

Overcoming Nature: Perception for Autonomous Navigation in Dense Vegetation

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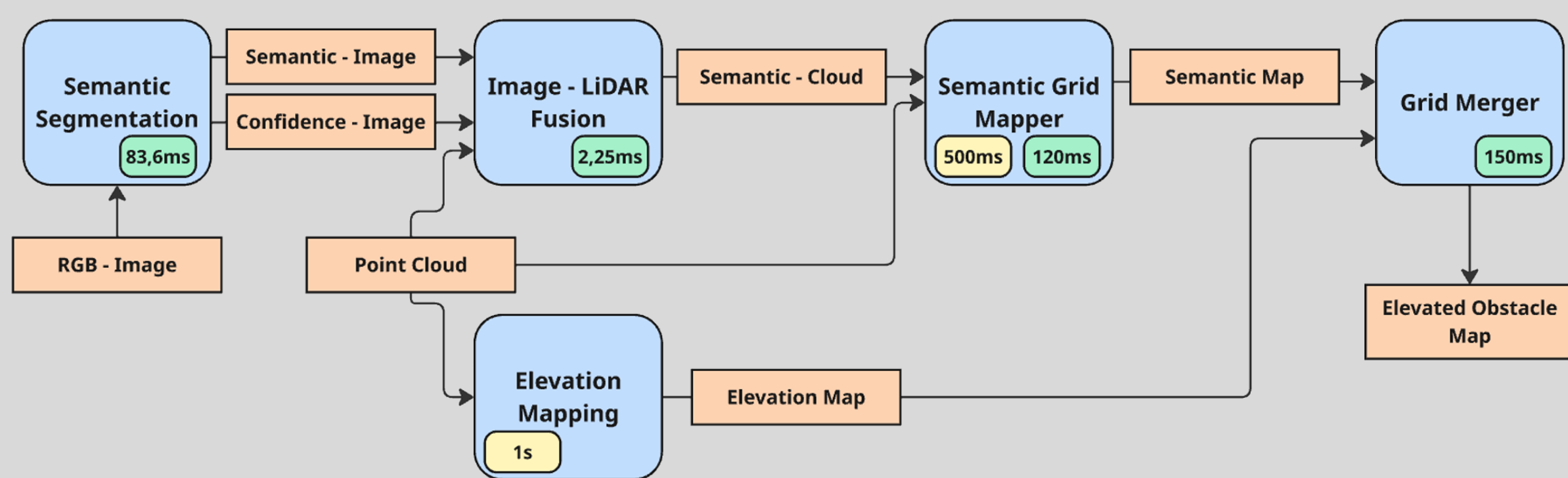
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Abstract

- Dense vegetation creates ambiguity: some structure must be avoided, some is traversable
- Standard elevation mapping techniques ([1],[2]) often interpret vegetation as solid structure: disturbances from dense vegetation, high grass, overhanging branches are marked as untraversable
- Solution: platform-agnostic semantic-based correction of elevation map using separate sectors for ground, obstacle and sky
- Real-world tests on multiple robots demonstrate improvements

Pipeline overview

- Semantic fusion:
 - Project LiDAR into image
 - Assign semantic classes to points
- Ground estimation:
 - Estimate minimum height of terrain surface based on LiDAR measurements
- Semantic grid mapping:
 - Divide space into **Ground**, **Sky** and **Obstacle** layers
 - Fuse semantic evidence over time using log-odd method
- Elevation correction:
 - Correct traversable vegetation artifacts
 - Preserve rigid obstacles
 - Correct overhanging branches via sky layer



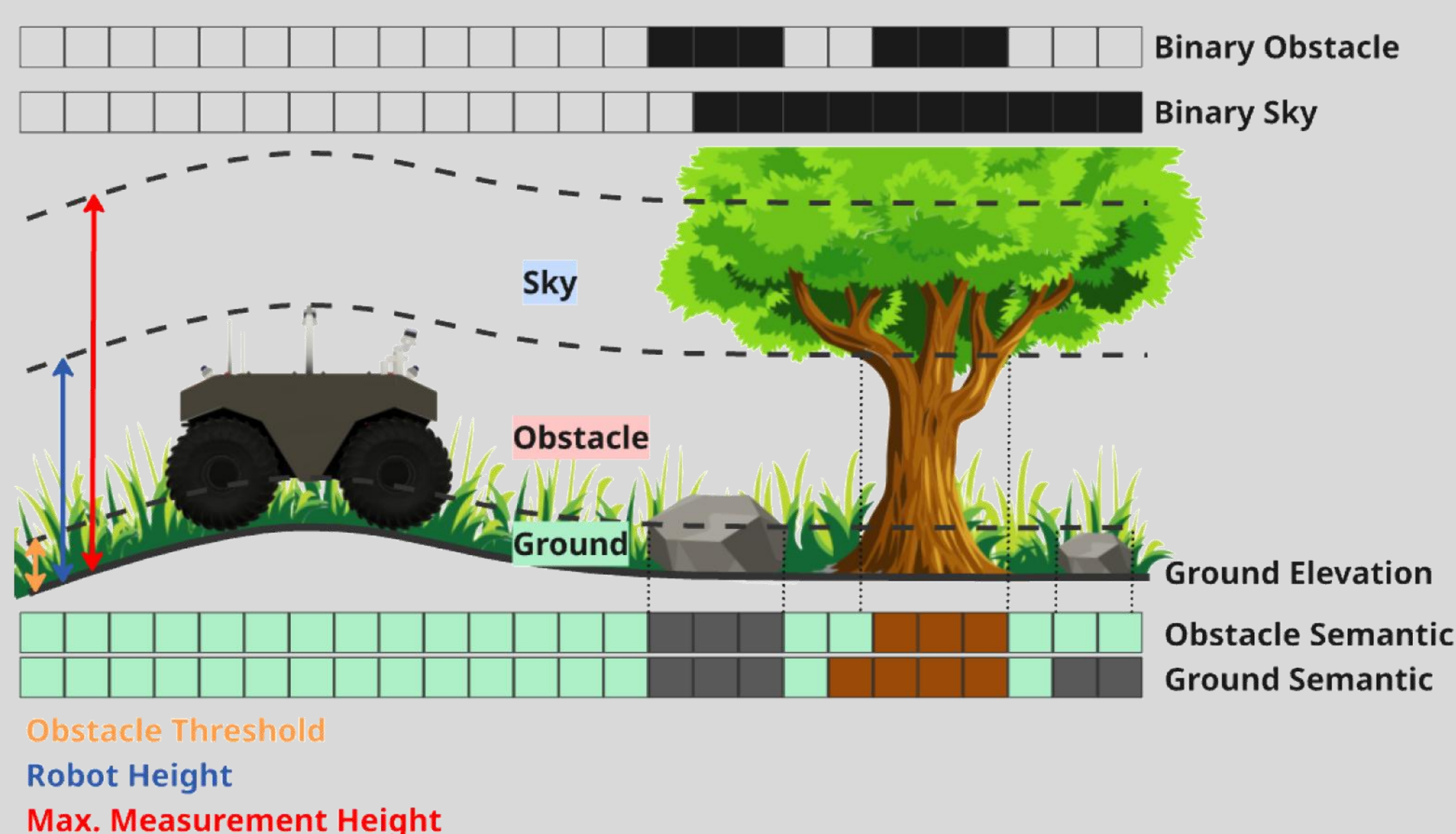
Methodology & Implementation

- RGB Images processed by Mask2Former Swin-L [3] → pixel-wise class prediction
- Semantic predictions projected to LiDAR Points using camera intrinsics and the transformation:

$$p_{cam} = T_{lidar \rightarrow cam} \cdot p_{lidar}$$
- Robot-centric grid map is created using estimated ground elevation:

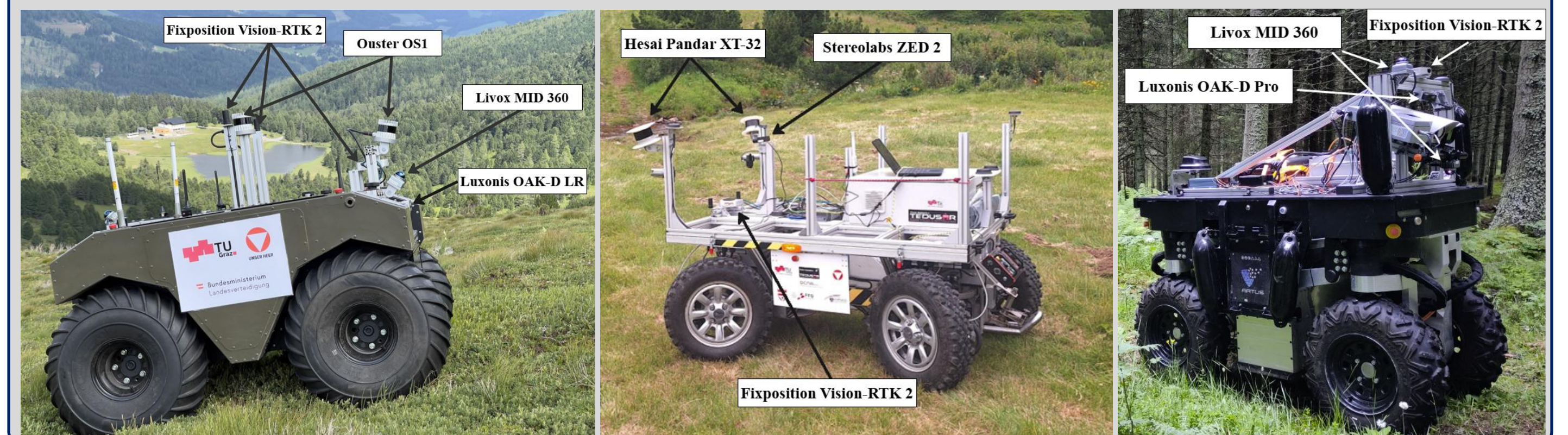
$$\hat{h}^+ = \min(\hat{h}^-, h(q))$$
- Using smoothed ground estimate, the space above the terrain is divided into three sectors: **Ground**, **Obstacle**, and **Sky**
- Semantic observations from the fused point cloud are accumulated in the Ground and Obstacle sectors to estimate class labels for each cell
- To avoid noisy measurements, class estimates ($\mathcal{L}_t(i, j, c)$) are fused over time using a log-odd ($L(p_{i,j}(c))$) representation:

$$\mathcal{L}_t(i, j, c) = \mathcal{L}_{t-1}(i, j, c) + L(p_{i,j}(c))$$
- The obstacle layer combines geometric measurements with semantic obstacles classes
- Sky layer captures structures above the robot's height to eliminate falsely classified overhanging vegetation
- Finally, the semantic grid representation is merged with a conventional elevation map, correcting disturbances



Setup

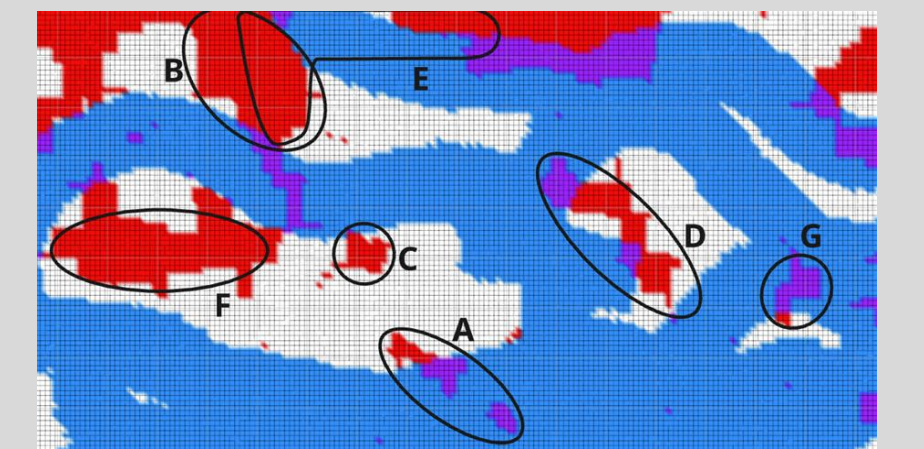
- Three different off-road robotic platforms specialized for off-road:
 - Warthog, Mercator, Artus
- Different sensor setups to showcase portability:
 - LiDAR: Ouster OS1, Livox MID 360, Hesai Pandar XT-32
 - Camera: Luxonis OAK-D Pro, Luxonis OAK-D LR, Stereolabs ZED 2
- All robots running ROS2 Humble on Ubuntu 22.04



Experiments and Results

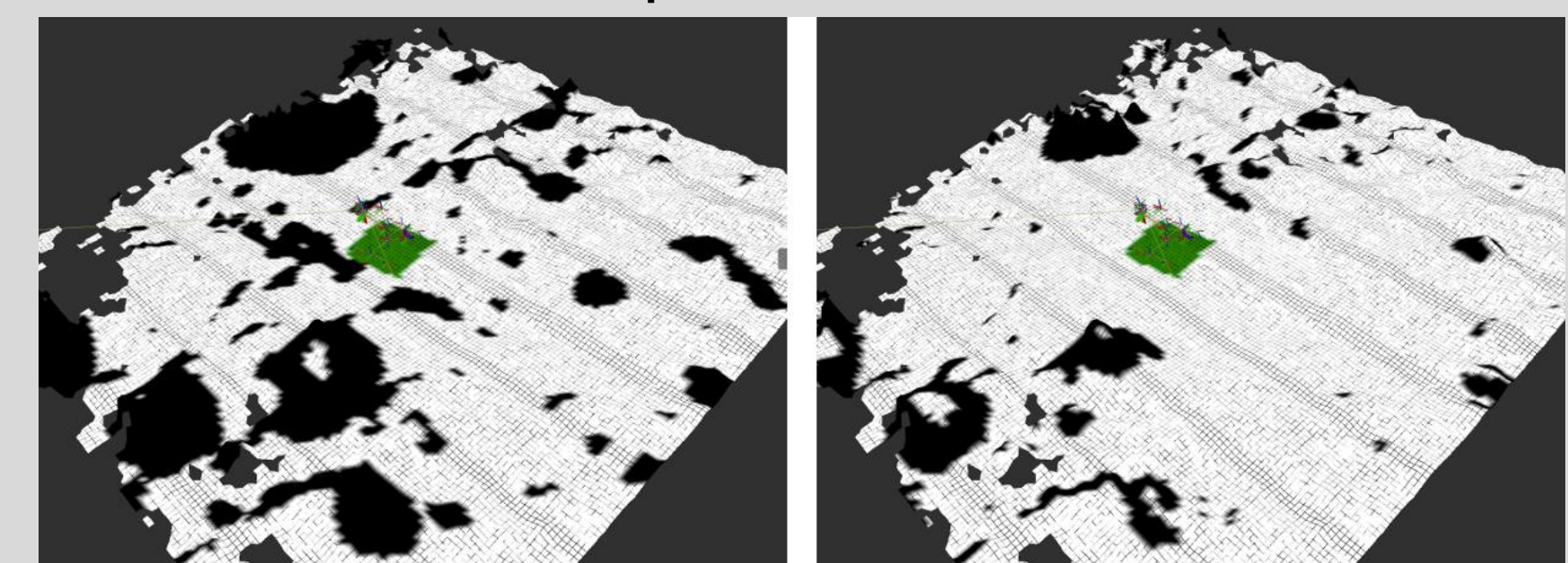
- Tests conducted in real-world scenarios in the Seetaler Alps
 - Dense vegetation and highly complex off-road environments
- Ablation study:
 - **Obstacle precision assessment** (teleoperated): Robot footprint projected onto the grid map used as a proxy for traversable ground truth.

	Scenario 1	Scenario 2
Cell Resolution [m]	0.1	0.1
Total Area [m ²]	187	225
Ground Truth Traversable [m ²]	115.55	137.26
Total Detected Obstacles [m ²]	25.83	8.55
Intersecting Obstacles ↓ [m ²]	5.92	1.83
Intersecting ↓ [%]	22.92	21.4



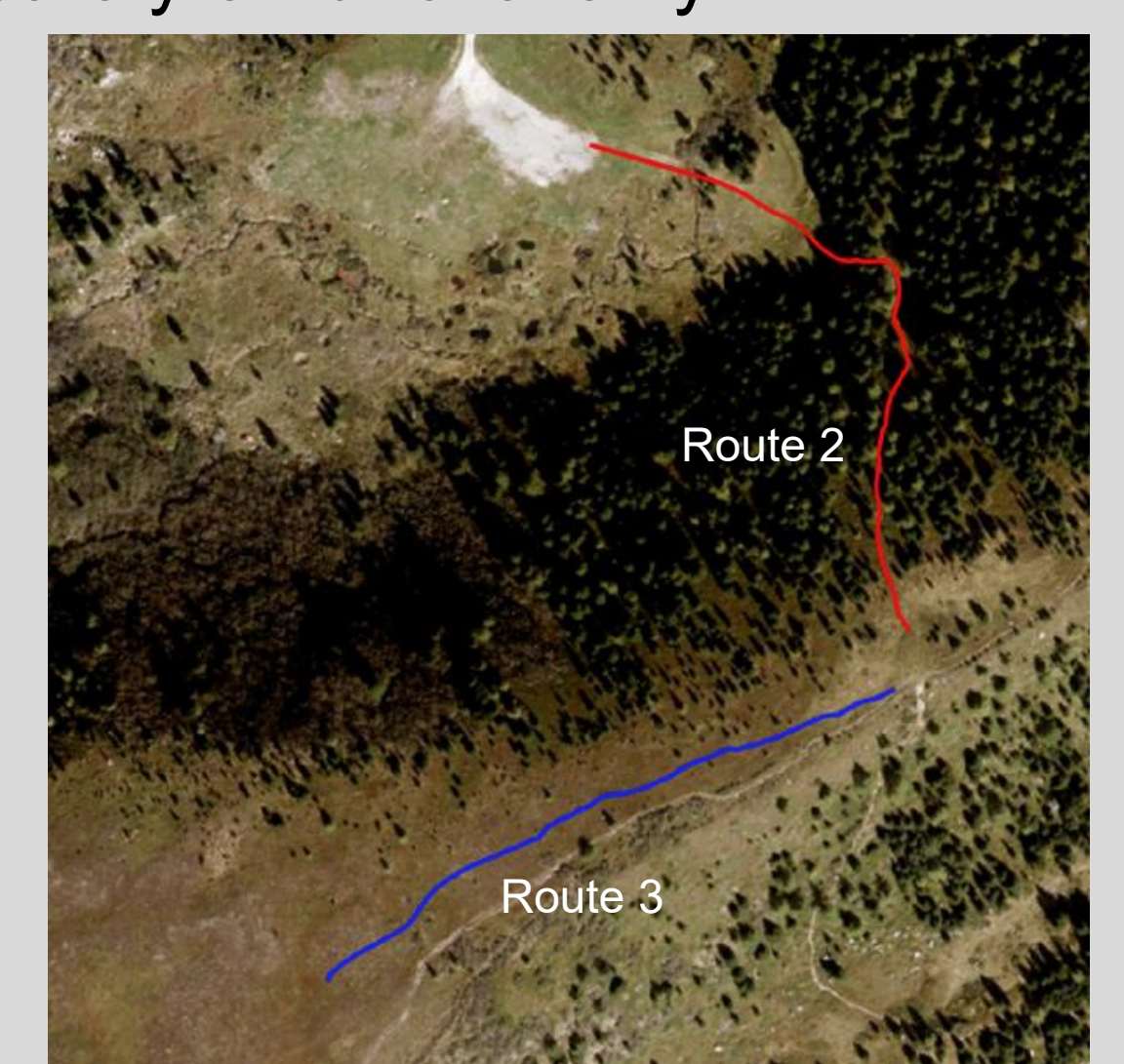
The system detects relevant obstacles while keeping the overlap with traversable regions moderate in both scenarios.

- **Merged Map quality** (teleoperated): compares the standard elevation map with the semantically corrected map with slope cells greater than 45° → reduction to 1/10 compared to standard elevation map



- **Autonomous navigation** (fully autonomous): Three predefined off-road routes, represented by GPS waypoints, with narrow and densely vegetated forest (Route 1), steep terrain with overhanging branches (Route 2) and grass, bushes, and small trees in open terrain (Route 3). Metric: manual interventions due to safety or functionality.

Route	Platform	Safety Interventions ↓	Functional Interventions ↓
Route 1	Artus	2	0
	Warthog	0	0
Route 2	Mercator	0	6
	Warthog	0	0
Route 3	Mercator	0	2
	Warthog	0	0



Summary and Next Steps

- The proposed system improves the distinction between traversable vegetation and rigid obstacles while reducing vegetation-induced artifacts. Field experiments on three robot platforms indicate more reliable navigation in dense natural terrain compared to conventional elevation mapping. Future work will focus on reducing system overhead, improving obstacle modeling for more nuanced traversability cases, and integrating synchronized RGB-D sensing

References

- [1] P. Fankhauser, M. Bloesch, and M. Hutter, "Probabilistic terrain mapping for mobile robots with uncertain localization, IEEE Robotics and Automation Letters (RA-L), vol. 3, no. 4, pp. 3019–3026, 2018.
- [2] H. Lee, J. Kwon, and C. Kwon, "Learning-based uncertainty-aware navigation in 3d off-road terrains," 2022.
- [3] B. Cheng, I. Misra, A. G. Schwing, A. Kirillov, and R. Girdhar, "Masked-attention mask transformer for universal image segmentation," 2022.