D has culminated in the organization of a combined workshop at the Robotics: Science and Systems (RSS) conference, titled "RSS 2025 Workshop on Resilient Off-road Autonomous Robotics (RSS-ROAR 2025)," demonstrating the dataset's continued relevance and the growing research momentum in off-road autonomous navigation.

2.3.3 Semantic Data over Loss Networks

Working with ARL POC Dr. Suya You, the DARES team created innovative Voronoi-based methods for simplifying raw RGB and semantically segmented images to generate scene abstractions, while also developing hierarchical representations of LiDAR point cloud data for off-road environments.[5–8] Most prominent is how this geometric-statistical algorithm generates computationally inexpensive multilevel scene abstractions for robot decision-making with a low network transmission footprint, winning the best paper award at the 2024 American Society of Mechanical Engineers IDETC/CIE conference in the advanced vehicle technologies track.

2.3.4 Augmented-/Virtual-Reality-based Structural Damage Assessment

The DARES team improved autonomous navigation, structural damage assessment, and simulation realism through extensive friction coefficient analysis, model-based verification frameworks using the Vinnicombe metric, and automated structural damage detection algorithms.[9–13] These approaches achieved a 20%–55% accuracy improvement over existing methods, validated across synthetic and realistic scenarios, thus enhancing rapid structural assessment capabilities.

2.3.5 Air–Ground Simulation in Unreal Engine 5

Through a collaboration with ARL, the DARES team developed a high-fidelity Collaborative Air–Ground Simulation Environment in Unreal Engine 5, extending Unreal/AirSim to support ground vehicles with realistic LiDAR sensor models and environmental effects including rain and wind. This outcome included successfully integrating ARL's ROS2 Ground and ARL's ROS 2 Maverick autonomy stacks, enabling seamless testing of perception, planning, and control algorithms across multiple autonomous platforms, and air–ground teaming in the same virtual environment.[14] This technical advancement has been tested by the ARL team and is currently being integrated as a core capability within ARL's Live, Virtual, Constructive Toolkit. It will become available to all researchers partnering with ARL air–ground autonomy.

3. Upcoming Option Year 4 Planning

The DARES CA has the option of a final option year beginning 1 October 2025. Three proposed research areas moving forward in line with ARL research goals are discussed below.

3.1 Digital Twin as a Service

The DARES team plans to scale our digital twin pipeline to further extend the R2C2 peninsula and the R2C2 model to include seasonal environmental variations (Spring, Summer, Fall, Winter) for enhanced realism, and to extend to additional Army sites where relevant. Custom vegetation models based on ARL's detailed site surveys will enable accurate representation of native flora, further improving simulation fidelity and analysis capabilities.

3.2 Generative Semantic Segmentation

The DARES team plans to apply structure-guided adaptive hierarchical clustering to develop novel point cloud convolution operators for learning semantic segmentation from LiDAR data. Comprehensive hierarchical representations will be generated for RELLIS-3D and other off-road datasets to create both generative and nongenerative models (similar to convolutional neural networks, generative adversarial network, diffusion, and transformers) over these representations, overcoming challenges related to partial data and computational efficiency.

3.3 Augmented-/Virtual-Reality-based Testing of Off-Road Air–Ground Autonomy

The DARES team is interested in developing Physics-Informed Neural Networks to establish motion equivalency maps for autonomous air and ground vehicles across diverse terrains, incorporating physics-informed priors to enforce physical symmetries and promote generalizability. Additionally, using Unreal Engine 5 enhances visual and physical realism to support navigation in unstructured environments including water bodies and marshes, with capabilities for complex fluid–structure interactions, realistic tire deformations, and detailed terrain, wind, and weather modeling for complex air–ground autonomous interactions.

4. Conclusions

This collaboration between TAMU and ARL has successfully demonstrated remote operation and real-time control of autonomous agents across geographically separated facilities while developing algorithms for network optimization under communication constraints.

The creation of RELLIS-3D stands as one of the project's most impactful contributions, representing the first comprehensive multimodal dataset for off-road autonomous navigation and addressing a critical gap in existing research that previously relied heavily on urban-focused datasets. Since its open-source release in March 2021, this dataset has achieved remarkable adoption with over 200 citations, significant GitHub engagement (>30,000 downloads, 317 stars, 51 forks). The dataset's comprehensive scope includes 13,556 annotated LiDAR scans and 6,235 annotated images with full-stack sensor data, democratizing access to high-quality off-road navigation data for researchers worldwide.

Complementing the dataset achievements, the development of the R2C2 Digital Twin represents a significant contribution in simulation capability, creating a comprehensive 200-acre high-fidelity virtual model that combines LiDAR scanning, photogrammetry, and geospatial data into unified real-time simulation platforms. This digital twin maintains compatibility across multiple platforms including Unity Game Engine, Omniverse, and Unreal Engine, and has been successfully integrated into ARL's Live, Virtual, Constructive Toolkit while supporting major research initiatives including ARL-NVIDIA collaborations, the DARPA TIAMAT program, and international partnerships. The project's advanced air–ground simulation capabilities in Unreal Engine 5 provide testing environments for multi-platform autonomous systems, while algorithmic innovations including physics-based modeling achieve greater than 95% agreement with high-fidelity models while enabling near real-time simulation capabilities.

The project's emphasis on open-source data sharing and multi-platform compatibility ensures continuing influence on autonomous systems development, while the proposed Option Year 4 activities position the initiative to maintain leadership in emerging research frontiers including generative semantic segmentation and physics-informed neural networks.

5. References

1. Jiang P, Osteen P, Wigness M, Saripalli S. RELLIS-3D dataset: data, benchmarks and analysis. 2021 IEEE International Conference on Robotics and Automation (ICRA); c2021. p. 1110–1116.

2. Chustz G, Saripalli S. Road: RELLIS off-road odometry analysis dataset. 2022 IEEE Intelligent Vehicles Symposium (IV); c2022. p. 1504–1510.

3. Jiang P, Pandey G, Saripalli S. 3DGS-ReLoc: 3D gaussian splatting for map representation and visual relocalization. arXiv; 2024. arXiv:2403.11367. https://doi.org/10.48550/arXiv.2403.11367

4. Jiang P, Saripalli S. Contrastive learning of features between images and lidar. 2022 IEEE 18th International Conference on Automation Science and Engineering (CASE); c2022. p. 411–417.

5. Viswanath K, Singh K, Jiang P, Sujit PB, Saripalli S. Offseg: a semantic segmentation framework for off-road driving. 2021 IEEE 17th International Conference on Automation Science and Engineering (CASE); c2021. p. 354–359.

6. Jiang P, Saripalli S. LiDARNet: a boundary-aware domain adaptation model for point cloud semantic segmentation. 2021 IEEE International Conference on Robotics and Automation (ICRA); c2021. p. 2457–2464.

7. Jiang P, Saripalli S. ROSS: radar off-road semantic segmentation. International Symposium on Experimental Robotics; 2023. Springer Nature Switzerland; c2023. p. 264–273.

8. Viswanath K, Jiang P, Sujit PB, Saripalli S. Off-road lidar intensity based semantic segmentation. International Symposium on Experimental Robotics; 2023. Springer Nature Switzerland; c2023. p. 608–617.

9. Nolan J. Quantifying the effect of friction coefficients on the sim-to-real gap in robotics [master's thesis]. Texas A&M University; 2023. OAKTrust. https://oaktrust.library.tamu.edu/items/97184670-68d6-45fa-9bc3-f3de104b61ec

10. Waheed A, Areti M, Gallantree L, Hasnain Z. Quantifying the Sim2Real gap: model-based verification and validation in autonomous ground systems. IEEE Robotics and Automation Letters. 2025;10(2):1234–1241. https://doi.org/10.1109/LRA.2025.3546126

11. Areti M, Hasnain Z. Leveraging local neighborhood features in 3D unstructured point cloud data for geometry-based automated damage delineation. Automation in Construction. 2024;162:Article 105393. https://doi.org/10.1016/j.autcon.2024.105393

12. Areti M, Hasnain Z. Bilevel thresholding-based iterative analysis for building-surface damage detection in a postearthquake environment. Journal of Computing in Civil Engineering. 2022;36(5):04022026. https://doi.org/10.1061/(ASCE)CP.1943-5487.0001036

13. Kolluri MP, Shelar SV, Sarwar SA, Hasnain Z. A physics-informed approach for learning vehicle dynamics in high-speed autonomy. AIAA SciTech 2025 Forum; 2025. https://doi.org/10.2514/6.2025-1726

14. Nagariya A et al. Advancing multi-agent autonomy: challenges and solutions in LVC Simulation testbeds. Proceedings of the 2025 I/ITSEC Conference [in review].

Appendix. RELLIS-3D Citations

Included is the current reference list for publications citing RELLIS-3D (sorted by data and then alphabetically).

2025

1. Agishev R, Zimmermann K. MonoForce: Learnable Image-conditioned Physics Engine. arXiv; 2025. arXiv:2502.10156. https://doi.org/10.48550/arXiv.2502.10156

2. Alam FF, Luricich F, Li N, Jia Y, Li B. Hierarchical feature-based localization using scene graphs in off-road navigation. SAE Technical Paper; 2025. Report No.: 2025-01-8046.

3. Arafin T, et al. Advances and trends in terrain classification methods for off-road perception. Journal of Field Robotics. 2025. https://doi.org/10.1002/rob.22586

4. Backhaus A, Luettel T, Maehlisch M. Knowledge distillation for semantic segmentation: A label space unification approach. arXiv; 2025. arXiv:2502.19177. https://doi.org/10.48550/arXiv.2502.19177

5. Benitez JPL. Multi-task networks and anomaly detection in computer vision [dissertation]. Tampere University, Finland; 2025.

6. Betsas T, Georgopoulos A, Doulamis A, Grussenmeyer P. Deep learning on 3D semantic segmentation: A detailed review. Remote Sensing. 2025;17(2):298.

7. Bu Y, et al. Self-supervised traversability learning with online prototype adaptation for off-road autonomous driving. arXiv; 2025. arXiv:2504.12109. https://doi.org/10.48550/arXiv.2504.12109

8. Butt MA, et al. R 2 S100K: Road-region segmentation dataset for semi-supervised autonomous driving in the wild. International Journal of Computer Vision. 2025;133(2):910-928.

9. Carvalho A, Portugal D, Peixoto P. On terrain traversability analysis in unstructured environments: recent advances in forest applications. Intelligent Service Robotics. 2025;1-19.

10. Chen H, Wang X, Wang, W. 3D semantic occupancy prediction for unmanned tracked vehicles in complex off-road environments. Transactions of Beijing institute of Technology. 2025;45(1):1-10.

11. Dao TG, Tran DT, Nguyen DM, Lee JH, Nguyen AQ. gTRAVEL+: enhancing ground segmentation for 3D point cloud with temporal noise removal and adaptive plane fitting for urban and off-road environments. IEEE Access. 2025;13:82431-82440.

12. Govindarajan H, et al. CleverDistiller: Simple and spatially consistent cross-modal distillation. arXiv; 2025. arXiv:2503.09878. https://doi.org/10.48550/arXiv.2503.09878

13. Huang S, Ma D, Wu J, Lin C, Liu J, Hu C. Application of semantic information module in LiDAR-based Simultaneous-Localization-and-Mapping algorithm. IEEE Access. 2025;10(5):4500-4507, doi: 10.1109/LRA.2025.3551536

14. Hwang JH, Kim D, Yoon HS, Kim DW, Seo SW. How to relieve distribution shifts in semantic segmentation for off-road environments. IEEE Robotics and Automation Letters. 2025;10(5):4500-4507.

15. Jia Z, Ma Y, Lai J, Wang Z. DOA-SLAM: An efficient stereo visual SLAM system in dynamic environment. International Journal of Control, Automation and Systems. 2025;23(4):1181-1198.

16. Jiang S, et al. Anomalies-by-synthesis: anomaly detection using generative diffusion models for off-road navigation. 2025 ICRA Conference; 2025_Submitted.

17. Jiang P, et al. GO: The great outdoors multimodal dataset. arXiv; 2025. arXiv:2501.19274. https://doi.org/10.48550/arXiv.2501.19274

18. Kabir MM, Jim JR, Istenes Z. Terrain detection and segmentation for autonomous vehicle navigation: A state-of-the-art systematic review. Information Fusion. 2025;113:102644.

19. Kabir MM, Jim JR, Istenes Z. Fusion-enhanced terrain detection and segmentation for autonomous vehicle navigation: A state-of-the-art systematic review. 2025. SSRN 4797592. https://doi.org/10.1016/j.inffus.2024.102644

20. Kim N, et al. GPT-4off: On-board traversability probability estimation for off-road driving via GPT knowledge distillation. Applied Sciences (2076-3417). 2025;15(4).

21. Kong L, et al. Multi-modal data-efficient 3D scene understanding for autonomous driving. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2025;47(5):3748-3765. doi: 10.1109/TPAMI.2025.3535625.

22. Kong L, et al. LargeAD: Large-scale cross-sensor data pretraining for autonomous driving. arXiv; 2025. arXiv:2501.04005. https://doi.org/10.48550/arXiv.2501.04005

23. Li W, et al. CRLNet: Cascaded resolution learning network for natural scenes segmentation. IEEE Intelligent Systems. 2025. doi: 10.1109/MIS.2025.3549432

24. Li R, et al. UE-extractor: A grid-to-point ground extraction framework for unstructured environments using adaptive grid projection. IEEE Robotics and Automation Letters. 2025;10(6):5991-5998.

25. Liu Y, Wang H, Zha Z, Hu W, Gao J. PFSD: A multi-modal pedestrian-focus scene dataset for rich tasks in semi-structured environments. arXiv; 2025. arXiv:2502.15342. https://doi.org/10.48550/arXiv.2502.15342

26. Mathur AD, Chapoutot A, Filliat D. Improving off-road LiDAR semantic segmentation with spatial context and auxiliary tasks. In European Robotics Forum 2025: Boosting the Synergies between Robotics and AI for a Stronger Europe; 2025 May; Springer Nature; c2025. Vol. 36, p. 300.

27. Mao L, Warnell G, Stone P, Biswas J. Pacer: Preference-conditioned all-terrain costmap generation. IEEE Robotics and Automation Letters. 2025;10(5):4572-4579. doi:10.1109/LRA.2025.3549645

28. Musau H, et al. A review of off-road datasets, sensor technologies and terrain traversability analysis. SAE International. 2025. https://doi.org/10.4271/2025-01-8339

29. Nazeri M, et al. VertiFormer: A data-efficient multi-task transformer for off-road robot mobility. arXiv; 2025. arXiv:2502.00543. https://doi.org/10.48550/arXiv.2502.00543

30. Noca A, et al. COARSE: Collaborative pseudo-labeling with coarse real labels for off-road semantic segmentation. arXiv; 2025. arXiv:2503.03947. https://doi.org/10.48550/arXiv.2503.03947

31. Noren C, Vundurthy B, Scherer S, Travers M. Interaction-aware control for robotic vegetation override in off-road environments. Journal of Terramechanics. 2025;117:101034.

32. Santo A, Heredia E, Viegas C, Valiente D, Gil A. Ground segmentation for LiDAR point clouds in structured and unstructured environments using a hybrid neural–geometric approach. Technologies. 2025;13(4):162.

33. Schreiber A, Driggs-Campbell K. Do you know the way? Human-in-the-loop understanding for fast traversability estimation in mobile robotics. IEEE Robotics and Automation Letters. 2025;10(6):5863-5870. doi: 10.1109/LRA.2025.3563819.

34. Steininger D, Simon J, Trondl A, Murschitz M. TimberVision: A multi-task dataset and framework for log-component segmentation and tracking in autonomous forestry operations. arXiv; 2025. arXiv:2501.07360. https://doi.org/10.48550/arXiv.2501.07360

35. Vidanapathirana K, et al. WildScenes: A benchmark for 2D and 3D semantic segmentation in large-scale natural environments. The International Journal of Robotics Research. 2025;44(4):532-549.

36. Wang M, Huang R, Xie W, Ma Z, Ma S. Compression approaches for LiDAR point clouds and beyond: A survey. ACM Transactions on Multimedia Computing, Communications and Applications. 2025. https://doi.org/10.1145/3715916

37. Wang H, et al. Traversability analysis for tracked vehicles in unstructured environments: An approach employing vehicle traversing capability and terrain's multi-modal data. Automotive Innovation. 2025;1-17.

38. Xu X, et al. LiMoE: Mixture of LiDAR representation learners from automotive scenes. arXiv; 2025. arXiv:2501.04004. https://doi.org/10.48550/arXiv.2501.04004

39. Xu X, et al. SuperFlow++: Enhanced spatiotemporal consistency for cross-modal data pretraining. arXiv; 2025. arXiv:2503.19912. https://doi.org/10.48550/arXiv.2503.19912

40. Xu T, et al. Verti-bench: A general and scalable off-road mobility benchmark for vertically challenging terrain. arXiv; 2025. arXiv:2502.11426. https://doi.org/10.48550/arXiv.2502.11426

41. Yang C, et al. Deep multimodal learning for time series analysis in social computing: a survey. International Journal of Multimedia Information Retrieval. 2025;14(2):15.

42. Yang Y, Zhang Z, Wang L. MCRL4OR: Multimodal contrastive representation learning for off-road environmental perception. arXiv; 2025. arXiv:2501.13988. https://doi.org/10.48550/arXiv.2501.13988

43. Yu Z. Advancing visual understanding in specialized domains [dissertation]. Arizona State University; 2025. https://keep.lib.asu.edu/items/199987.

44. Zhao D, et al. Exploring geographic information systems (GIS) for smart city analytics. (Preprint) Research Gate.

45. Zhao L, Wei S, Hays J, Gan L. (2025). GaussianFormer3D: Multi-Modal Gaussian-based Semantic Occupancy Prediction with 3D Deformable Attention. arXiv; 2025. arXiv:2505.10685. https://doi.org/10.48550/arXiv.2505.10685

46. Zhao H, et al. M2CS: A multimodal and campus-scapes dataset for dynamic SLAM and moving object perception. Journal of Field Robotics. 2025;42(3):787-805.

2024

1. Agishev R, Zimmermann K, Kubelka V, Pecka M, Svoboda T. MonoForce: Self-supervised learning of physics-informed model for predicting robot-terrain interaction. In 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2024 October. p. 12896-12903.

2. Ahat A, Firkat E, Yuan X, Zhu J, Hamdulla A. Off-fusion: Robust LiDAR fusion for complex off-road scenes. IEEE Transactions on Intelligent Vehicles; 2024. doi: 10.1109/TIV.2024.3416352

3. Atha D, et al. Few-shot semantic learning for robust multi-biome 3D semantic mapping in off-road environments. arXiv; 2024. arXiv:2411.06632. https://doi.org/10.48550/arXiv.2411.06632

4. Azhar MHB, Mészáros Z, Islam T. Application of transformer models for autonomous off-road vehicle control: challenges and insights. In 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA); c2024 December. p. 537-542.

5. Barzdins P, Pretkalnins I, Barzdins G. From captions to pixels: Open-set semantic segmentation without masks. Baltic Journal of Modern Computing. 2024;12(1):97-109.

6. Beycimen S, Art A, Unal MM, Ignatyev D, Zolotas A. On real-time semantic segmentation with comprehensive off-road datasets for enhanced terrain classification. 2024. SSRN 4947521. http://dx.doi.org/10.2139/ssrn.4947521

7. Bhosale M, Gupta P, Kumar RP, Jia Y. AI-enhanced proactive model predictive control for off-road autonomous vehicles (No. 2024-01-4067). 2024. SAE Technical Paper.

8. Boxan M, et al. FoMo: A proposal for a multi-season dataset for robot navigation in forêt montmorency. arXiv; 2024. arXiv:2404.13166. https://doi.org/10.48550/arXiv.2404.13166

9. Buschiazzo A, Russell M, Osteen P, Uplinger J. (). Automatic segmentation using knowledge distillation with ensemble models (ASKDEM). In Unmanned Systems Technology XXVI. 2024 June;13055:196-211.

10. Butt MA, et al. R 2 S100K: Road-region segmentation dataset for semi-supervised autonomous driving in the wild. International Journal of Computer Vision. 2025;133(2):910-928.

11. Chen Z, et al. Semantic scene completion based 3D traversability estimation for off-road terrains. arXiv; 2024. arXiv:2412.08195. https://doi.org/10.48550/arXiv.2412.08195

12. Cheung KL, Lee C.C. ARCH2S: Dataset, benchmark and challenges for learning exterior architectural structures from point clouds. arXiv; 2024. arXiv:2406.01337. https://doi.org/10.48550/arXiv.2406.01337

13. Duan Y, et al. LESA-Net: Semantic segmentation of multi-type road point clouds in complex agroforestry environment. Heliyon. 2024;10(17).

14. Faykus III MH, Pickeral A, Marquez E, Smith MC, Calhoun JC. Efficient vision transformers for autonomous off-road perception systems. Journal of Computer and Communications. 2024;12(9):188-207.

15. Feng Y, Li X, Ni P, Liu X, Jiang T. Multi-sensor fusion network for unstructured scene segmentation with surface normal incorporated. IEEE Sensors Journal. 2024;24(8):13589-13603.

16. Frey J, et al. Roadrunner-learning traversability estimation for autonomous off-road driving. IEEE Transactions on Field Robotics. 2024;1:192-212. doi: 10.1109/TFR.2024.3464369.

17. Gardner SD, et al. Shadow removal in off-road terrain perception with multi-sensor signal processing (No. 2024-01-4073). 2024. SAE Technical Paper.

18. Hagmanns R, Mortimer P, Granero M, Luettel T, Petereit J. Excavating in the Wild: The GOOSE-Ex Dataset for Semantic Segmentation. arXiv; 2024 arXiv:2409.18788. https://doi.org/10.48550/arXiv.2409.18788

19. Hausler, S., Griffiths, E., Ramezani, M., & Moghadam, P. Towards long-term robotics in the wild. arXiv; 2024. arXiv:2404.18477. https://doi.org/10.48550/arXiv.2404.18477

20. Honigfort HB, et al. Investigation into autolabeling a novel dataset for off-road autonomy using transfer learning. In Artificial Intelligence for Security and Defence Applications II. 2024 November;13206:462-468.

21. Huang S, Tian W. Towards Non-Flat Road Perception: Simulation and Analysis. In 2024 8th CAA International Conference on Vehicular Control and Intelligence (CVCI); c2024 October. p. 1-6.

22. Indah DA. Topological data analysis for off-road navigation of autonomous vehicles in unstructured terrain [master's thesis]. South Carolina State University; 2024.

23. Jeon Y, Son EI, Seo SW. Follow the footprints: Self-supervised traversability estimation for off-road vehicle navigation based on geometric and visual cues. In 2024 IEEE International Conference on Robotics and Automation (ICRA); c2024 May. p. 1774-1780.

24. Jeong S, Kim H, Cho Y. Diter: Diverse terrain and multimodal dataset for field robot navigation in outdoor environments. IEEE Sensors Letters. 2024;8(3):1-4.

25. Jung S, Lee J, Meng X, Boots B, Lambert A. V-strong: Visual self-supervised traversability learning for off-road navigation. In 2024 IEEE International Conference on Robotics and Automation (ICRA); 2024 May. p. 1766-1773.

26. Khan TD, Vyas S, Krishnamurthy VR. A Geometrico-statistical representation for off-road environments captured by LiDAR. In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. 2024 August;88339:V001T01A022. American Society of Mechanical Engineers.

27. Kim J, Seo J. Uncertainty-aware semantic mapping in off-road environments with dempster-shafer theory of evidence. arXiv; 2024. arXiv:2405.06265. https://doi.org/10.48550/arXiv.2405.06265

28. Kim J, Seo J, Min J. Evidential semantic mapping in off-road environments with uncertainty-aware Bayesian kernel inference. In 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2024 October. p. 1420-1427.

29. Kim O, Seo J, Ahn S, Kim CH. Ufo: Uncertainty-aware lidar-image fusion for off-road semantic terrain map estimation. In 2024 IEEE Intelligent Vehicles Symposium (IV); c2024 June. p. 192-199.

30. Land HB, Price SR, Carley SS, Butler SJ, Price SR. Investigation into deep learning methods for in-the-wild applications. In Autonomous Systems: Sensors, Processing, and Security for Ground, Air, Sea, and Space Vehicles and Infrastructure 2024. 2024 June;13052:144-150.

31. Latsaheb B, Sharma S, Hasija S. Semantic road segmentation using encoder-decoder architectures. Multimedia Tools and Applications. 2024;1-23.

32. Li Y, Kong L, Hu H, Xu X, Huang X. Is your lidar placement optimized for 3d scene understanding? Advances in Neural Information Processing Systems. 2024;37:34980-35017.

33. Li W, Liao M, Hua G, Zhang Y, Zou W. Terrain segmentation network in wild environments with hybrid plus downsampling. IEEE MultiMedia. 2024;32(1):16-28. doi: 10.1109/MMUL.2024.3442306

34. Li W, et al. Crlnet: Cascaded resolution learning network for unstructured semantic segmentation in natural scenes. Available at SSRN 4760357. 2024. http://dx.doi.org/10.2139/ssrn.4760357

35. Li W, et al. Strip and asymmetric aggregation network for unstructured terrain segmentation in wild environments. Engineering Applications of Artificial Intelligence. 2024;137:109016.

36. Lin N, Zhao W, Liang S, Zhong M. Real-time segmentation of unstructured environments by combining domain generalization and attention mechanisms. Sensors. 2023;23(13):6008.

37. Liu Y, et al. Botanicgarden: A high-quality dataset for robot navigation in unstructured natural environments. IEEE Robotics and Automation Letters. 2024;9(3):2798-2805.

38. Liu X, Hong T, Yang Y, Gui Y. GPNet: Point cloud semantic segmentation network for off-road scenes. In 2024 China Automation Congress (CAC); c2024 November. p. 1991-1996.

39. Liu Y, et al. Multi-space alignments towards universal lidar segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition; c2024. p. 14648-14661.

40. Liu X, Xue F, Du X. Attention regulation for efficient semantic segmentation on unstructured terrain. In 2024 24th International Conference on Control, Automation and Systems (ICCAS); c2024 October. p. 1529-1534.

41. Liu Y, et al. Accurate 3D semantic segmentation of point clouds for intelligent vehicles based on multi-view edge guidance and fusion. IEEE Sensors Journal. 2024;24(16);26853-26865.

42. Lv Y, Liu Z, Li G, Chang X. Noise-aware intermediary fusion network for off-road freespace detection. IEEE Transactions on Intelligent Vehicles. 2024.

43. Małek K, Dybała J, Kordecki A, Hondra P, Kijania K. OffRoadSynth open dataset for semantic segmentation using synthetic-data-based weight initialization for autonomous UGV in off-road environments. Journal of Intelligent & Robotic Systems. 2024;110(2):76.

44. Massa KJ, Grobler H. Adapting projection-based LiDAR semantic segmentation to natural domains. Journal of Visual Communication and Image Representation. 2024;100:104111.

45. McVicker M. An evaluation of the performance of lidar based semantic segmentation algorithms in structured and unstructured environments. The University of Alabama. 2024.

46. McVicker M, Ervin L, Yang Y, Ricks KG. Comparison of lidar semantic segmentation performance on the structured SemanticKITTI and off-road RELLIS-3D datasets. International Journal of Intelligent Robotics and Applications. 2024;1-17.

47. Medellin A, et al. Applications of unifying off-road datasets through ontology (No. 2024-01-4074). 2024. SAE Technical Paper.

48. Meng X. Learning for robot-centric autonomy [dissertation]. University of Washington; 2024. https://hdl.handle.net/1773/52767

49. Min C, et al. Autonomous driving in unstructured environments: How far have we come?. arXiv; 2024. arXiv:2410.07701. https://doi.org/10.48550/arXiv.2410.07701

50. Mortimer P, et al. The goose dataset for perception in unstructured environments. In 2024 IEEE International Conference on Robotics and Automation (ICRA); c2024 May. p. 14838-14844.

51. Nambiar N, Nageli V, Jamal A. HIET: Height images for enhanced terrain perception for robot navigation. In 2024 IEEE Pune Section International Conference (PuneCon); c2024 December. p. 1-6.

52. Ni P, Li X, Xu W, Zhou X, Jiang T, Hu W. Robust 3D semantic segmentation method based on multi-modal collaborative learning. Remote Sensing. 2024;16(3):453.

53. Oh M, et al. B-TMS: Bayesian traversable terrain modeling and segmentation across 3D LiDAR scans and maps for enhanced off-road navigation. In 2024 IEEE Intelligent Vehicles Symposium (IV); c2024 June. p. 200-205.

54. Peng J, Hua G, Tian S, Wu Y, Zou W. Lightweight boundary-assisted network for freespace segmentation in unstructured road scenes. Displays. 2024;83:102688.

55. Plangger JL. Class-based approach to mitigating class imbalance issues in vision-based off-road terrain type recognition [dissertation]. Carleton University; 2024. https://hdl.handle.net/20.500.14718/41430

56. Price SR, et al. Expanding ground vehicle autonomy into unstructured, off-road environments: Dataset challenges. Applied Sciences. 2024;14(18);8410.

57. Uplinger J, et al. Improved 2D image segmentation for rough terrain navigation using synthetic data. In Synthetic Data for Artificial Intelligence and Machine Learning: Tools, Techniques, and Applications II. 2024 June;13035:141-149.

58. Rahi A, et al. Deep semantic segmentation for identifying traversable terrain in off-road autonomous driving. IEEE Access. 2024;12:162977-162989.

59. Ramirez-Robles E, Starostenko O, Alarcon-Aquino V. Real-time path planning for autonomous vehicle off-road driving. PeerJ Computer Science. 2024;10:e2209.

60. Ramtekkar VV, et al. Robust depth-aided segmentation for drivable region detection in challenging environments. In ICRA 2024 Workshop on Resilient Off-road Autonomy. c2024.

61. Ruetz FA, Lawrance N, Hernández E, Borges PV, Peynot T. ForestTrav: 3D LiDAR-only forest traversability estimation for autonomous ground vehicles. IEEE Access. 2024;12:37192-37206.

62. Ryu C, et al. Words to wheels: Vision-based autonomous driving understanding human language instructions using foundation models. arXiv; 2024. arXiv:2410.10577. https://doi.org/10.48550/arXiv.2410.10577

63. Sani E, Sgorbissa A, Carpin S. Improving the ROS 2 navigation stack with real-time local costmap updates for agricultural applications. In 2024 IEEE International Conference on Robotics and Automation (ICRA); c2024 May. p. 17701-17707.

64. Santo A, Cabrera JJ, Valiente D, Viegas C, Gil A. TE-NeXt: A LiDAR-Based 3D Sparse Convolutional Network for Traversability Estimation. arXiv; 2024. arXiv:2406.01395. https://doi.org/10.48550/arXiv.2406.01395

65. Schmidt F, et al. ROVER: A multi-season dataset for visual slam. arXiv; 2024. arXiv:2412.02506. https://doi.org/10.48550/arXiv.2412.02506

66. Serdel Q, Marzat J, Moras J. Continuous online semantic implicit representation for autonomous ground robot navigation in unstructured environments. Robotics. 2024;13(7):108.

67. Shao S, et al. Dual-branch transformer network for enhancing LiDAR-based traversability analysis in autonomous vehicles. IEEE Transactions on Intelligent Transportation Systems. 2024;26(2):2582-2595.

68. Sharma S, Raizada A, Sundaram S. IRisPath: Enhancing off-road navigation with robust IR-RGB fusion for improved day and night traversability. arXiv; 2024. arXiv:2412.03173. https://doi.org/10.48550/arXiv.2412.03173

69. Shu Y, Dong L, Liu J, Liu C, Wei W. Overview of terrain traversability evaluation for autonomous robots. Journal of Field Robotics. 2024. https://doi.org/10.1002/rob.22461

70. Sivaprakasam M, et al. Tartandrive 2.0: More modalities and better infrastructure to further self-supervised learning research in off-road driving tasks. In 2024 IEEE International Conference on Robotics and Automation (ICRA); c2024 May. p. 12606-12606.

71. Son JW, Moon H.P. A real-time point cloud ground segmentation study for outdoor autonomous robots. In Annual Conference of KIPS; c2024. p. 482-483. Korea Information Processing Society.

72. Szabó L, Weltsch Z. A comprehensive review of existing datasets for off-road autonomous vehicles. In 2024 IEEE 22nd World Symposium on Applied Machine Intelligence and Informatics (SAMI); c 2024 January. p. 000403-000410.

73. Tong Z, Chen H, Li Y, Cao D. AgriDrive: Data, benchmarks and analysis. In 2024 IEEE International Conference on Unmanned Systems (ICUS); c2024 October. p. 1539-1544.

74. Urrea C, Vélez M. Enhancing autonomous visual perception in challenging environments: Bilateral models with vision transformer and multilayer perceptron for traversable area detection. Technologies. 2024;12(10):201.

75. Vidanapathirana K, et al. WildScenes: A benchmark for 2D and 3D semantic segmentation in large-scale natural environments. The International Journal of Robotics Research. 2024;44(4):532-549.

76. Viswanath K, Jiang P, Saripalli S. Reflectivity is all you need!: Advancing LiDAR semantic segmentation. arXiv; 2024. arXiv:2403.13188. https://doi.org/10.48550/arXiv.2403.13188

77. Wang Z, Liao Z, Zhou B, Yu G, Luo W. SwinURNet: Hybrid transformer-CNN architecture for real-time unstructured road segmentation. IEEE Transactions on Instrumentation and Measurement. 2024;73.

78. Wei H, et al. Fusionportablev2: A unified multi-sensor dataset for generalized slam across diverse platforms and scalable environments. The International Journal of Robotics Research. 2024;44(7).

79. Wilson J, et al. Convbki: Real-time probabilistic semantic mapping network with quantifiable uncertainty. IEEE Transactions on Robotics. 2024;40:4648-4667.

80. Wijayathunga L, Dabare D, Rassau A, Chai D, Islam SMS. OUTBACK: A multimodal synthetic dataset for rural Australian off-road robot navigation. In 2024 International Conference on Digital Image Computing: Techniques and Applications (DICTA); c2024 November. p. 397-402.

81. Xie G, et al. M3-GMN: A multi-environment, multi-LiDAR, multi-task dataset for grid map based navigation. In 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2024 October. p. 13213-13220.

82. Xu X, et al. 4D contrastive superflows are dense 3D representation learners. In European Conference on Computer Vision; c2024 September. p. 58-80.

83. Xu F, Xiao Y, Mei J, Hu Y, Fu Q. Domain-adaptive point cloud semantic segmentation from urban to off-road scenes based on knowledge-augmented deep learning. In 2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC); c2024 September. p. 2972-2978.

84. Xu M, et al. Transformer-based traversability analysis for autonomous navigation in outdoor environments with water hazard. IEEE Transactions on Intelligent Vehicles. 2024;1-14.

85. Yakubu M, et al. SlipNet: Enhancing slip cost mapping for autonomous navigation on heterogeneous and deformable terrains. arXiv; 2024 arXiv:2409.02273. https://doi.org/10.48550/arXiv.2409.02273

86. Yang A, Li W, Hu Y. Speed planning based on terrain-aware constraint reinforcement learning in rugged environments. IEEE Robotics and Automation Letters. 2024;9(3):2096-2103.

87. Yang B, et al. FRPNet: An improved Faster-ResNet with PASPP for real-time semantic segmentation in the unstructured field scene. Computers and Electronics in Agriculture. 2024;217:108623.

88. Zhai H, et al. WildOcc: A benchmark for off-road 3D semantic occupancy prediction. arXiv; 2024. arXiv:2410.15792. https://doi.org/10.48550/arXiv.2410.15792

89. Zhang A, et al. Towards robust robot 3D perception in urban environments: The UT campus object dataset. IEEE Transactions on Robotics. 2024;40: 3322-3340.

90. Zhang Y, Hou J. (2024). Is contrastive distillation enough for learning comprehensive 3D representations? arXiv; 2024. arXiv:2412.08973. https://doi.org/10.48550/arXiv.2412.08973

91. Zhang Z, Lu F, Xu Y, Chen J, Ma Y. Sparse point cloud registration network with semantic supervision in wilderness scenes. Elektronika ir Elektrotechnika. 2024;30(1):32-43.

92. Zhao H, et al. M2CS: A multimodal and campus-scapes dataset for dynamic SLAM and moving object perception. Journal of Field Robotics. 2024;42(3):787-805.

2023

1. Ahat A, Firkat E, Mijit T, Hamdulla A. Obstacle detection in off-road environments based on LiDAR. In 2023 IEEE 4th International Conference on Pattern Recognition and Machine Learning (PRML); c2023 August. p. 61-68.

2. Bhamri A, et al. Unifying ontological framework for all-terrain datasets. In 2023 Seventh IEEE International Conference on Robotic Computing (IRC); c2023 December. p. 292-296.

3. Chen E, Ho C, Maulimov M, Wang C, Scherer, S. Learning-on-the-drive: Self-supervised adaptation of visual offroad traversability models. arXiv; 2023. arXiv:2306.15226. https://doi.org/10.48550/arXiv.2306.15226

4. Chen Z, Pushp D, Gregory JM, Liu L. Pseudo-trilateral adversarial training for domain adaptive traversability prediction. Autonomous Robots. 2023;47(8):1155-1174.

5. Chen Y, et al. Fastc: A fast attentional framework for semantic traversability classification using point cloud. In ECAI 2023; c2023. p. 429-436.

6. Cockran S, et al. Application of variational quantum algorithms to autonomous ground vehicle mobility. DEVCOM Ground Vehicle Systems Center (US); 2023. AD1218362.

7. Dokania S, Hafez AH, Subramanian A, Chandraker M, Jawahar CV. IDD-3D: Indian driving dataset for 3D unstructured road scenes. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision; c2023. p. 4482-4491.

8. Duraisamy P, Natarajan S. Multi-sensor fusion based off-road drivable region detection and its ROS implementation. In 2023 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET); c2023 March. p. 1-5.

9. Faykus MH, Selee B, Smith M. Utilizing neural networks for semantic segmentation on rgb/lidar fused data for off-road autonomous military vehicle perception (No. 2023-01-0740). 2023. SAE Technical Paper.

10. Firkat E, et al. FGSeg: Field-ground segmentation for agricultural robot based on LiDAR. Computers and Electronics in Agriculture. 2023;211:107965.

11. Guan T, He Z, Song R, Manocha D, Zhang L. TNS: Terrain traversability mapping and navigation system for autonomous environments. arXiv; 2023. arXiv:2109.06250. https://doi.org/10.48550/arXiv.2109.06250

12. Guan T, He Z, Song R, Zhang, L. TNES: Terrain traversability mapping, navigation and excavation system for autonomous excavators on worksite. Autonomous Robots. 2023;47(6):695-714.

13. Han B, et al. GardenMap: Static point cloud mapping for garden environment. Computers and Electronics in Agriculture. 2023;204:107548.

14. Iqbal N, Niemeyer M, Krause JC, Hertzberg J. Scalable evaluation pipeline of CNN-based perception for robotic sensor data under different environment conditions. In 2023 European Conference on Mobile Robots (ECMR); c2023 September. p. 1-6.

15. Jiang P. Sensors and data: Representation to semantics to deep features [dissertation]. Texas A&M University; 2023. https://hdl.handle.net/1969.1/198958

16. Jiang P, Saripalli S. Ross: Radar off-road semantic segmentation. In International Symposium on Experimental Robotics; 2023 November. p. 264-273.

17. Karnan H, et al. STERLING: Self-supervised terrain representation learning from unconstrained robot experience. arXiv; 2023. arXiv:2309.15302. https://doi.org/10.48550/arXiv.2309.15302

18. Karjalainen K. Image segmentation for forestry scenes. Electrical Engineering. 2023.

19. Kim N, An J. Knowledge distillation for traversable region detection of LiDAR scan in off-road environments. Sensors. 2023;24(1):79.

20. Klokov AA, et al. Daps3d: Domain adaptive projective segmentation of 3D lidar point clouds. IEEE Access. 2023;11:79341-79356.

21. Knights J, et al. Wild-places: A large-scale dataset for lidar place recognition in unstructured natural environments. In 2023 IEEE international conference on robotics and automation (ICRA); c2023 May. p. 11322-11328.

22. Li J, Firkat E, Zhu B, Zhu J, Hamdulla A. Off-road environment localization of unmanned vehicles based on visual-inertial. 2023. https://doi.org/10.21203/rs.3.rs-3080448/v1

23. Lin N, Zhao W, Liang S, Zhong M. Real-time segmentation of unstructured environments by combining domain generalization and attention mechanisms. Sensors. 2023;23(13):6008.

24. Liu Y, et al. Segment any point cloud sequences by distilling vision foundation models. Advances in Neural Information Processing Systems. 2023;36:37193-37229.

25. Liu H, Yao M, Xiao X, Cui H. A hybrid attention semantic segmentation network for unstructured terrain on Mars. Acta Astronautica. 2023;204:492-499.

26. Liu P, et al. Uncertainty-aware point-cloud semantic segmentation for unstructured roads. IEEE Sensors Journal. 2023;23(13):15071-15080.

27. Lagos J, Lempiö U, Rahtu E. Finnwoodlands dataset. In Scandinavian Conference on Image Analysis; c2023 April. p. 95-110.

28. Liu H, Yao M, Xiao X, Cui H. A hybrid attention semantic segmentation network for unstructured terrain on Mars. Acta Astronautica. 2023;204:492-499.

29. Markó N, Szirányi T, Ballagi Á. Terrain depth estimation for improved inertial data prediction in autonomous navigation systems. In 2023 IEEE International Automated Vehicle Validation Conference (IAVVC); c2023 October. p. 1-6.

30. Meng X, et al. TerrainNet: Visual modeling of complex terrain for high-speed, off-road navigation. arXiv; 2023. arXiv:2303.15771. https://doi.org/10.48550/arXiv.2303.15771

31. Msallam M, Syrymkin VI. A quick review of 3D point cloud semantic segmentation. К57 Материалы V международного форума (24-25 ноября 2022 г.)/под ред. ВИ Сырямкина.–Томск: STT, 2022–147с., 139. 2023.

32. Ni P, Li X, Kong D, Wei K, Hu Y. Scene-adaptive 3-D semantic segmentation method based on multiphase edge enhancement for intelligent vehicles. IEEE Sensors Journal. 2023;23(24):31471-31482.

33. Ni P, et al. Robust 3D semantic segmentation based on multi-phase multi-modal fusion for intelligent vehicles. IEEE Transactions on Intelligent Vehicles. 2023;9(1):1602-1614.

34. Park J, Hwang H. BumpyPatch: Heightmap-based outdoor point cloud segmentation to find less bumpy road. In 2023 Seventh IEEE International Conference on Robotic Computing (IRC); c2023 December. p. 265-272.

35. Pereira A, Carvalho P, Pereira N, Viana P, Côrte-Real L. From a visual scene to a virtual representation: a cross-domain review. IEEE Access. 2023;11:57916-57933.

36. Plangger J, Atia M, Chaoui H. FCIoU: A targeted approach for improving minority class detection in semantic segmentation systems. Machine Learning and Knowledge Extraction. 2023;5(4):1746-1759.

37. Racinskis P, Arents J, Greitans M. Constructing maps for autonomous robotics: An introductory conceptual overview. Electronics. 2023;12(13):2925.

38. Santo A, Gil A, Valiente D, Ballesta M, Peidró A. computing the traversability of the environment by means of sparse convolutional 3D Neural Networks. In ICINCO (1); c2023. p. 383-393.

39. Santo A, Gil A, Valiente D, Ballesta M, Reinoso Ó. Estimación de zonas transitables en nubes de puntos 3D con redes convolucionales dispersas. In XLIV Jornadas de Automática; c2023. p. 737-737.

40. Sathyamoorthy AJ, et al. Vern: Vegetation-aware robot navigation in dense unstructured outdoor environments. In 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2023 October. p. 11233-11240.

41. Schuster A, et al. Synthetic data generation for the continuous development and testing of autonomous construction machinery. at-Automatisierungstechnik. 2023;71(11):953-968.

42. Selee B. Improving inference speed of perception systems in autonomous unmanned ground vehicles [masters thesis]. Clemson University; 2023. https://open.clemson.edu/all_theses/4053

43. Selee B, Faykus M, Smith M. Semantic segmentation with high inference speed in off-road environments (No. 2023-01-0868). SAE Technical Paper. 2023.

44. Seo J, Kim T, Kwak K, Min J, Shim I. Scate: A scalable framework for self-supervised traversability estimation in unstructured environments. IEEE Robotics and Automation Letters. 2023;8(2):888-895.

45. Seo J, Sim S, Shim I. Learning off-road terrain traversability with self-supervisions only. IEEE Robotics and Automation Letters. 2023;8(8):4617-4624.

46. Serdel Q, Marzat J, Moras, J. SMaNa: Semantic mapping and navigation architecture for autonomous robots. In ICINCO (1); c2023 November. p. 453-464.

47. Shi X, Shao S, Wang T, Zhang Q. A terrain recognition method based on semantic segmentation for field robot under sample imbalance. In 2023 IEEE International Conference on Unmanned Systems (ICUS); c2023 October. p. 1053-1058.

48. Sivaprakasam M, et al. Tartandrive 1.5: Improving large multimodal robotics dataset collection and distribution. In ICRA2023 Workshop on Pretraining for Robotics (PT4R). 2023.

49. Viswanath K, Jiang P, Sujit PB, Saripalli S. Off-road lidar intensity based semantic segmentation. In International Symposium on Experimental Robotics; c2023 November. p. 608-617.

50. Weerakoon K, et al. Graspe: Graph based multimodal fusion for robot navigation in outdoor environments. IEEE Robotics and Automation Letters. 2023;8(12):8090-8097.

51. Wijayathunga L, Rassau A, Chai D. Challenges and solutions for autonomous ground robot scene understanding and navigation in unstructured outdoor environments: A review. Applied Sciences. 2023;13(17):9877.

52. Williams WR, Glandon SR, Morris LL, Cheng JRC. Benchmarking performance of deep learning model for material segmentation on two HPC systems. arXiv; 2023. arXiv:2307.14921. https://doi.org/10.48550/arXiv.2307.14921

53. Wu K, et al. Semantic Segmentation Based on Multiple Granularity Learning. In 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2023 October. p. 9065-9070.

54. Xu W, et al. Multiview fusion driven 3-D point cloud semantic segmentation based on hierarchical transformer. IEEE Sensors Journal. 2023;23(24):31461-31470.

55. Xue H, et al. Traversability analysis for autonomous driving in complex environment: A LiDAR-based terrain modeling approach. Journal of Field Robotics. 2023;40(7):1779-1803.

56. Xue H, et al. Contrastive label disambiguation for self-supervised terrain traversability learning in off-road environments. arXiv; 2023. arXiv:2307.02871. https://doi.org/10.48550/arXiv.2307.02871

57. Yang B, et al. FRPNet: An improved Faster-ResNet with PASPP for real-time semantic segmentation in the unstructured field scene. Computers and Electronics in Agriculture. 2023;217:108623.

58. Yin X, Li X, Ni P, Xu Q, Kong D. A novel real-time edge-guided lidar semantic segmentation network for unstructured environments. Remote Sensing. 2023;15(4):1093.

59. Yu J, Chen J, Dabbiru L, Goodin CT. Analysis of LiDAR configurations on off-road semantic segmentation performance. In Autonomous Systems: Sensors, Processing, and Security for Ground, Air, Sea, and Space Vehicles and Infrastructure 2023. 2023 June;12540:6-25.

60. Zhang Y, Hou J. Fine-grained Image-to-LiDAR Contrastive Distillation with Visual Foundation Models. arXiv; 2023. arXiv:2405.14271. https://doi.org/10.48550/arXiv.2405.14271

61. Zhang X, Rodriguez S. Advanced optimization techniques for vehicle dynamics in robotics. Association Journal of Interdisciplinary Technics in Engineering Mechanics. 2023;1(1):1-13.

62. Zhang Q, et al. Ground mobile robot traversable area recognition based on 3D CNN and attention mechanism. In 2023 IEEE International Conference on Unmanned Systems (ICUS); c2023 October. p. 1086-1091.

63. Zhang Z, et al. Enhanced low-resolution lidar-camera calibration via depth interpolation and supervised contrastive learning. In ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); c2023 June. p. 1-5.

64. Zhao T, et al. RSRD: A road surface reconstruction dataset and benchmark for safe and comfortable autonomous driving. arXiv; 2023. arXiv:2310.02262. https://doi.org/10.48550/arXiv.2310.02262

65. Zhao Y, et al. Road grid segmentation in desert with geometry and appearance features. In 2023 5th International Conference on Robotics, Intelligent Control and Artificial Intelligence (RICAI); c2023 December. p. 429-435.

66. Zhou X, Feng Y, Li X, Zhu Z, Hu Y. Off-road environment semantic segmentation for autonomous vehicles based on multi-scale feature fusion. World Electric Vehicle Journal; 2023;14(10):291.

2022

1. Ahmed M, et al. Benchmarking domain adaptation for semantic segmentation. In Unmanned Systems Technology XXIV. 2022 May;12124:150-161.

2. Atik ME. Investigation of artificial intelligence-based point cloud semantic segmentation [doctoral thesis]. Istanbul Technical University; 2022. http://hdl.handle.net/11527/24368

3. Atik ME, Duran Z. An efficient ensemble deep learning approach for semantic point cloud segmentation based on 3D geometric features and range images. Sensors. 2022;22(16):6210.

4. Bailey P, Clevenger A, Sevil HE. Traversability assessment and reachability analysis for unmanned ground vehicles through image segmentation. In 2022 IEEE Applied Imagery Pattern Recognition Workshop (AIPR); c2022 October. p. 1-5.

5. Borges PV, et al. A survey on terrain traversability analysis for autonomous ground vehicles: Methods, sensors, and challenges. Field Robotics. 2022;2:1567-1627.

6. Carruth DW, Walden CT, Goodin C, Fuller SC. Challenges in low infrastructure and off-road automated driving. In 2022 Fifth International Conference on Connected and Autonomous Driving (MetroCAD); c2022 April. p. 13-20.

7. Chen Z, Pushp D, Liu L. CALI: Coarse-to-fine alignments based unsupervised domain adaptation of traversability prediction for deployable autonomous navigation. arXiv; 2022. arXiv:2204.09617. https://doi.org/10.48550/arXiv.2204.09617

8. Chustz G, Saripalli S. Road: RELLIS off-road odometry analysis dataset. In 2022 IEEE Intelligent Vehicles Symposium (IV); 2022 June. p. 1504-1510.

9. Faykus MH, Selee B, Calhoun JC, Smith MC. Lossy compression to reduce latency of local image transfer for autonomous off-road perception systems. In 2022 IEEE International Conference on Big Data (Big Data); c2022 December. p. 3146-3152.

10. Firkat E, et al. ARDformer: Agroforestry road detection for autonomous driving using hierarchical transformer. Sensors. 2022;22(13):4696.

11. Gardner S, et al. Lidar semantic segmentation with a multi-reservoir echo state network for off-road terrain perception. In Proceedings of the Ground Vehicle Systems Engineering and Technology Symposium (GVSETS), NDIA; 2022 August; Novi, MI.

12. Guan T, et al. Ga-nav: Efficient terrain segmentation for robot navigation in unstructured outdoor environments. IEEE Robotics and Automation Letters. 2022;7(3):8138-8145.

13. Huang K, et al. Multi-modal sensor fusion for auto driving perception: A survey. arXiv; 2022. arXiv:2202.02703. https://doi.org/10.48550/arXiv.2202.02703

14. Islam F, Nabi MM, Ball JE. Off-road detection analysis for autonomous ground vehicles: A review. Sensors. 2022;22(21):8463.

15. Jeon Y, Seo SW. EFGHNet: A versatile image-to-point cloud registration network for extreme outdoor environment. IEEE Robotics and Automation Letters. 2022;7(3):7511-7517.

16. Jiang P, Osteen P, Wigness M, Saripalli S. RELLIS-3D: A multi-modal dataset for off-road robotics. GitHub; 2022. https://github.com/unmannedlab/RELLIS-3D

17. Kalyanram VP. Vision-based stair detection and terrain classification algorithms for multi-terrain mobile robots [dissertation]. Texas A&M University; 2022. https://hdl.handle.net/1969.1/197306

18. Leung THY, Ignatyev D, Zolotas A. Hybrid terrain traversability analysis in off-road environments. In 2022 8th International Conference on Automation, Robotics and Applications (ICARA); 2022 February. p. 50-56.

19. Loiseau R, Aubry M, Landrieu L. Online segmentation of lidar sequences: Dataset and algorithm. In European Conference on Computer Vision; c2022 October. p. 301-317.

20. Min C, et al. ORFD: A dataset and benchmark for off-road freespace detection. In 2022 international conference on robotics and automation (ICRA); c2022 May. p. 2532-2538.

21. Min C, et al. ORFD: A dataset and benchmark for off-road freespace detection. In 2022 international conference on robotics and automation (ICRA); c2022 May. p. 2532-2538.

22. Peltola E. Terrain segmentation with neural networks for off-road applications [masters thesis. Tampere University; 2022. https://urn.fi/URN:NBN:fi:tuni-202203132504

23. Ruetz F, Borges P, Suenderhauf N, Hernández E, Peynot T. Forest traversability mapping (FTM): Traversability estimation using 3D voxel-based normal distributed transform to enable forest navigation. In 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2022 October. p. 8714-8721.

24. Sathyamoorthy AJ, Weerakoon K, Guan T, Liang J, Manocha D. Terrapn: Unstructured terrain navigation using online self-supervised learning. In 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2022 October. p. 7197-7204.

25. Schmid R, et al. Self-supervised traversability prediction by learning to reconstruct safe terrain. In 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS);c 2022 October. p. 12419-12425.

26. Shaban A, Meng X, Lee J, Boots B, Fox D. Semantic terrain classification for off-road autonomous driving. In Conference on Robot Learning; c2022 January. p. 619-629.

27. Spector A, Zhu W, Hossain J, Roy N. Simulated forest environment and robot control framework for integration with cover detection algorithms. In 2022

IEEE/ACM International Conference on Big Data Computing, Applications and Technologies (BDCAT); c2022 December. p. 277-283.

28. Sun C, Xie J, Qian Y, Yang M. An All-terrain Mobile Platform for Multi-Modal Perception and Traversability Estimation. In International Conference on Cognitive Computation and Systems; 2022 December. Singapore: Springer Nature Singapore. c2022. p. 368-379.

29. Triest S, et al. Tartandrive: A large-scale dataset for learning off-road dynamics models. In 2022 International Conference on Robotics and Automation (ICRA); 2022 May. p. 2546-2552.

30. Vishwanath K, Sujit PB, Saripalli S. CAMEL: Learning Cost-maps Made Easy for Off-road Driving. arXiv; 2022. arXiv:2209.12413. https://doi.org/10.48550/arXiv.2209.12413

31. Walch W, Eder M, Mautner-Lassnig K, Steinbauer-Wagner G. Offroad terrain classification for mobile robots. In Proceedings of the ARW 2022; c2022. p. 6-11.

32. Wei H, et al. BushNet: Effective semantic segmentation of bush in large-scale point clouds. Computers and Electronics in Agriculture. 2022;193:106653.

33. Wolf P, Deoli P, Thangellapally SK, Berns K. Traction optimization for robust navigation in unstructured environments using deep neural networks on the example of the off-road truck Unimog. In International Conference on Intelligent Autonomous Systems; 2022 June; Cham: Springer Nature Switzerland; c2022. p. 561-579.

34. Xie J, Qian Y, Wang B, Wang C, Yang M. Off-load semantic terrain classification using 3D LiDAR data. In 2022 China Automation Congress (CAC); c2022 November. p. 5960-5965.

35. Yan T, Zheng X, Liu W, Liang B, Chen Z. The Synthetic Off-road Trail Dataset for Unmanned Motorcycle. In 2022 IEEE 95th Vehicular Technology Conference:(VTC2022-Spring); c2022 June. p. 1-7.

36. Yang Z, et al. Uncertainty-aware perception models for off-road autonomous unmanned ground vehicles. arXiv; 2022. arXiv:2209.11115. https://doi.org/10.48550/arXiv.2209.11115

37. Zhang W, et al. Analysis of robot traversability over unstructured terrain using information fusion. In 2022 International Conference on Advanced Robotics and Mechatronics (ICARM); c2022 July. p. 413-418.

2021

1. Dabbiru L, et al. Traversability mapping in off-road environment using semantic segmentation. In Autonomous Systems: Sensors, Processing, and Security for Vehicles and Infrastructure 2021. 2021 April;11748:78-83.
2. Guan T. Terrain classification and navigability analysis in unstructured outdoor environments [master’s thesis]. University of Maryland, 2021. http://hdl.handle.net/1903/28387
3. Guan T, He Z, Manocha D, Zhang L. TTM: Terrain traversability mapping for autonomous excavator navigation in unstructured environments. arXiv; 2021. arXiv:2109.06250. https://doi.org/10.48550/arXiv.2109.06250
4. Guan T, He Z, Song R, Manocha D, Zhang L. TNS: Terrain traversability mapping and navigation system for autonomous excavators. arXiv; 2021. arXiv:2109.06250. https://doi.org/10.48550/arXiv.2109.06250
5. Guan T, Kothandaraman D, Chandra R, Sathyamoorthy AJ, Manocha D. GANav: Group-wise attention for classifying navigable regions in unstructured outdoor environments. arXiv; 2021. arXiv:2103.04233v2. https://doi.org/10.48550/arXiv.2103.04233
6. Gummidipundi MM. Terrain traversability analysis for off-road robot S: emphasis on semantic segmentation and terrain classification with terrain assessment [master’s thesis]. The University of Texas at San Antonio; 2021.
7. Hu J, Zhao G, You S, Kuo CJ. Evaluation of multimodal semantic segmentation using RGB-D data. In Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications III; c2021 April. Vol. 11746, pp. 368-379.
8. Jiang P, Osteen P, Saripalli S. Calibrating LiDAR and camera using semantic mutual information. arXiv; 2021. arXiv:2104.12023. https://doi.org/10.48550/arXiv.2104.12023
9. Jiang P, Osteen P, Saripalli S. Semcal: Semantic LiDAR-camera calibration using neural mutual information estimator. In 2021 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI); c2021 September. p. 1-7.
10. Jiang P, Osteen P, Wigness M, Saripalli S. RELLIS-3d dataset: Data, benchmarks and analysis. In 2021 IEEE international conference on robotics and automation (ICRA); c2021 May. p. 1110-1116.

11. Jin Y, Han D, Ko H. Memory-based semantic segmentation for off-road unstructured natural environments. In 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2021 September. p. 24-31.

12. Singh A, Singh K, Sujit PB. Offroadtranseg: Semi-supervised segmentation using transformers on offroad environments. arXiv; 2021. arXiv:2106.13963. https://doi.org/10.48550/arXiv.2106.13963

13. Viswanath K, Singh K, Jiang P, Sujit PB, Saripalli S. Offseg: A semantic segmentation framework for off-road driving. In 2021 IEEE 17th international conference on automation science and engineering (CASE); c2021 August. p. 354-359.

14. Jin Y, Han D, Ko H. Memory-based semantic segmentation for off-road unstructured natural environments. In 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS); c2021 September. p. 24-31.

15. Zhao G, Hu J, You S, Kuo CCJ. Calibdnn: multimodal sensor calibration for perception using deep neural networks. In Signal Processing, Sensor/Information Fusion, and Target Recognition; c2021 April. Vol. 11756, pp. 324-335.

List of Symbols, Abbreviations, and Acronyms

2D/3D	two-/three-dimensional
ARL	Army Research Laboratory
CA	cooperative agreement
DARES	Distributed Autonomous Robotic Experiments and Simulations
DARPA	Defense Advanced Research Projects Agency
DEVCOM	U.S. Army Combat Capabilities Development Command
DoD	Department of Defense
FEA	finite element analysis
GPS	global positioning system
GVSC	Ground Vehicle Systems Center
HF-FEM	high-fidelity finite element model
IDETC/CIE	International Design Engineering Technical Conferences & Computers and Information in Engineering
LiDAR	Light Detection and Ranging
MF-FEM	medium-fidelity finite element model
M-LOD	multi-level-of-detail
PI	principal investigator
POC	point of contact
R2C2	Robotics Research Collaboration Campus
RELLIS	Respect, Excellence, Leadership, Loyalty, Integrity, and Selfless Service
RGB	red–green–blue
ROS	Robot Operating System
RSS	Robotics: Science and Systems
TAMU	Texas A&M University
TIAMAT	Transfer from Imprecise and Abstract Models to Autonomous Technologies

1 (PDF)	DEFENSE TECHNICAL INFORMATION CTR DTIC OCA
1 (PDF)	DEVCOM ARL FCDD RLB CI TECH LIB