The accuracy analysis of the Visual-SLAM and LiDAR-SLAM methods: A case study

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Abstract

Simultaneous Localisation and Mapping (SLAM) is a technique that allows a vehicle to determine its location and map its surroundings simultaneously. This study was carried out to produce a 3-dimensional (3D) model of the environment using the SLAM technique by processing the data obtained from Light Detection and Ranging (LiDAR) and stereo camera sensors mounted on an Unmanned Ground Vehicle (UGV) capable of operating in an indoor-outdoor area. The environment was modelled using LiDAR-SLAM and Visual Simultaneous Localisation and Mapping (VSLAM) methods, using the LiDAR sensor and the stereo camera integrated into the UGV. The accuracy assessment of the produced models was made by comparing the real sizes of the objects in the environment with the sizes in the produced model. In addition, the model's surface accuracies were tested by examining the linearity of flat surfaces selected from the study area.

1. Introduction

Simultaneous Localisation and Mapping (SLAM) is a technique that allows a robot or autonomous system to simultaneously create a map of its surroundings and determine its location on the map while navigating an environment with the help of various sensors (Ahmed et al., 2023). With the developments in sensor and computer technologies, as well as the reduction of sensor sizes and costs, SLAM is now widely used in many fields such as robotics, artificial intelligence, autonomous driving systems, industry and academia (Barros et al., 2022). Although the traditional methods used for positioning, Global Navigation Satellite Systems (GNSS), and Real-Time Kinematic (RTK) (Ilci and Toth, 2020), provide high accuracy in open areas; however, they are insufficient in indoor and complex environments due to signal obstacles (Cheng et al., 2022). In contrast, SLAM offers a much more reliable and flexible solution in these environments, as it performs mapping and positioning simultaneously by processing environmental data directly with sensors. Thanks to SLAM, robots can create maps by identifying structural elements such as wall corners and doors in their environment, plan paths using this data, and move safely by maintaining their balance even when faced with unexpected situations (Roy et al., 2023).

SLAM technique is divided into two main categories, Visual-SLAM (VSLAM) and Light Detection and Ranging based SLAM (LiDAR-SLAM), depending on the sensor types used to collect data from the environment (Dai et al., 2023). VSLAM works with stereo, monocular or RGB-D cameras; it analyses the environment and performs mapping and positioning operations (Chen et al., 2022). Thanks to advanced algorithms such as Oriented FAST and Rotated BRIEF (ORB-SLAM) (Mur-Artal et al., 2015) and Direct Sparse Odometry (DSO) (Engel et al., 2018), positioning accuracy has increased, and the system has become faster and more efficient. VSLAM stands out with its economical, lightweight, and easy-to-install structures. It can run on microprocessor computers, embedded systems, and even smartphones. However, performance loss may occur in environments where there is not enough light or where there are no distinct visual details on the surfaces (Özbayrak and İlçi, 2024).

VSLAM are divided into two main categories based on using information from images: feature-based and direct. Feature-based VSLAM systems detect salient visual features in images and perform SLAM by tracking the movement of these points over time. The tracking process becomes more stable thanks to feature extractors (SIFT, ORB) and descriptors widely used in image processing. These methods are usually based on filtering-based models (e.g. Extended Kalman Filter (EKF)) and bundle adjustment-based optimisation methods (BA) (Beghdadi and Mallem, 2022). Unlike feature-based methods, direct-based methods do not detect any features directly using pixel information in the image. These methods use photometric consistency as an error metric to estimate camera motion and directly evaluate the sensor data without preprocessing. They aim to achieve accurate positioning by minimising photometric error (Barros et al., 2022).

On the other hand, LiDAR-SLAM is a system that works with laser technology and can map the environment with high precision and density (Başaran and İlçi, 2025). Thanks to its wide Field of View (FoV) and ability to provide 3D data, it provides more accurate results in large-scale and complex applications, less affected by light changes, dust and night conditions. These advantages of LiDAR technology have enabled the development of various solution approaches in SLAM algorithms. Particularly, 3D LiDAR technology is widely used in many fields, especially in autonomous vehicles, robotic systems and mapping applications, thanks to the high resolution and dense coordinate data it provides (Raj et al., 2020), (Sun et al., 2019), (Yan et al., 2018). However, the high cost of LiDAR systems and the long development process limit the widespread use of this technology.

Scan matching is an introductory module in LiDAR-SLAM systems that allows for estimating the robot's pose over consecutive scans. This method is widely used in applications with six degrees of freedom (DoF), especially where precise positioning is required. It is divided into two categories: direct matching methods and feature-based matching methods. Classical algorithms such as Iterative Closest Point (ICP) and Normal Distributions Transform (NDT), which are direct matching methods, estimate pose by aligning point clouds iteratively. Additionally, matching methods based on environmental characteristics are also available (Wang et al., 2023). Raster matching can be performed based on raw points and low-level geometric features such as normals, planes, and edges extracted from point clouds. Such feature-based matching methods extract these attributes automatically and then perform matching between scans. Considering the advantages and limitations of both SLAM methods, the method appropriate for the application and purpose is preferred (Huang, 2021).

This study aims to test the accuracy provided by LiDAR-SLAM and VSLAM techniques. LiDAR and Stereo camera systems were placed on a developed Unmanned Ground Vehicle (UGV), and a 3D model of the work area was produced with the SLAM technique. For the data's accuracy analysis, the actual lengths of objects whose dimensions can be easily measured via a total station in the environment were compared with the 3D model lengths. Additionally, the linearity of flat surfaces in the environment was analysed through 3D reference models obtained using terrestrial laser scanners, and the surface accuracies provided by SLAM applications were interpreted.

2. Experimental Studies

2.1 Mobile Platform

This study aims to create a 3D model of indoor areas using sensors integrated into the developed UGV. VSLAM and LiDAR-SLAM techniques were used to generate a 3D model of the indoor environment. ZED 2i stereo camera datacwas used for VSLAM (Figure 1), and OS1-128 LiDAR data was used for LiDAR-SLAM (Figure 2). Jetson AGX Orin was the operating system for collecting and processing data.

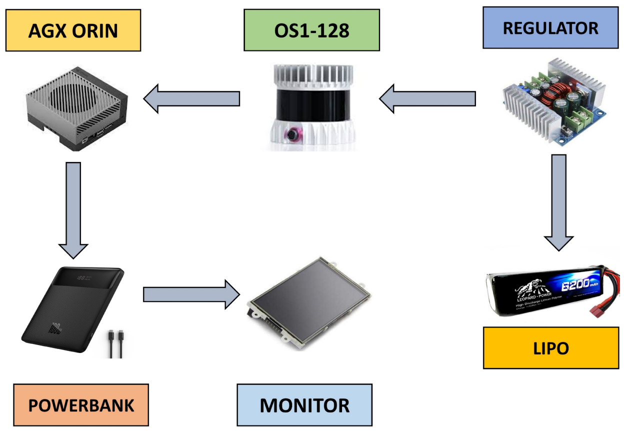

Figure 1. LiDAR system connection diagrams.

The ZED 2i stereo camera mounted on the vehicle developed in the project uses a stereo matching algorithm to create 3D model data, thus determining the depth map in millimetres (mm). The ZED 2i has an advanced positional tracking algorithm for robotic applications, thanks to a 120-degree wide-angle FoV and thermal calibration for significantly improved positional tracking sensitivity and accuracy. It also has a built-in IMU, barometer, temperature sensor and magnetometer (Stereolabs, 2022). Figure 3 presents the real-time model of the study area produced using the 3D modeling system.

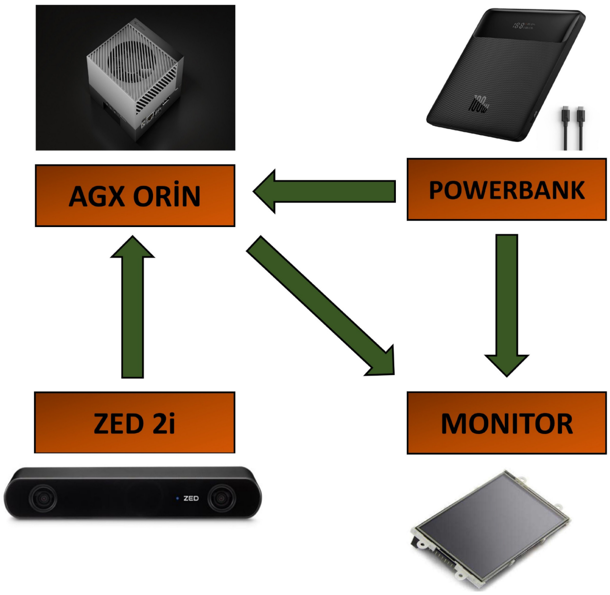

Figure 2. Camera system connection diagrams.

Figure 3. The real-time model of the study area produced using the 3D modeling system.

Another sensor on the vehicle, the OS1-128 LiDAR, provides high-density and detailed point cloud data thanks to its 128-channel resolution, allowing for highly detailed mapping of environmental objects. With a target detection range of up to 200 meters, reliable and precise data can be obtained within a wide working area. The sensor's approximately 45-degree FoV enables comprehensive analysis of complex environmental conditions such as dense urban areas or indoor spaces. Thanks to these features, the OS1-128 sensor is especially preferred in autonomous systems, robotic applications and precision mapping projects. Its high resolution offers superior performance in critical tasks such as environmental perception, object recognition and detailed mapping (Ouster, 2025) (Figure 4).

2.2 3D SLAM Modelling

In order to test the accuracy of the model to be obtained, the 120 m long corridor, which contains objects such as doors, radiators,

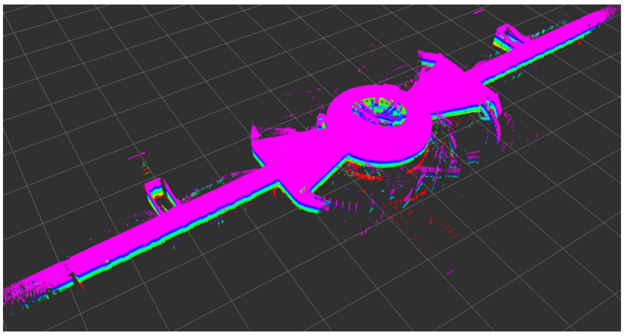

Figure 4. Instant picture of OUSTER 128 Channel LiDAR while modelling the environment.

fire cabinets, etc., whose dimensions can be easily measured, was selected as the application area of the project. Figure 5 shows the mobile platform and the camera, and LiDAR sensors mounted on the UGV.

Figure 5. Unmanned ground vehicle.

For the VSLAM application, images collected with the ZED2i stereo camera were evaluated using the ZEDfu application, which is part of the ZED-SDK software. Sequential image data were processed using the VSLAM method in ZEDfu, and a 3D model of the study area was obtained in true colours. A 128-channel 3D LiDAR sensor was used for LiDAR-SLAM, and the HDL Graph SLAM algorithm was used in the data processing (Koide et al., 2019). This algorithm adopts a direct matching approach and performs pose estimation between consecutive scans with the NDT algorithm. Alignment is achieved over the entire point cloud without feature extraction, and loop closure detection is performed by checking similarity with past scans at specific intervals to maintain the system's consistency. The 3D LiDAR-SLAM and VSLAM models that were produced are given in Figure 6.

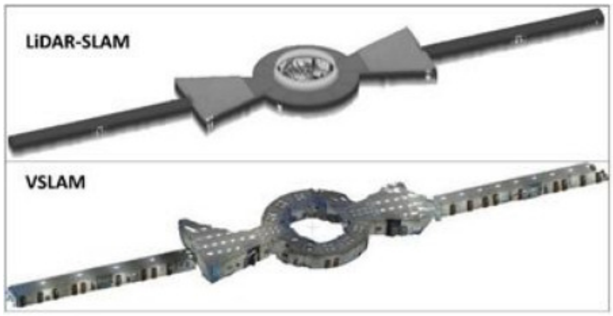

Figure 6. 3D SLAM models (top: LiDAR-SLAM, bottom: VSLAM).

3. Results

In order to test the accuracy of the 3D models obtained with LiDAR-SLAM and VSLAM, firstly, the length and height values of thirteen heater radiators, four fire boxes, two doors, two red panels, one fire exit door and one column, which were located in the study area and whose dimensions could be easily measured with the Total Station. The real dimensions of these objects and the dimensions measured from the 3D model are shown in Figure 8. The difference values measured from the real and model dimensions are given in Table 1.

Another analysis performed to evaluate the accuracy of the produced models is the examination of surface accuracy. For this analysis, 10 ground and 14 right and left wall surfaces were selected in the area modelled in Figure 7, and a Root Mean Square Error (RMSE) analysis was performed (Table 2). According to the direction determined as reference, the right wall was named Right (R), the left wall was named Left (L), and the ground was named Ground (G).

The RMSE values for the plane of the surfaces are shown in Table 2. The RMSE values are calculated using Equation 1.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n}} \tag{1}$$

where e_i is the distance between the predicted and actual (for sample i), and n is the number of points.

4. Conclusions

In this study, the data collected with LiDAR and camera sensors integrated on the UGV were processed using LiDAR-SLAM and VSLAM techniques, and a 3D model of the selected interior space was created.

In order to test the accuracy of the produced 3D model, two different analyses were performed. In the first analysis, based on the measurements performed on the objects, the maximum value of the "width" differences of the LiDAR system was determined as ±0.05 m and the average value as ±0.01 m. Likewise, the maximum difference for LiDAR-SLAM in "height" differences was ±0.02 m, and the average was ±0.01 m. In the

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Object	Actual size		Model (LiDAR)		Model (Camera)		Difference LiDAR		Difference Camera	
	Width (m)	Height (m)	Width (m)	Height (m)	Width (m)	Height (m)	Width (m)	Height (m)	Width (m)	Height (m)
Heater Radiator	1.40	0.60	1.40	0.60	1.40	0.61	0.00	0.00	0.00	0.01
Red Panel	1.25	0.90	1.20	0.88	1.20	0.90	-0.05	-0.02	-0.05	0.00
Fire Exit	1.04	2.17	1.04	2.18	1.05	2.19	0.00	0.01	0.01	0.02
Fire Box	0.88	0.69	0.89	0.68	0.90	0.71	0.01	-0.01	0.02	0.02
Column	0.55	1.64	0.56	1.62	0.55	1.63	0.01	-0.02	0.00	-0.01
Door	1.08	2.24	1.09	2.23	1.07	2.24	0.01	-0.01	-0.01	0.00

Table 1. Accuracy values of objects' dimensions

Wall Surface (cm)			Wall Surface (cm)			Floor (cm)		
S.N.	VSLAM	LiDAR	**S.N.**	VSLAM	LiDAR	**F.N.**	VSLAM	LiDAR
R1	0.61	0.78	**R5**	0.31	0.84	**G1**	0.13	0.69
L1	0.75	0.87	**L5**	2.85	0.84	**G2**	0.09	2.84
R2	0.20	0.96	**R6**	0.29	0.75	**G3**	0.27	0.95
L2	0.66	0.90	**L6**	0.33	0.71	**G4**	0.20	1.28
R3	0.65	1.53	**R7**	0.25	0.76	**G5**	0.18	10.24
L3	4.66	1.21	**L7**	0.65	0.72	**G6**	0.27	1.75
R4	7.46	17.08				**G7**	11.50	0.13
L4	1.48	1.36				**G8**	0.12	1.53
						G9	0.24	0.97
						G10	0.12	1.11

Table 2. RMSE values of the surfaces.

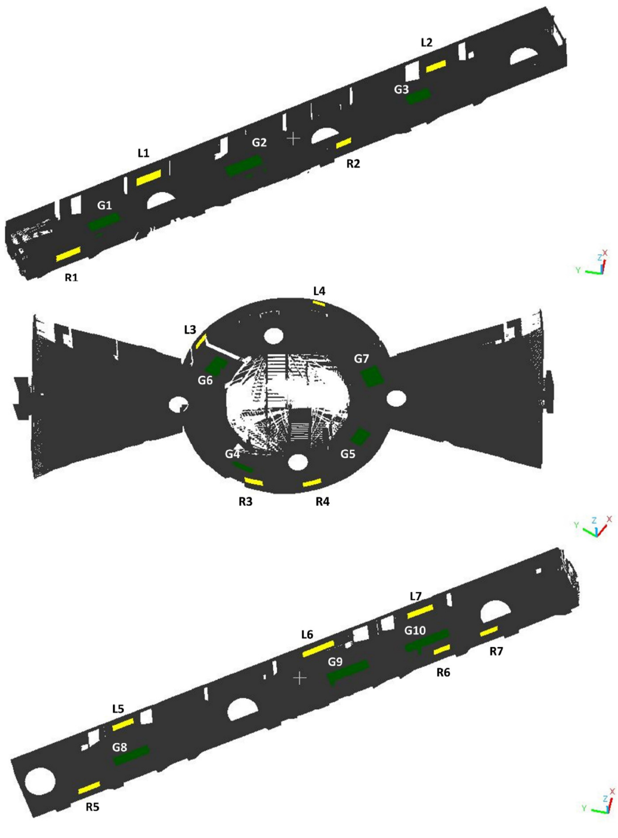

Figure 7. Chosen areas for surface accuracy.

analyses performed for the camera system, the maximum difference in the "width" measurement was calculated as ±0.05 m, and the average was ±0.01 m; it was observed that the maximum difference in "height" was ±0.02 m, and the average was ±0.01 m. These results indicate that both LiDAR-SLAM and VSLAM produce similar errors in width and height measurements, showing no significant difference in these dimensions. Therefore, the accuracy levels of both systems vary depending on the measurement dimension and environmental conditions.

The second analysis aims to evaluate the overall surface accuracy of the models. For this purpose, surfaces with homogeneous distribution were examined using LiDAR and a stereo camera. After this alignment, 24 surfaces (seven left walls, seven right walls and 10 ground) were selected, and the RMSE values of the VSLAM and LiDAR-SLAM data were calculated for each. The obtained RMSE values were analysed, and the average RMSE value of the surfaces belonging to the VSLAM was found to be 1.5 cm, while the average RMSE value of the LiDAR-SLAM system was found to be 2.1 cm. These results show that the camera-based system generally measures with lower errors and offers higher accuracy, especially in indoor conditions. One of the main reasons the LiDAR-SLAM produces higher RMSE values is the range limitations, especially in indoor environments and narrow corridors. In long but narrow areas such as corridors, the fact that the laser beams emitted from the LiDAR sensor cannot reach certain surfaces at a right angle or produce data with insufficient intensity negatively affects the measurement accuracy. This situation increases the measurement noise, especially on surfaces viewed from far away or at narrow angles, and leads to deviation of the results. In general, although the camera-based system provided higher surface accuracy in this study, it was concluded that both systems exhibit variable performance according to different surface types and spatial conditions and that the appropriate system choice should be made in the application context.

As a result of the study, it was determined that LiDAR-SLAM and VSLAM have different advantages and disadvantages. VSLAM is especially successful in perceiving visual details and colour-texture information; this makes it advantageous in applications such as object recognition and classification. For example, while the camera sensor can detect paintings on the wall surface, LiDAR-SLAM cannot reflect these objects in the model. However, cameras are dependent on environmental light conditions, and their performance may decrease in low-light environments. On the other hand, LiDAR sensors can also collect data in dark envir-

Figure 8. The dimensions of the objects in the study area were measured from the model and their actual dimensions.

onments. However, LiDAR-SLAM systems can make inaccurate measurements on semi-transparent surfaces such as glass and water and are more costly.

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