13th International Conference on Applied Informatics
Eszterházy Károly Catholic University
Eger, Hungary, February 19–21, 2026

Ground-Centric Experience-Based Navigation in Unstructured Off-Road Environments

Nour Elhouda Ben Saadi[a], Ines Meliani[b], Zoltán Istenes[c]

[a]Eötvös Loránd University
nfs@inf.elte.hu

[b]Eötvös Loránd University
dbpgo8@inf.elte.hu

[c]Eötvös Loránd University
istenes@inf.elte.hu

Abstract

Abstract. Autonomous navigation in unstructured off-road environments remains a challenging problem due to extreme variability in terrain appearance, physical properties, and environmental conditions. Unlike structured urban scenes, off-road images frequently contain heterogeneous surfaces within a single frame, such as dust, gravel, mud, vegetation, and uneven soil. As a result, global image embeddings often conflate visually irrelevant regions with physically traversed terrain, leading to unreliable similarity comparisons and degraded decision-making when past experiences are retrieved [2, 4].

This work introduces a **ground-centric, experience-based navigation pipeline** that focuses on **region-aware visual representations of traversable terrain**, rather than using global image descriptors. Visual embeddings are extracted only from the **ground regions the robot actually traverses**, and are **augmented with inertial and LiDAR motion cues**. By storing these embeddings along with **contextual metadata and weak outcome indicators derived from future sensor data**, the system can learn whether traversing a given terrain patch was successful or risky. This enables the construction of a **database of past experiences** from recorded sequences, linking observations with actual outcomes [3, 5, 6].

The pipeline is evaluated using the RELLIS-3D dataset, which provides synchronized RGB images, LiDAR, IMU, and pose information in complex

off-road environments. Visually irrelevant regions, such as the sky, are removed using semantic segmentation, and ground points are extracted from LiDAR data and projected into the camera frame to ensure the embeddings correspond directly to traversable terrain [8, 9]. To handle mixed terrain within a single scene, **patch-level embeddings pooled over ground regions** are used instead of a single global descriptor. These embeddings are stored in a vector database along with metadata, enabling retrieval of similar experiences and evaluation of terrain risk based on **how past trajectories actually turned out** [1, 7].

At inference, the current ground embedding retrieves similar past experiences to estimate terrain risk and uncertainty, **leveraging knowledge of future outcomes from prior sequences**. This enables the system to make **conservative and informed navigation decisions**, rather than relying solely on visual similarity [10–13]. Unlike prior work, our approach **avoids dense supervision and explicit terrain classification**, while remaining **scalable and interpretable**.

Main contributions:

- A novel **ground-centric embedding pipeline** that associates each observed terrain patch with actual traversal outcomes from recorded sequences.
- Integration of **visual, inertial, and LiDAR signals** to form a multimodal, experience-based framework for robust terrain risk estimation.
- A **scalable and interpretable architecture** that enables incremental learning from additional datasets and sensor configurations.

Summary and Future Work: This work demonstrates that **experience-based, ground-centric representations** can effectively guide navigation in complex off-road environments using only weak supervision from sensor data. The proposed approach is **extensible**, allowing future integration of additional modalities, temporal prediction, or larger datasets to further improve robustness and generalization. This positions the framework as a foundation for **incremental learning and adaptive autonomous navigation in unstructured environments**.

References

[1] M. Bhosale, J. Whitson, Y. Jia: *A Review of Learning Off-Road Terrain Traversability For Autonomous Ground Vehicles*, ASME Journal of Autonomous Vehicles and Systems (2025), Accepted Manuscript, doi: 10.1115/1.4070847, url: https://asmedigitalcollection.asme.org/autonomousvehicles/article/doi/10.1115/1.4070847/1229986/A-Review-of-Learning-Off-Road-Terrain.

[2] A. Datar, A. Pokhrel, M. Nazeri, M. Rao, C. Pan, Y. Zhang, A. Harrison, M. Wigness, P. Osteen, J. Ye, X. Xiao: *M2P2: A Multi-Modal Passive Perception Dataset for Off-Road Mobility in Extreme Low-Light Conditions*, http://arxiv.org/abs/2410.01105 (2024), pp. 13690–13696, doi: 10.48550/arxiv.2410.01105.

[3] M. Faykus, B. Selee, M. Smith: *Utilizing Neural Networks for Semantic Segmentation on RGB/LiDAR Fused Data for Off-road Autonomous Military Vehicle Perception*, https://doi.org/10.4271/2023-01-0740 1 (2023), doi: 10.4271/2023-01-0740.

[4] J. Frey, M. Patel, D. Atha, J. Nubert, D. Fan, A. Agha, C. Padgett, P. Spieler, M. Hutter, S. Khattak: *RoadRunner – Learning Traversability Estimation for Autonomous Off-road Driving*, http://arxiv.org/abs/2402.19341 (2024), doi: 10.48550/arxiv.2402.19341.

[5] Z. Fu, A. Kumar, A. Agarwal, H. Qi, J. Malik, D. Pathak: *Coupling Vision and Proprioception for Navigation of Legged Robots*, arXiv preprint arXiv:2112.02094v2 (2021).

[6] T. Guan, R. Song, Z. Ye, L. Zhang: *VINet: Visual and Inertial-based Terrain Classification and Adaptive Navigation over Unknown Terrain*, http://arxiv.org/abs/2209.07725 (2022), doi: 10.48550/arxiv.2209.07725.

[7] M. Kabir, J. Jim, Z. Istenes: *Fusion-Enhanced Terrain Detection and Segmentation for Autonomous Vehicle Navigation: A State-of-The-Art Systematic Review*, https://doi.org/10.2139/ssrn.4797592 (2024), doi: 10.2139/ssrn.4797592.

[8] O. Kim, J. Seo, S. Ahn, C. Kim: *UFO: Uncertainty-aware LiDAR-image Fusion for Off-road Semantic Terrain Map Estimation*, arXiv preprint arXiv:2403.02642v1 (2024).

[9] J. Liang, M. Elnoor, P. Sankaralingam, V. Rajagopal, D. Manocha, G. Seneviratne, K. Mudiyanselage, R. Chandra: *DR. Nav: Semantic-Geometric Representations for Proactive Dead-End Recovery and Navigation*, arXiv preprint (2025).

[10] Y. Liu, Y. Fu, M. Qin, Y. Xu, B. Xu, F. Chen, B. Goossens, P. Sun, H. Yu, C. Liu, L. Chen, W. Tao, H. Zhao, H. Zhao: *BotanicGarden: A High-Quality Dataset for Robot Navigation in Unstructured Natural Environments*, https://doi.org/10.1109/lra.2024.3359548 9.3 (2024), pp. 2798–2805, doi: 10.1109/lra.2024.3359548.

[11] H. Su, F. Song, C. Ma, W. Wu, J. Yan: *RoboSense: Large-scale Dataset and Benchmark for Egocentric Robot Perception and Navigation in Crowded and Unstructured Environments*, Computer Vision and Pattern Recognition (2024), doi: 10.1109/CVPR52734.2025.02556.

[12] *Towards Fully Autonomous Robot Navigation in Complex Outdoors: A Multi-Modal Perception and Learning-Based Approach*, https://doi.org/10.13016/nbd1-i3om (2025), doi: 10.13016/nbd1-i3om.

[13] L. Wijayathunga, Rassau, L. Wijayathunga, A. Rassau, D. Chai: *Challengesand Solutions for Autonomous Ground Robot Scene Understanding and Navigation in Unstructured Outdoor Environments: A Review*, https://doi.org/10.3390/app13179877 13.17 (2023), pp. 9877–9877, doi: 10.3390/app13179877.