

Autonomous navigation using 3D LiDAR point clouds in complex real-world environments remains a challenging task despite extensive research. Uncertainty in environmental factors, such as the probabilistic motion of dynamic objects, varying levels of occlusion, and rare scenes, adds to the complexity. These challenges increase manifold in several adverse and constrained real-life situations, including the absence of labeled information, extreme sparsity, and susceptibility to adversarial attacks. Many real-world navigation scenarios lack precise labeled information due to numerous factors.

We observe that under such circumstances, standard solutions that assist 3D LiDAR navigation do not work. Segmentation, object detection, panoptic segmentation, etc., are not possible with existing solutions. New strategies need to be figured out to achieve these without labeled information while also accounting for adverse constraints. Label-averse settings limit the capacity of autonomous systems, making them susceptible to adversaries and deteriorating navigation. The thesis studies and addresses some of these challenges by proposing innovative methods for 3D LiDAR-based navigation in these challenging and restricted scenarios.

We develop a novel method to distinguish dynamic objects from static environments without requiring labeled data, addressing the limitations of existing segmentation-based approaches for accurate segmentation of dynamic objects. Our solution extracts moving and movable objects from 3D LiDAR point clouds without labels by inferring hidden scene parts occluded by dynamic objects. This inferred static background, akin to a static environment, enables object segmentation in dynamic scenes.

We also handle 3D LiDAR point cloud sparsity, where we propose a technique to augment dynamic sparse LiDAR point clouds with missing information, improving navigation accuracy in constrained environments. Higher sparsity reduces point density on objects, but the overall topology of a 3D LiDAR point cloud remains intact. We leverage tools from Algebraic Topology—particularly 0-dimensional Persistent Homology—to capture this global shape and guide point augmentation along existing static structures. This property generates attention focused on the global topology of a static 3D LiDAR point cloud while augmenting points to a sparse LiDAR point cloud.

We investigate a new paradigm that uses differentiable SLAM in a self-supervised setup to train deep learning models for 3D LiDAR-based applications, enhancing their efficiency. Our proposed approach augments standard navigation tasks with a self-supervised differentiable SLAM framework. It enables end-to-end training of deep learning models with SLAM error, which minimizes the discrepancy between model output and ground truth via trajectory estimates. We demonstrate that our approach outperforms existing methods and achieves improvements in navigation-allied deep learning tasks.

We also explore the vulnerability of 3D LiDAR-based systems to adversarial attacks. Unlike existing passive black-box attack systems, we demonstrate a very simple white-box attack that directly affects the acquired 3D LiDAR point cloud while maintaining the 3D LiDAR point cloud

quality to prevent detection. We minimally augment 3D LiDAR point clouds with point injections to destabilize navigation while preserving data integrity. This white-box attack uses adversarial LiDAR point clouds to induce suboptimal trajectory estimates in SLAM, exploiting its reliance on precise 3D LiDAR data.

Our research contributes to advancing the state-of-the-art in 3D LiDAR-based autonomous navigation by addressing critical challenges in restricted settings and providing practical solutions. The proposed methods have the potential to enhance the safety, reliability, and performance of autonomous systems operating in complex and dynamic environments.