Slope Estimation for Obstacle Detection in Simultaneous Localization and Mapping

Kürşat Kömürcü[1[0009–0006–1149–8686]], **Linas Petkevičius**[2[0000–0003–2416–0431]]

[1] *Vilnius University*
Institute of Computer Science, Vilnius University,
Didlaukis str. 47, LT-08303 Vilnius, Lithuania
e-mail: kursat.komurcu@mif.stud.vu.lt, linas.petkevicius@mif.vu.lt

Abstract. *This work presents an integrated approach to obstacle detection for Simultaneous Localization and Mapping (SLAM), leveraging LIDAR, stereo cameras, and laser scan sensors, refined by the RANSAC algorithm. Developed using C++, PCL, and ROS Noetic, our system demonstrates enhanced detection capabilities in dynamic environments, validated through our achievement in the Kangal Autonomy Competition. The research is accompanied by the data and reproducible code at Github repository.*
Keywords: *SLAM, LIDAR Mapping, Obstacle Detection, Point Cloud, Slope Estimation*

1. Introduction

The development of Simultaneous Localization and Mapping (SLAM) technologies, notably through the use of LIDAR, stereo cameras, ultrasound, and laser scan sensors, has been instrumental in advancing autonomous navigation by enabling systems to dynamically map and locate themselves within environments [1]. LIDAR sensors, recognized for their accuracy in measuring distances and creating detailed 3D maps, are fundamental for static obstacle detection [2]. Concurrently, stereo cameras contribute to dynamic obstacle detection by estimating slopes and leveraging image disparity for depth and movement analysis [3]. Additionally, the integration of laser scan sensors enhances obstacle detection capabilities beyond the scope of LIDAR and stereo cameras by analyzing point cloud data derivatives, thus identifying a wider range of obstacles [4].

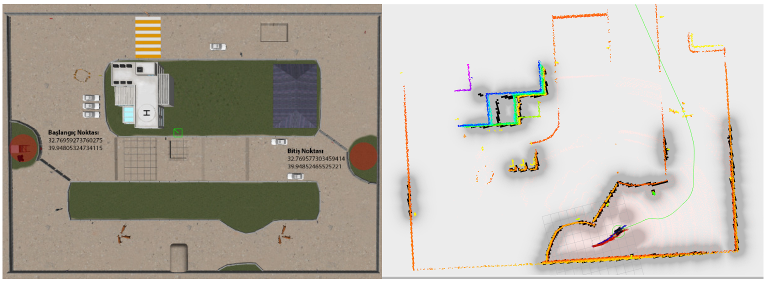

Figure 1. Experiment Map and Simulation of Autonomous Driving

However, while these technologies represent significant advancements, research indicates a need for more integrated and noise-robust solutions for obstacle detection [5, 6]. This study addresses such gaps by proposing a unified sensor fusion approach that combines the strengths of LIDAR, stereo cameras, and laser scan sensors. Through the application of Random Sample Consensus (RANSAC) segmentation on point cloud data, our method not only refines obstacle detection but also improves accuracy in obstacle localization [7], filling a critical void in existing methodologies.

2. Methodology

2.1. Slope Estimation

Integrating both LIDAR and depth camera technologies significantly enhances our autonomous system's obstacle detection and navigation capabilities. This synergistic approach not only capitalizes on the high-resolution obstacle mapping afforded by LIDAR but also harnesses the depth camera's adeptness at identifying dynamic obstacles in close proximity for final navigation setup[1] see Figure 1.

2.1.1. LIDAR for Obstacle Mapping

LIDAR sensors are instrumental in developing detailed maps of the environment, accurately capturing static obstacles. The efficacy of LIDAR in mapping and

[1] The experimentation setup and algorithm implementation can be access at https://github.com/kursatkomurcu/outdoor_robot Github repository.

its principles of operation have been well-documented in literature, underscoring its critical role in autonomous navigation systems [8]. The processing of LIDAR data to calculate surface slopes involves analyzing the normal vectors of the points in the generated point cloud. This analysis is pivotal for distinguishing between navigable surfaces and potential obstacles. The slope is calculated as:

$$Slope = \arctan 2(normal_z, \sqrt{normal_x^2 + normal_y^2}) \times \frac{180}{\pi} \tag{1}$$

This methodology for slope calculation based on surface normals is derived from techniques commonly used in digital elevation model (DEM) analysis, highlighting the adaptability of geospatial analysis methods to autonomous navigation [9].

2.1.2. Depth Camera For Dynamic Obstacle Detection

The depth camera is utilized specifically for detecting obstacles that LIDAR may miss, particularly in scenarios involving close-range dynamic objects using obstacle positions and the robot positions. Its real-time responsiveness is crucial for navigating environments with moving obstacles that LIDAR may not effectively detect in immediate proximity [10]. The depth camera's output is processed to calculate the distance of each point in its field of view from the robot's current position:

$$Distance = \sqrt{(x - x_{robot})^2 + (y - y_{robot})^2 + (z - z_{robot})^2} \tag{2}$$

Utilizing this distance measurement, along with the slope information derived from the depth camera's point cloud, we can detect dynamic obstacles. A threshold is set for the slope degree to determine navigability, while also considering the proximity to the robot based on a predefined safety radius [1].

2.1.3. Occupancy Grid Update

Both lidar and camera sensors' data are fused to update an occupancy grid, a discretized representation of the environment where each cell's value indicates the presence of an obstacle [11]. The grid indices are calculated as follows:

$$GridX = \lfloor (x - OriginX) \times InvResolution \rfloor$$

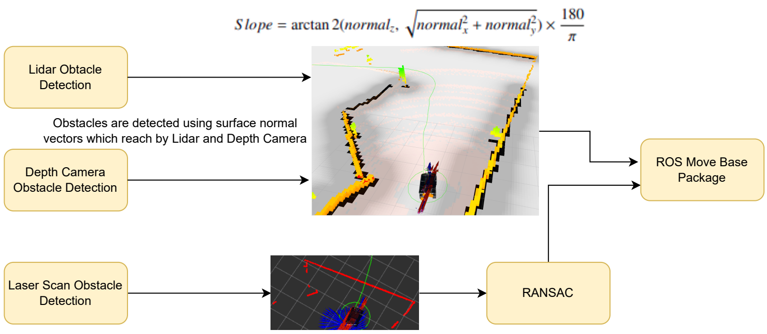

Figure 2. The obstacles assigment to occupancy grid and sensor fusion schema.

$$GridY = \lfloor (y - OriginY) \times InvResolution \rfloor$$

Cells are identified as occupied or free based on a calculation that considers the x and y coordinates of an object, the OriginX and OriginY coordinates of the grid's origin, and the inverse resolution of the occupancy grid in ROS [12]. Occupied cells signal potential hazards outside the robot's safety radius, whereas free cells indicate safe navigation areas. This strategy employs the object's location relative to the grid's origin and the grid's scale to enhance the autonomous system's obstacle detection and navigation [11], ensuring safe maneuverability in varied environments.

2.2. Algorithm and RANSAC for robust estimation

The proposed pipeline first address the problem of address outliers to occupancy grid via slope estimation. The updated grid is combined with other sensors information, the lidar and depth camera. The filtering and combination is finally integrated to the robot's move base package with laser scan data. The full sensor fusion pipeline can be see Figure 2.

Upon gathering and processing the environment data using depth cameras, LIDAR, and laser scan sensors, we implemented the Random Sample Consensus (RANSAC) algorithm to further refine our results. RANSAC is a robust method for fitting a model to observational data that may contain a significant proportion of outliers [13]. It is particularly effective in environments with a high likelihood of measurement errors or in scenarios where the object's boundaries are not distinctly outlined. In the context of our methodology, RANSAC is employed after the preliminary identification of potential obstacles to distinguish between actual obstacles and spurious data points. The RANSAC algorithm iteratively selects a random subset of the original data points and attempts to fit a model (e.g., a plane or a line) to these points. The fitted model is then used to identify inliers—points that fit the model well within a certain tolerance. The process is repeated a fixed number of times, and the model with the highest number of inliers is selected as the best representation of the data. This experimenting setup is not tested on dynamic obstacles and we will focus on this in future research.

3. Conclusions

Our study has successfully demonstrated the use of a multi-sensor approach, incorporating depth cameras, LIDAR, and laser scanners, to improve obstacle detection in autonomous navigation systems. The integration of slope estimation and the RANSAC algorithm further refined our obstacle detection process, leading to our system's notable performance in the Kangal Autonomy Competition. The research is accompanied by the data and reproducible code at Github repository.

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