A Comparative Study of 2D and 3D LiDAR Technologies in the Industrial Applications of Autonomous Navigation

Ha Quang Thinh Ngo
FPT University, Ho Chi Minh City
Vietnam

Thanh Phuong Nguyen
HUTECH Institute of Engineering
HUTECH University, Ho Chi Minh City
Vietnam

In the field of robotics, four tasks of autonomous robots such as navigation, localization, object tracking, and motion planning, play a crucial role to ensure the autonomy and intelligence of system in the complex and diverse environment. All of its operation relies on the working ability of laser scanner or LiDAR (Light Detection and Ranging) sensor which becomes a promising tool for these tasks due to the accurate distance measurement and wide field of view. The objective of this paper is to evaluate and compare the working performance between 2D and 3D LiDAR sensor in the specific tasks. In the different applications, 2D LiDAR sensor scans on a single plane while the 3D one uses lasers to capture precise 3D data of objects and environments. A series of real-world experiments are conducted in a laboratory setting, focusing on three main tasks: object detection and tracking, mapping capabilities, and motion planning. Owing to these practical tests, the results highlight the strengths and weaknesses of both 2D and 3D LiDAR sensors in such tasks. Experimental results show that, compared with 2D LiDAR, the 3D LiDAR reduces measurement error by up to 59% in the Y-axis, improves human detection accuracy by 28.8% under occlusion conditions, and eliminates navigation collisions caused by planar blind spots, albeit at the cost of a lower frame rate.

Keywords: *Autonomous robot, precise navigation, Simultaneous Locali–zation and Mapping, 2D LiDAR, 3D LiDAR.*

1. INTRODUCTION

Autonomous mobile robots have become an essential component of modern industrial and service applications [1-3], including warehouse logistics, manufacturing automation, inspection, and human–robot collaborative environments. To operate safely and efficiently, such robots must be capable of perceiving their surroundings [4], estimating their own position [5], identifying obstacles and humans [6], and planning collision-free paths in real time. Among the available perception technologies, LiDAR sensors are widely adopted due to their robustness to lighting conditions, accurate distance measurement, and wide field of view.

In robotic navigation systems, LiDAR sensing un–derpins several fundamental capabilities, most notably environment mapping, human and obstacle detection, and path planning or optimization. The performance of these tasks is directly influenced by the characteristics of the sensing modality employed. In practice, LiDAR sensors are commonly categorized into 2D LiDAR and 3D LiDAR, which differ significantly in sensing dimensionality, data density, computational require–ments, and cost. Selecting an appropriate LiDAR configuration is therefore a critical design decision in autonomous robotic systems [7-9].

A 2D LiDAR typically performs planar scanning at a fixed height, providing range measurements in a single horizontal plane. Owing to its high update rate, low computational load, compact size, and relatively low cost, 2D LiDAR has been extensively deployed in indoor navigation, warehouse automation, and struc–tured industrial environments [10]. However, the inhe–rent limitation of planar sensing introduces blind spots for objects located above or below the scanning plane, which may degrade performance in environments with height-varying obstacles or complex geometry.

In contrast, a 3D LiDAR employs multi-layer laser scanning to acquire three-dimensional point cloud data, enabling comprehensive spatial perception of the envi–ronment. This capability allows robots to detect obs–tacles of varying height, navigate through cluttered or unstructured environments, and operate reliably in scenarios where vertical information is essential [11]. These advantages come at the expense of higher cost, increased sensor weight, greater computational demand, and typically lower frame rates compared to 2D LiDAR systems.

Although the advantages and limitations of 2D and 3D LiDAR technologies are widely recognized in general terms, many existing studies investigate these sensors under different platforms, algorithms, or appli–cation contexts, making it difficult to draw fair and practical comparisons [12-14]. In particular, some

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Correspondence to: Ha Quang Thinh Ngo, FPT University, Ho Chi Minh City, Vietnam
E-mail: thinhnhq2@fpt.edu.vn
E-mail: nt.phuong@hutech.edu.vn
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results of investigations are often inferred from task-specific studies or simulation-based evaluations, rather than from controlled experimental comparisons conduc–ted on the same robotic platform under identical opera–ting conditions. Moreover, while prior research has addressed mapping accuracy, human detection, or navi–gation performance individually, a unified experimental evaluation covering all three tasks using both 2D and 3D LiDAR remains limited. This gap makes it chal–lenging for engineers and practitioners to objectively assess the trade-offs between sensing dimensionality, accuracy, robustness, and computational efficiency when designing real-world robotic systems.

Motivated by these limitations, this study aims to provide a systematic and experimentally grounded com–parison of 2D and 3D LiDAR sensors for autonomous navigation applications. Rather than proposing new perception or navigation algorithms, the focus of this work is on system-level evaluation, where both sensing modalities are assessed under identical experimental conditions on the same mobile robot platform. Speci–fically, the performance of 2D and 3D LiDAR sensing is evaluated with respect to three representative tasks:

1. Mapping accuracy, including measurement er–ror, standard deviation, and variance;
2. Human detection performance, particularly un–der occlusion and cluttered conditions;
3. Path optimization and navigation behavior, inc–luding collision avoidance and trajectory robustness.

By conducting repeated real-world experiments in a controlled laboratory environment, this work seeks to clarify when the additional complexity of 3D LiDAR is justified and when 2D LiDAR remains a sufficient and efficient solution.

The main contributions of this paper are summarized such as (i) Unified experimental framework: A single wheeled mobile robot platform integrating both a 2D LiDAR and a 3D LiDAR sensor is developed, enabling fair and direct comparison under identical sensing range, field-of-view, and environmental conditions, (ii) Multi-task comparative evaluation: The study experi–mentally contrasts 2D and 3D LiDAR performance across map–ping, human detection, and path optimization tasks using consistent metrics and repeated trials, (iii) Quantitative system-level insights: Measurement accuracy, detection reliability, frame-rate behavior, and navigation robustness are analyzed to reveal practical trade-offs between planar and volumetric sensing, (iv) Application-oriented gui–dance: The results provide evidence-based recommen–dations for LiDAR sensor selection in industrial autonomous navigation applications.

The remainder of this paper is organized as follows. Section 2 reviews related work on 2D and 3D LiDAR-based mapping, human detection, and path optimization, highlighting existing limitations and open challenges. Section 3 introduces the technical preliminaries and methodological foundations relevant to the studied tasks. Section 4 presents the experimental setup and de–tailed validation results for both LiDAR configurations. Finally, Section 5 discusses the findings, potential prospects, and future research directions, followed by the conclusions.

2. PREVIOUS WORKS

2.1 LiDAR-Based Mapping and Localization

LiDAR sensors have been extensively used for robot mapping and localization due to their ability to provide accurate range measurements independent of ambient lighting conditions. Early and widely adopted appro–aches rely on 2D LiDAR-based simultaneous localiza–tion and mapping (SLAM), where planar laser scans are used to estimate robot pose and construct occupancy grid maps [15,16]. These methods have demonstrated reliable performance in structured indoor environments such as corridors, factories, and warehouses, benefiting from high scan rates and relatively low computational cost.

However, several studies [17-19] have reported that 2D LiDAR-based mapping suffers from limitations when deployed in environments containing height-vary–ing obstacles, uneven terrain, or overhanging structures. Because only a single horizontal scanning plane is observed, important spatial information may be omitted, leading to localization drift or incomplete maps.

To address these limitations, 3D LiDAR-based map–ping approaches [23-25] have been proposed, levera–ging multi-layer scanning and dense point clouds to generate three-dimensional maps. Such methods have shown improved robustness in complex environments, including outdoor scenes, cluttered indoor spaces, and semi-structured industrial settings. Prior studies report that the inclusion of vertical information can signifi–cantly improve map consistency and localization accu–racy, particularly in scenarios where planar assumptions are violated.

Despite these advantages, 3D LiDAR-based map–ping typically incurs higher computational complexity, increased data-processing requirements, and greater sys–tem cost [26]. As a result, many works focus on optimizing point cloud processing pipelines or selec–tively reducing data density, highlighting an inherent trade-off between mapping fidelity and system efficiency.

2.2 Human Detection and Obstacle Perception Using LiDAR

Human detection is a critical capability for mobile robots operating in shared environments, particularly in industrial and service applications where safety is paramount. LiDAR-based human detection methods co–mmonly rely on geometric clustering, feature extraction, and learning-based classification applied to range mea–surements.

For 2D LiDAR, human detection approaches [20-22] often exploit leg patterns, shape descriptors, or temporal motion cues extracted from planar scans. These methods are computationally efficient and have demonstrated good performance in controlled indoor environments. However, their effectiveness decreases in crowded scenes, under occlusion, or when humans adopt non-standard postures, due to the lack of height information.

In contrast, 3D LiDAR-based human detection met–hods [27-30] benefit from volumetric perception, allo–wing the extraction of height, body shape, and spatial continuity features. Prior research shows that 3D point cloud representations can improve detection robustness in complex and dynamic environments, especially where partial occlusions occur. Nevertheless, these app–roaches often require more sophisticated data processing and higher computational resources.

Existing studies typically evaluate human detection performance either using 2D or 3D LiDAR independently, often under different experimental setups or application assumptions. As a result, direct and fair comparisons between planar and volumetric LiDAR sensing for human detection remain relatively limited [31, 32].

Table 1. List of the cutting-edge techniques in related fields.

Type of laser scanner	Publication year	Author(s)	Fusing device(s)	Classification	Outcome(s)	Challenge(s)
2D LiDAR	2021	Liu, R. et al [18]	Hokuyo URG-04LX, Decawave DWM1001, wheel encoder	Mapping	This approach that was proposed has as high as 85.5% reduction in mapping error, and reaches up to 0.199 m average error using four UWB nodes for indoor area of 400 m^2	Growing the number of UWB nodes improves map quality, but also improves computational cost, and does not work well with large open or low-feature areas unless used in conjunction with UWB
	2021	Ranđelović, D. M. et al [19]	Garmin LIDAR-Lite v3HP, HC-SR04 Ultrasonic, Sharp GP2Y0A710K0F Infrared rangefinder, Bosch BME280 Barometric	Mapping	By combining readings from several inexpensive sensors, the system would better handle environmental change (e.g., temperature/ humidity fluctuations) than if it had any individual sensor alone	Significant calibration and filtering is needed to normalize barometric readings and map response times to true altitude changes
	2023	Yao, Q. Y. et al [20]	2D LiDAR, DBSCAN	Human detection	The system identifies aberrant trajectories associated with a fall and gives real-time alerts	Some falling maneuvers were classified as walking path anomalies, especially when people walked out of view of the LiDAR
	2020	Ngo, H. Q. T. et al [21]	Hokuyo URG-04LX, positioning sensor, Realsense d435	Path optimization	Researchers developed the fused method from multiple sensors to navigate the shortest path in front of patients	Its ability of autonomy and the accurate tracking error of human-aware navigation was not mentioned
	2022	Nuha, H. et al [22]	3D LiDAR	Path optimization	The RELM model uses observations only for 10–40 m heights to extrapolate wind speed	Performance of RELM is dependent on careful tuning of the regularization parameter (D) and number of hidden neurons (M)
3D LiDAR	2021	Koide, K. et al [23]	3D LiDAR sensor, GPU-accelerated CPU	Mapping	This technique ensured consistency across the whole map, even in huge environments with loop closures	The voxel matching cost term is prone to local minima, and solutions obtained may be resolution and environment density dependent

	2023	Yin, H. et al [24]	A Velodyne VLP-16 3D LiDAR, BIM-based semantic map	Mapping	It reduces setup and computation costs in static environments with a maximum of 34% decrease in translation error	There are some map points mislabeled or ambiguously labeled and this work cannot handle global re-localization from scratch
	2024	Shao, W. et al [25]	3D+RGB IP67 Kit	Human detection	Merging the work provides better F1 score (17.1%) and accuracy up to 0.807	Manual subject segmentation and annotation are limited to only four-participant datasets
	2023	Wang, J. et al [26]	Velodyne HDL-64E, VLP-16	Path optimization	Localization is performed frame-to-keyframe only, without any loop closure usage, which in some scenes may not always be feasible in real-world scenarios	The method assumes good initial correspondence between keyframes and LiDAR frames. Poor initialization may still lead to divergence

2.3 LiDAR-Based Path Planning and Navigation

Path planning and navigation constitute another major application area of LiDAR sensing. In many robotic systems [33, 34], LiDAR-derived maps and obstacle representations serve as inputs to local and global plan–ners responsible for collision avoidance and trajectory generation.

2D LiDAR-based navigation has been widely adop–ted in indoor robotics due to its simplicity and efficiency. Numerous studies [35-37] demonstrate that planar sensing is sufficient for navigation in environ–ments where obstacles are predominantly vertical and well-represented at the scanning height. However, failures may occur when obstacles are missed due to height variation, leading to unsafe navigation behavior.

3D LiDAR-based navigation, on the other hand, enables robots to reason about the environment in three dimensions, improving obstacle avoidance and path robustness. Prior works [38, 39] report smoother tra–jectories and enhanced safety in cluttered environments. Nonetheless, these benefits must be weighed against increased computational burden and system complexity.

As summarized in Table 1, recent studies employing 2D LiDAR primarily focus on indoor mapping, human detection, and short-range path optimization, benefiting from high frame rates and low computational cost [40-42]. However, these approaches frequently report limitations related to planar sensing, including reduced robustness under occlusion, sensitivity to obstacle height, and degraded performance in cluttered or low-feature environments. In contrast, 3D LiDAR-based approaches demonstrate superior mapping consistency and improved detection accuracy, with reported reduc–tions in localization or translation error of up to 34% in complex environments [43, 44]. These advantages come at the expense of increased computational complexity and lower frame rates.

3. METHODOLOGY AND TECHNICAL PRELIMINARIES

This part presents the technical foundations and rese–arch methodology adopted in the present study. Unlike Section 2, which reviews related literature, the tech–niques described here correspond to the algorithms and system components actually implemented in the experi–mental validation unless otherwise stated.

3.1 System Overview

The experimental system is built around a wheeled mo–bile robot equipped with interchangeable LiDAR sen–sing configurations. The robot operates within a cont–rolled indoor environment and executes identical per–ception and navigation tasks using either a 2D LiDAR or a 3D LiDAR sensor. The overall processing pipeline consists of four main stages:

1. LiDAR data acquisition
2. Environment representation and mapping
3. Human and obstacle detection
4. Navigation and path execution

All system components are implemented within the Robot Operating System (ROS) framework to ensure modularity, reproducibility, and consistent data handling across experiments.

3.2 LiDAR Data Representation

3.2.1 2D LiDAR Data

The 2D LiDAR provides planar range measurements in polar coordinates, represented as:

$$S_{2D} = \{(r_i, \theta_i)\}_{i=1}^{N} \pi r^2 \tag{1}$$

where r_i denotes the measured distance and θ_i the corresponding scan angle. These measurements are transformed into Cartesian coordinates for mapping and obstacle detection tasks.

3.2.2 3D LiDAR Data

The 3D LiDAR produces multi-layer range measure–ments that form a three-dimensional point cloud:

$$P_{3D} = \{(x_i, y_i, z_i)\}_{i=1}^{M} \tag{2}$$

Compared to 2D scans, 3D point clouds provide explicit vertical information, enabling volumetric envi–ronment representation. To maintain computational ef–ficiency, point cloud preprocessing includes downsam–pling and outlier filtering prior to further processing.

3.3 Mapping Methodology

Mapping is performed using a Graph SLAM-based framework, which is applied consistently for both sen–sing configurations to ensure a fair comparison.

- Nodes represent robot poses over time.
- Edges encode relative pose constraints derived from LiDAR measurements and odometry.

For the 2D LiDAR configuration, constraints are generated from planar scan matching, while for the 3D LiDAR configuration, constraints are derived from point cloud registration. Importantly, the underlying SLAM formulation remains unchanged; only the dimensionality of the sensory input differs. The resulting maps are:

- 2D occupancy grids for the 2D LiDAR case
- 3D spatial representations for the 3D LiDAR case

This design isolates the impact of sensing dimen–sionality on mapping performance.

3.4 Human and Obstacle Detection

3.4.1 Detection Using 2D LiDAR

Human and obstacle detection using 2D LiDAR relies on segmentation of planar scan data. Consecutive scan points are grouped into clusters based on Euclidean distance thresholds. Extracted clusters are then clas–sified based on geometric features such as width, curvature, and temporal consistency.

3.4.2 Detection Using 3D LiDAR

For the 3D LiDAR configuration, detection is perfor–med on point cloud data using three-dimensional Eucli–dean clustering. Height information is explicitly considered to distinguish humans and obstacles from background structures. Temporal filtering is applied to improve detection stability across consecutive frames.

In both configurations, the detection output is rep–resented in the robot's local coordinate frame and forwarded to the navigation module.

3.5 Navigation and Path Execution

Navigation is implemented using a standard local plan–ning framework that consumes LiDAR-derived obstacle information. The planner generates collision-free velo–city commands in real time based on the robot's current pose, goal position, and perceived environment.

The navigation logic remains identical across both sensing configurations. Any differences in navigation performance therefore stem from differences in envi–ronmental perception rather than from changes in planning algorithms.

3.6 The Proposed Method

To eliminate ambiguity regarding the scope of this chapter, the techniques actually employed in this work are summarized as follows:

- Mapping: Graph SLAM with planar scan matching for 2D LiDAR and point cloud registration for 3D LiDAR.
- Human detection: Geometric clustering-based detection for both sensing modalities, extended with height information for 3D LiDAR.
- Navigation: LiDAR-based local path planning with real-time obstacle avoidance.

The contribution lies in the controlled experimental application and comparison of these established techniques under identical conditions.

4. EXPERIMENTAL VERIFICATIONS

4.1 Platform Setup

Guided by the performance indicators and limitations reported in Table 1, the experimental validation focuses on three representative tasks—mapping accuracy, hu–man detection reliability, and path optimization effi–ciency—using identical sensing ranges and operating conditions for both 2D and 3D LiDAR. To validate the working performance of those sensors, a series of experiments in the laboratory level are conducted. In our tests, the experimental platform as Fig. 1 is based on a Pioneer 3-AT wheeled mobile robot, which provides sufficient payload capacity, stability, and modularity for multi-sensor integration. The robot is equipped with two LiDAR sensors: a Hokuyo URG-04LX-UG01 2D LiDAR and a Velodyne VLP-32C 3D LiDAR, mounted at different heights to reflect typical deployment scena–rios in indoor robotic navigation. This 2D LiDAR is mounted near the base of the robot and provides planar range measurements for close-range obstacle detection and mapping. The 3D LiDAR is mounted on the top plate of the robot and provides multi-layer point cloud data for full three-dimensional environmental percep–tion. Our configuration is especially useful for appli–cations requiring fine-grained navigation and localiza–tion in narrow, constrained spaces, i.e., indoor environ–ments or those with a high density of obstacles.

All experiments in this study were conducted fol–lowing a fixed and repeatable protocol to ensure the re–liability and consistency of the results. For each expe–rimental scenario, identical environmental conditions, sensor configurations, and algorithmic parameters were maintained for both 2D and 3D LiDAR evaluations as Table 2. Experiments were repeated multiple times, and all reported performance metrics correspond to averaged results over repeated trials.

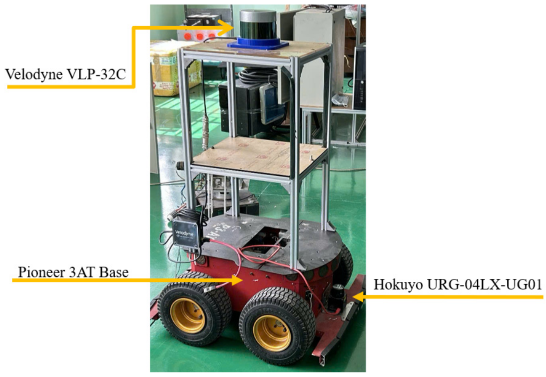


Figure 1. Illustration of our target platform.

Table 2. Comparison of 2D and 3D LiDAR sensors used in our study.

Parameter	2D LiDAR (Hokuyo URG-04LX-UG01)	3D LiDAR (Velodyne VLP-32C)
Measurement dimension	2D (single scanning plane)	3D (32 vertical channels)
Weight	~160 g	~925 g
Dimensions	50 × 50 × 70 mm	Ø103 × 72 mm
Typical cost (USD)	Low (≈ 1–2k)	High (≈ 6–8k)
Angular resolution	0.36°	0.1°–0.4° (horizontal)
Vertical resolution	Not available	1.33°
Frame rate	Up to 40 Hz	Up to 20 Hz
Effective range	Up to 4 m	Up to 200 m
Data output	2D range scans	3D point clouds
Computational demand	Low	High

Despite its advantages in simplicity, low cost, and high frame rate, the 2D LiDAR is inherently limited by planar sensing, resulting in blind spots for obstacles located above or below the scanning plane. This limi–tation directly contributes to navigation failures obser–ved in Experiment E-3. In contrast, the 3D LiDAR provides rich spatial information that improves obstacle detection and mapping robustness; however, this comes at the expense of increased sensor weight, higher cost, greater power consumption, and higher computational requirements. These trade-offs are critical conside–rations when selecting LiDAR sensors for autonomous robotic systems.

In our initial mapping experiment, we would capture several important performance metrics, including LiDAR error and the speed of data processing in terms of frames per second. To measure LiDAR error, some scans of an object of known size using LiDAR sensors would be recorded and computed those metrics for ins–tance error, standard deviation, and variance. Besides, we compare the results of both 2D and 3D LiDAR systems. Data processing speed would be measured under mapping scan when our robot moves in work–space, and updating real-time protocol and correction in dynamic environments.

In the second experiment, we would focus on human detection. Subsequently, the bounding box of detected human would be saved to estimate the data processing speed of the computational algorithm for both LiDAR types in the same environment. In addition, we would evaluate the accurate detection by recording the error rate of all detections in relation to the actual number of people within the field of view of LiDAR. Each experimental configuration was repeated at least N = 30 times to account for sensor noise and environmental variability. The robot remained stationary during accuracy and human detection experiments to eliminate motion-induced uncertainty. Statistical metrics including mean error, standard deviation, and variance were computed across repeated trials to assess measurement repeatability.

Thirdly, in the path optimization experiment, we are going to have a test case with the robot traveling in a structured environment, and using the 2D and 3D LiDAR sensors in turn. The key consideration para–meters for this experiment are the number of reori–entations or stops made by our robot during navigation, distance covered, time taken to complete the task, and crosschecking for collision errors along the path of robot. These parameters would help to identify how effectively each configuration of LiDAR supports this robot to optimize its path and complete the task of navigation under different conditions.

4.2 Experiment 1 (E-1)

Experimental results demonstrate that the 3D LiDAR achieves lower absolute measurement errors (5.5 cm and 5.2 cm along the X and Y axes, respectively) compared to the 2D LiDAR (7.9 cm and 12.8 cm). Moreover, the variance in 3D LiDAR measurements is reduced by up to 20.4% along the Y-axis, indicating superior measurement stability. It could be attributed to the design and sensing nature of both sensors. The 3D LiDAR employs several layers of scanning and complex laser arrays to generate denser point cloud data for a more precise description of the surroundings. Reversely, the 2D LiDAR scans one plane and cannot capture fine details.

To quantitatively evaluate the sensing performance of the 2D and 3D LiDAR sensors, statistical error metrics including mean absolute error, standard deviation, and variance are computed. Ground-truth distances are obtained using manual tape measurements of calibration objects with known dimensions placed at fixed locations in the laboratory environment. All LiDAR measurements are recorded while the robot remains stationary to eliminate motion-induced uncertainty.

For each LiDAR sensor, a set of N repeated distance measurements is collected for calibration objects with known positions. The measurement error along each axis is defined as the absolute difference between the LiDAR-measured distance and the corresponding ground-truth value. For the 2D LiDAR, errors are evaluated along the X and Y axes in the horizontal plane, whereas for the 3D LiDAR, errors are evaluated along the X, Y, and Z axes. Let d_i denote the LiDAR-measured distance in a given axis and d_{gt} the corres–ponding ground-truth distance. The measurement error e_i is computed as:

$$e_i = \left| d_i - d_{gt} \right| \quad (3)$$

The standard deviation reflects the dispersion of repeated measurements around their mean value and is computed as

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(d_i - \bar{d}\right)^2} \tag{4}$$

where $\bar{d}$ is the mean measured distance. The variance is defined as the square of the standard deviation. These metrics quantify the stability and repeatability of the LiDAR measurements rather than absolute accuracy.

Table 3. List of error, standard deviation and variance of competitive lidars in each axis.

Lidar	Axis	Comparison factor		
		Error	Standard deviation	Variance
3D	X	5.5	1.1	1.3
	Y	5.2	2.8	7.8
	Z	11.3	2.9	8.6
2D	X	7.9	1.1	1.2
	Y	12.8	3.1	9.8

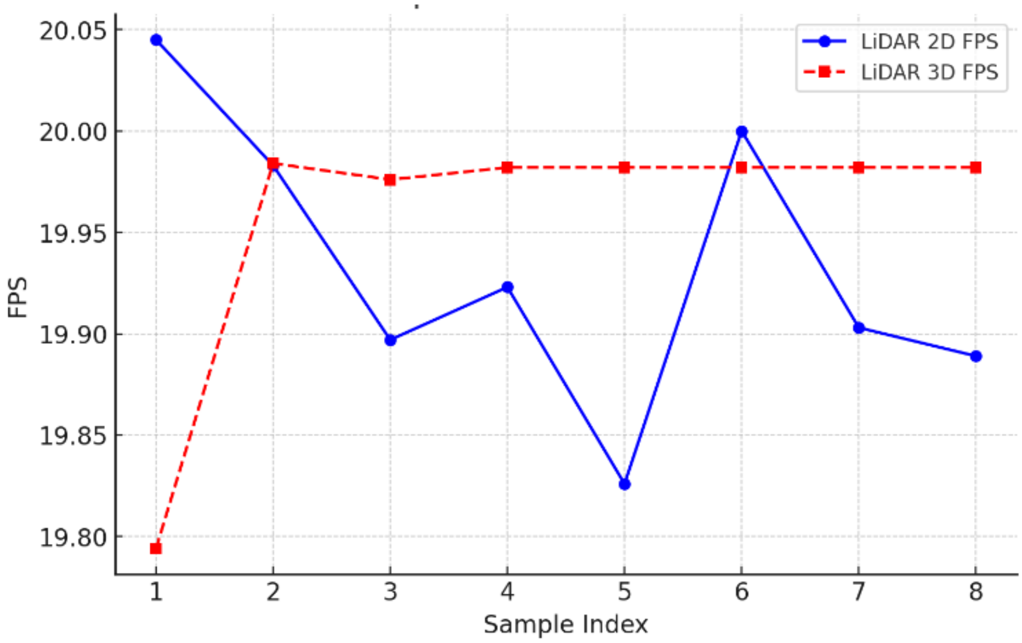


Figure 2. Experimental validation of comparative speed between 2D and 3D LiDAR sensor in case E-1.

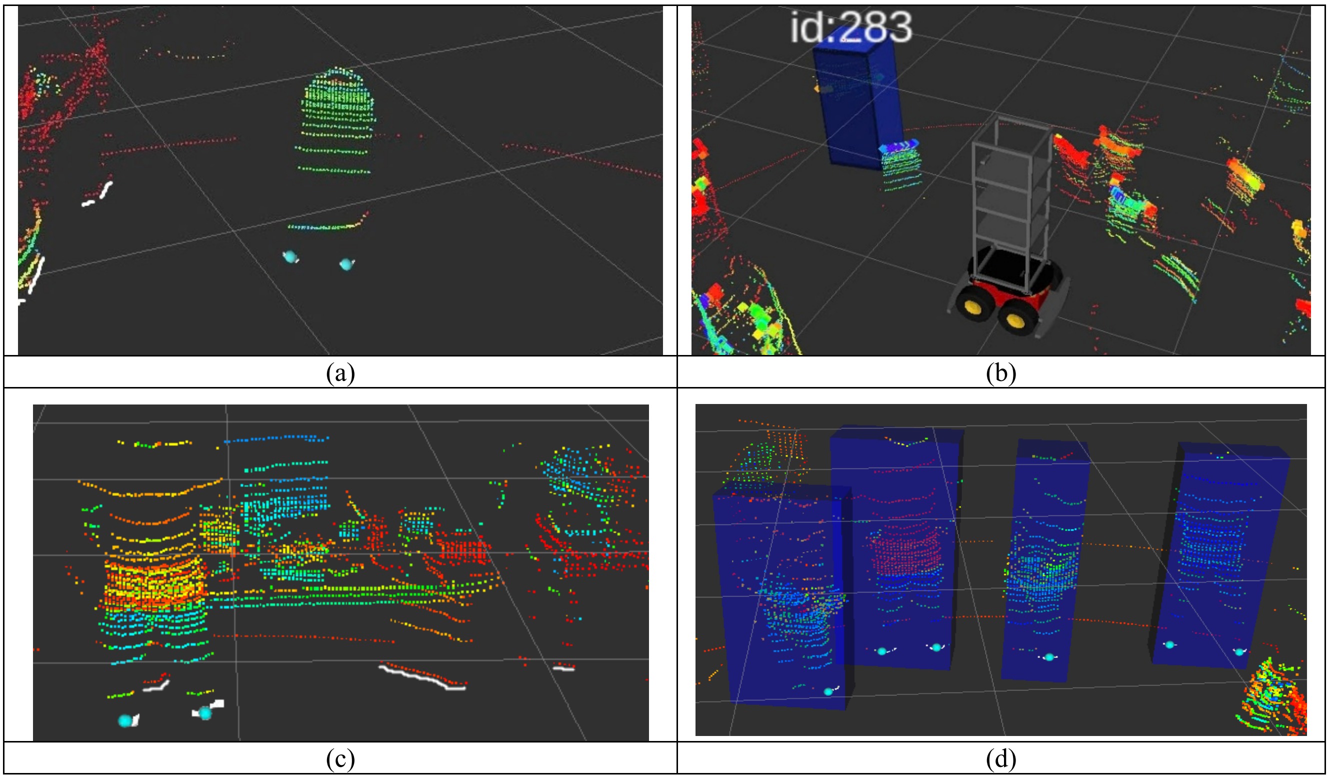


Figure 3. Experimental validation of human detection using two competitive LiDAR sensors in case E-2, (a) 3D data of target object, (b) human closed to an object, (c) human obscured by an object, and (d) 3D data of a group of humans. (The blue box represents for the data of 3D LiDAR sensor while the blue small sphere indicates for the data of 2D LiDAR sensor).

It should be noted that the accuracy metrics reported in Table 3 correspond to system-level spatial accuracy under identical sensing range and field-of-view constraints. Although 2D LiDAR sensors are often considered highly precise in planar measurements, the lack of vertical information introduces ambiguity when estimating object position in three-dimensional space. In contrast, the 3D LiDAR benefits from denser point clouds and multi-layer scanning, which leads to lower positional error in the present experimental setup. Specifically, the 3D LiDAR yields a standard deviation of 1.1 in the X-axis and 2.8 in the Y-axis compared to the respective values of 1.1 and 3.1 for the 2D LiDAR. Variance values also indicate this discrepancy, in which 3D LiDAR variances are 1.3 and 7.8 and 2D LiDAR variances are 1.2 and 9.8. Low and stable standard deviation and variance indicate the 3D LiDAR constantly is providing more steady and consistent information, which reduces uncertainty in environmental perception. This stability is particularly important in the case where high accuracy of measurement is required for real-time navigation choices, e.g., when moving through tight angles or avoiding small hindrances.

The second key advantage of the 3D LiDAR, as is evident from this test, is that it scans dimensions in the Z-axis, enabling the reception of data on the height of the environment. This enables robots to identify obstacles at varying levels, such as suspended objects, staircases, or terrain—obstacles that the 2D LiDAR cannot identify due to its limitation of planar scanning. Thanks to this 3D mapping capability, the 3D LiDAR robot can move around complex spaces such as multi-story warehouses, closely bunched industrial complexes, or outdoor environments with huge elevation variations. On the other hand, the 2D LiDAR is functional only in flat areas where objects rest on the ground and never form low-height holes or tunnels that are still higher than the height of the LiDAR. This does make it more appropriate for simpler uses such as indoor navigation or warehouse management on a two-dimensional plane.

To compare, the frame rate (FPS) capability of these sensors also supplements the strengths of 2D Lidar. Fig. 3 illustrates the frame-rate variation of the 2D and 3D LiDAR sensors across repeated trials in Experiment E-1. The average frame rates are 20.05 Hz for the 2D LiDAR and 19.80 Hz for the 3D LiDAR, indicating that the difference in frame rate under the imposed experimental constraints is minimal. Therefore, Figure 3 is not intended to demonstrate superiority of one sensor over the other in terms of update rate, but rather to confirm the temporal stability and repeatability of data acquisition across repeated experiments.

4.3 Experiment 2 (E-2)

In LiDAR sensor human detection as Fig. 3, 2D performance and accuracy compared to 3D LiDAR have broad differences. Although both possess their individual strengths, 3D LiDAR is found to be better in terms of minimizing errors in human detection since it owns the capability to acquire three-dimensional spatial information. Detection errors in 3D LiDAR are significantly lesser than in 2D LiDAR, essentially because the former can separate objects at varying heights and locations and reduce misclassification in complicated environments.

As can be seen in Table 4, all these 2D LiDAR errors occur in most of the cases, for example, partial occlusion of a person by an object, confusion with objects that have a human leg-like shape, and when a person and an object are close to each other. These errors mainly arise due to the few data points and scanning angles that restrict the dataset. Furthermore, the numbers in this table show overall disparities in 2D and 3D Lidar detection performance in varying conditions. When the object is near the sample as Fig. 3a, detection rate of 2D Lidar (52.6%) is far greater than the results of 3D Lidar (10.5%). This means that 2D Lidar performs better in easier cases. Under more congested conditions, both types of Lidar behave similarly, 3D Lidar with 15.6% and 2D Lidar with 14.2%. From these results, under congested conditions, the enhanced spatial perception benefit of 3D Lidar is not a major benefit compared to 2D Lidar.

But in complex scenes, particularly when people are close to objects or obstructed by objects, there is obvious superiority displayed by 3D Lidar. For instance, where people are close to objects as Fig. 3b, In complex scenarios involving partial occlusion, the 3D LiDAR achieves a human detection rate of 82.7%, significantly outperforming the 2D LiDAR (53.9%). Conversely, in simple, unobstructed cases, the 2D LiDAR exhibits higher detection responsiveness due to its higher frame rate. Where people are obstructed by objects as Fig. 3c, 3D Lidar is able to detect 22.3% whereas 2D Lidar can only detect 68.4%. This refers to the higher ability of 3D Lidar to scan more cluttered and dynamic areas, and hence making it extremely useful in actual applications where obstructions are of variable height or not accessible, showing the function it performs in more complex and random situations.

Table 4. List of percentage of detection error of human in each situation.

LiDAR	Situation			
	Object similar to the sample	Crowded	People close to object	People obscured by object
3D	10.5%	15.6%	82.7%	22.3%
2D	52.6%	14.2%	53.9%	68.4%

For 3D LiDAR, human detection accuracy is significantly higher, and such excellent performance in most scenarios except the case when a human and an object are very close to each other as Fig. 3d. Overlapped points in the point cloud under such conditions make the differentiation and accurate identification of humans difficult. Such a weakness highlights the importance of point cloud segmentation algorithms for enhancing detection performance for dense scenes.

Alternatively, Fig. 4 show a wide speed difference of detection between the systems. 2D LiDAR has double the frame rate of 3D LiDAR, i.e., at 18 FPS, at 36 FPS. The higher frame rate means that 2D LiDAR will respond quickly to changes in the environment, with rapid updates permissible for use in real-time applications. But speed comes at the cost of accuracy as 2D LiDAR does not capture vertical data to easily detect humans from other objects. Therefore, in complex scenes containing multiple overlapping objects or objects at various heights, 2D LiDAR is more prone to missed detection and false positives.

Results also highlight the difference in performance between 2D and 3D Lidar in autonomous robot navigation. That is, the robot covered a longer distance and took more time to reach the destination when 2D Lidar was used as compared to when it used 3D Lidar. This is because of the limited perception ability of 2D Lidar to scan only one plane in a horizontal direction. As a result, the robot could not detect some obstacles with a scanning distance longer than the scanning range. Precisely, in the experiment, the robot collided with a table. This is because 2D Lidar was mounted close to the floor, thus having the scanning plane too low to detect the table, which, though lower than shelves of robot, was above the detection range of the Lidar.

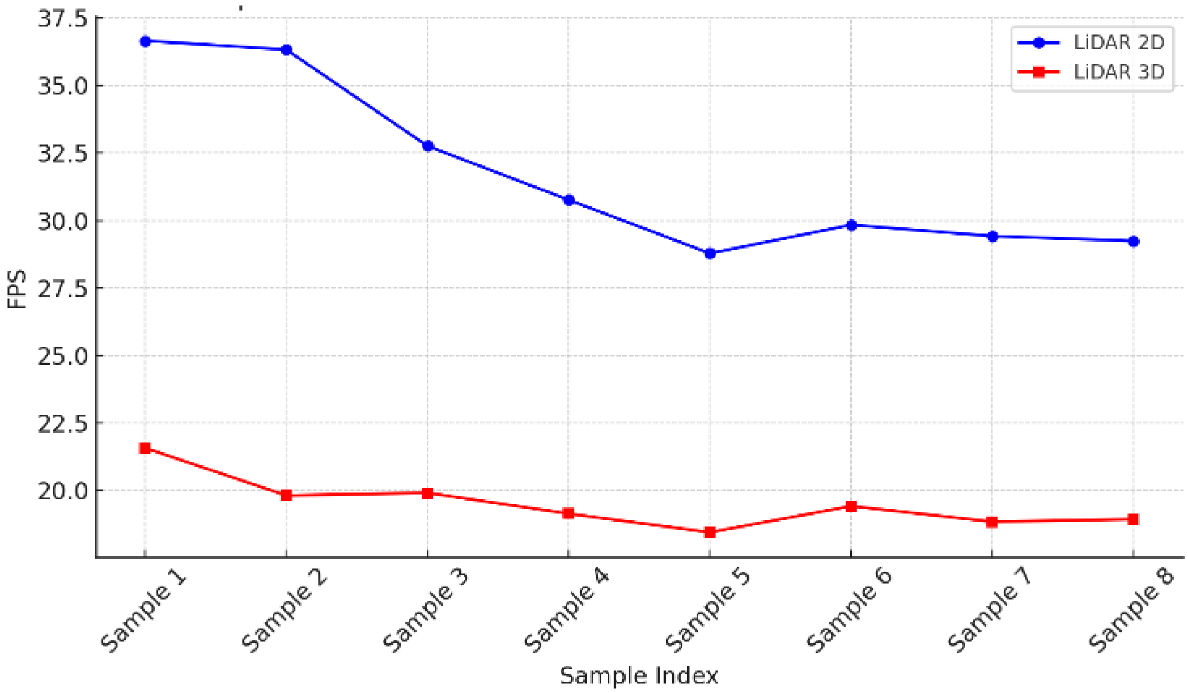
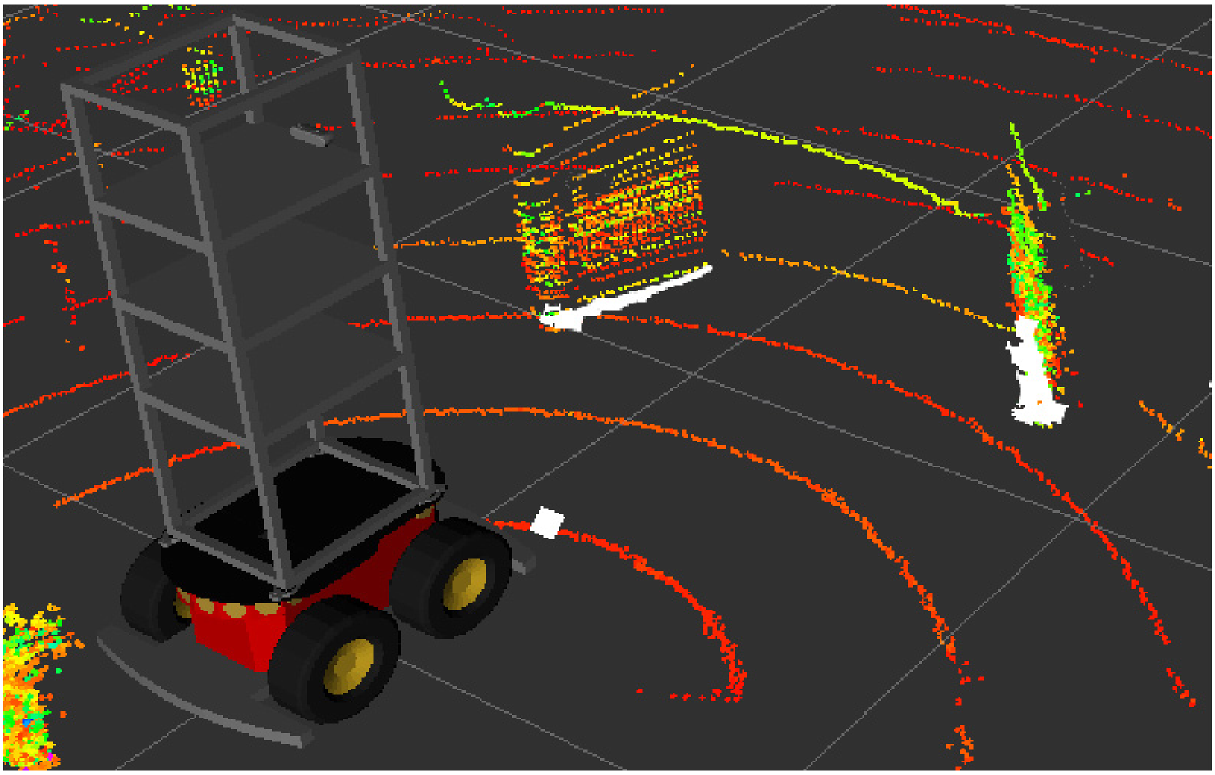
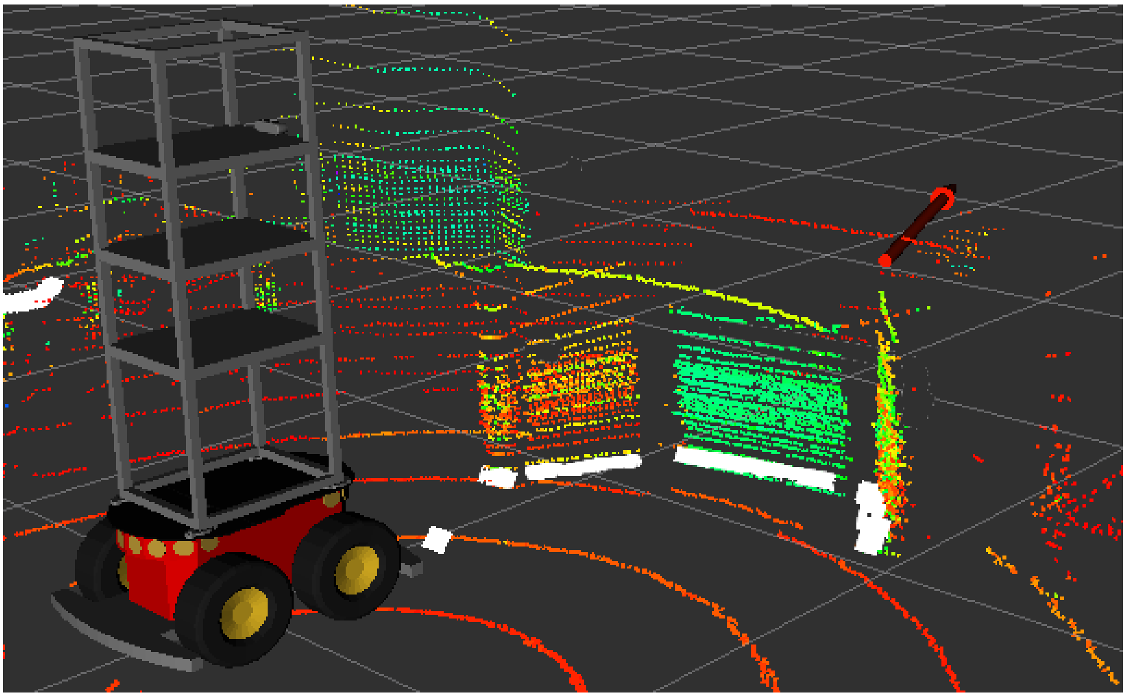


Figure 4. Experimental validation of comparative speed between 2D and 3D LiDAR sensor in case E-2.



(a)



(b)

Figure 5. Experimental validation of autonomous navigation in Experiment E-3: (a) three-dimensional LiDAR perception of the environment, (b) collision-free navigation path enabled by 3D LiDAR sensing.

4.4 Experiment 3 (E-3)

To enable a direct comparison between 2D and 3D LiDAR-based navigation, several path-related features were analyzed, including total path length, number of reorientations, collision occurrence, and path smooth–ness. Under identical start–goal configurations, the robot equipped with 3D LiDAR consistently gene–rated smoother trajectories with fewer abrupt heading chan–ges, whereas the 2D LiDAR-based navigation exhibited additional reorientations caused by incomplete obstacle perception. In the tested scenario, the 3D LiDAR-based navigation achieved a shorter effective path length and zero collision events, owing to its ability to perceive obstacle height and spatial continuity. In contrast, the 2D LiDAR-based navigation relied solely on planar sensing, resulting in incomplete obstacle representation and occasional path interruption. In Fig. 5, only the pla–nar navigation outcome was shown to maintain visual consistency with the 2D LiDAR representation. How–ever, this did not sufficiently reflect the three-dimen–sional perception advantage of the 3D LiDAR. To evaluate navigation reliability, each path-planning ex–periment was executed repeatedly under identical initial and goal configurations. Performance indicators such as travel distance, completion time, number of reorien–tations, and collision events were recorded for each run. A navigation outcome was considered reliable if consistent behavior and collision-free operation were observed across repeated trials.

Nevertheless, under conditions of lower complexity and obstructions as well that are stationary to the sur–face as well, the performance difference between 2D and 3D Lidar is less apparent. As indicated by Fig. 6b, for the table of this figure, even Lidar 2D and 3D also mark it as an impassable area to be shunned. The robot equipped with 3D LiDAR completed navigation tasks with fewer reorientations, shorter travel distances, and zero collision events, whereas the 2D LiDAR configu–ration experienced collision due to blind spots caused by planar scanning. The distance covered and travel time to the target location for both Lidar sensors is virtually similar, given that the robot will mostly be moving in the ground plane and has very little vertical components to deal with. For such cases, the additional vertical range of 3D Lidar is not as advantageous because the terrain itself is not as demanding of three-dimensional mapping. This is to say that while 3D Lidar works incredibly well in dense obstacle and terrain scenarios, the application of 3D scanning lowers in less dense, flatter terrain where 2D Lidar also works well.

5. DISCUSSIONS AND POTENTIAL PROSPECT

The experiment findings indicate the superiority of 3D Lidar over 2D Lidar in guiding an autonomous robot through sophisticated and changing environments. The experiment validates the manner in which 3D Lidar provides more accurate measurement but also provides more competent obstacle detection ability by leveraging the vertical dimensionality. This advantage enables 3D Lidar-enabled robots to plot more optimal routes and to recognize obstacles, shortening travel distances and travel times compared to 2D Lidar-enabled robots.

In addition to the use of 3D LiDAR sensors, an alternative approach to overcoming the planar sensing limitation of 2D LiDAR involves the deployment of multiple 2D LiDAR units arranged in parallel or perpendicular scanning planes. Such configurations can enrich spatial perception by capturing complementary height or angular information, thereby enabling partial three-dimensional reconstruction of the environment while retaining the advantages of low cost, low power consumption, and high frame rate associated with 2D

LiDAR sensors. Nevertheless, multi-2D-LiDAR confi–gurations also introduce additional challenges, including sensor calibration, synchronization, data fusion comp–lexity, and increased mechanical integration effort. Furthermore, the resulting spatial representation remains sparse compared to dense point clouds provided by a single 3D LiDAR sensor, particularly in environments with complex geometry or dynamic obstacles.

While 2D Lidar has a higher frame rate and hence offers quicker detection updates, this is balanced against its lower precision measurement and inability to mea–sure vertically differences. Nevertheless, 3D Lidar, tho–ugh at a lower frame rate, offers higher and more accu–rate data and is therefore better suited for navigation in highly complex obstacle geometry environments. Being at a lower frame rate is generally not a minus, as the additional information from sensing vertically is well worth a slight delay in updates, provided that this improves safety and path planning capability.

Though 3D Lidar is of immense value in spatial perception, 2D Lidar remains the optimal choice for an application that requires a low-profile solution and height-limited robots. In a majority of cases, robots inhabit a two-dimensional world and where objects' heights are not such a critical issue. Hence, the appli–cation of 2D Lidar conserves energy, saves capital, and simplifies data processing. Typical applications for 2D Lidar are delivery robots for indoor use, cleaning robots for indoor use, warehouse vehicles that are autonomous, and factory production lines, where the environment is relatively stationary and does not require vertical object detection. Such an environment usually exploits the low cost, fast speed, and simplicity of 2D Lidar, especially if the activity is constrained to a specific horizontal plane.

Where there is a need for high-end environmental perception, 3D Lidar is a must. Every outdoor autono–mous robot, search and rescue robot, unmanned aerial vehicle (UAV), and mobile robot in unstructured envi–ronments employ 3D Lidar for complete terrain and object detection. 3D Lidar's multi-layer scanning enab–les robots to detect obstacles of different heights, enab–les detailed map construction, and enables safe naviga–tion in difficult environments. Its ability to perceive and report three-dimensional environments best fits it to be used in scenarios where the robots must move over different terrains, i.e., woods, towns, or stretches of hills.

Furthermore, advances in even more sophisticated algorithms and machine learning policies that have the ability to process and analyze the vast amount of data generated by 3D Lidar have also further increased its application in real-world scenarios. As the technologies develop further, the application of 3D Lidar in autonomous systems will be even more indispensable in enabling even greater degrees of autonomy, safety, and efficiency. These advancements also enable 3D Lidar to be mounted on more compact, cost-efficiently engi–neered robots, rendering its advantages available to an even wider range of industries and applications.

Briefly, although both the 2D and 3D Lidar technologies find their applications within autonomous navigation, the greater vision and penetration capability of 3D Lidar through complex, dynamic environments place it as an indispensable tool for more advanced robotic implementations. For these reasons, the present study focuses on a direct comparison between a single 2D LiDAR and a single 3D LiDAR to clearly highlight the fundamental trade-offs between planar and volu–metric sensing. A systematic investigation of multi-2D-LiDAR configurations and their performance relative to 3D Li–DAR constitutes an important direction for future work.

6. CONCLUSION

This study presented a systematic experimental compa–rison between 2D and 3D LiDAR sensing for autono–mous navigation using a unified robotic platform and identical operating conditions. Unlike many existing studies that focus on algorithmic improvements or single-task evaluations, the present work provides a multi-task, system-level assessment supported by repe–ated real-world experiments. Quantitative results from Experiment E-1 demonstrate that the tested 3D LiDAR achieves lower positional error and reduced measu–rement variability compared to the tested 2D LiDAR, highlighting the benefit of multi-layer sensing for spa–tial accuracy. Experiment E-2 further shows that while both sensors perform comparably in simple detection scenarios, the human detection rate of the 3D LiDAR is significantly higher in occluded and cluttered environ–ments, directly linking three-dimensional perception to detection robustness. Experiment E-3 confirms that these sensing differences propagate to navigation per–formance, where 3D LiDAR perception enables smoot–her trajectories and collision-free operation in environ–ments containing height-varying obstacles.

Importantly, the results also reveal that the advantages of 3D LiDAR are not universal: the 2D LiDAR remains highly competitive in planar, structured environments, offering benefits in terms of simplicity, cost, and computational efficiency. These findings un–derscore that sensor selection should be driven by application context rather than generic assumptions about sensing accuracy. The novelty of this work lies in its controlled experimental framework and its quantitative, task-spanning comparison of 2D and 3D LiDAR sensing, rather than in the proposal of new algorithms. By isolating the impact of sensing dimen–sionality under fair conditions, this study provides prac–tical, evidence-based guidance that complements and extends existing literature on LiDAR-based autonomous navigation.

REFERENCES

[1] Wu, Y., Wang, Y., Zhang, S., Ogai, H. (2020). Deep 3D object detection networks using LiDAR data: A review. *IEEE Sensors Journal*, *21*(2), 1152-1171.

[2] Di Stefano, F., Chiappini, S., Gorreja, A., Balestra, M., & Pierdicca, R. (2021). Mobile 3D scan LiDAR: A literature review. *Geomatics, natural hazards and risk*, *12*(1), 2387-2429.

[3] Koide, K., Yokozuka, M., Oishi, S., & Banno, A. (2021). Globally consistent 3D LiDAR mapping with GPU-accelerated GICP matching cost factors. *IEEE Robotics and Automation Letters*, *6*(4), 8591-8598.

[4] Chen, X., Vizzo, I., Läbe, T., Behley, J., Stachniss, C. (2021, May). Range image-based LiDAR localization for autonomous vehicles. In *2021 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 5802-5808). IEEE.

[5] Li, Z., Wang, F., Wang, N. (2021). Lidar r-cnn: An efficient and universal 3d object detector. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 7546-7555).

[6] Nguyen, T. T., Truong, T. M. H., Nguyen, H. T. T., Ngo, N. M., Dinh, M., Nguyen, M. K. N., Ngo, H. Q. T. (2023, December). Investigation of Indoor Navigation Based on Proxemics for Mobile Robot Using the Robot Operating System (ROS). In *EAI International Conference on Renewable Energy and Sustainable Manufacturing* (pp. 547-561). Cham: Springer Nature Switzerland.

[7] Wang, G., et al. (2023). Development of a search and rescue robot system for the underground building environment. *Journal of field robotics*, *40*(3), 655-683.

[8] Nguyen, T. P., Nguyen, H., Thinh Ngo, H. Q. (2022). Planning the Emergency Collision Avoidance Strategy Based on Personal Zones for Safe Human□Machine Interaction in Smart Cyber□Physical System. *Complexity*, *2022*(1), 2992379.

[9] Yang, X., Lin, X., Yao, W., Ma, H., Zheng, J., Ma, B. (2022). A robust LiDAR SLAM method for underground coal mine robot with degenerated scene compensation. *Remote Sensing*, *15*(1), 186.

[10] Xu, X. et al. (2022). A review of multi-sensor fusion slam systems based on 3D LIDAR. *Remote Sensing*, *14*(12), 2835.

[11] Li, Y., Zhao, L., Chen, Y., Zhang, N., Fan, H., Zhang, Z. (2023). 3D LiDAR and multi-technology collaboration for preservation of built heritage in China: A review. *International Journal of Applied Earth Observation and Geoinformation*, *116*, 103156.

[12] Yin, C., Wang, B., Gan, V. J., Wang, M., Cheng, J. C. (2021). Automated semantic segmentation of industrial point clouds using ResPointNet++. *Automation in Construction*, *130*, 103874.

[13] Tripicchio, P., D'Avella, S., & Unetti, M. (2022). Efficient localization in warehouse logistics: a comparison of LMS approaches for 3D multilateration of passive UHF RFID tags. *The International Journal of Advanced Manufacturing Technology*, *120*(7), 4977-4988.

[14] Jiménez, V., Godoy, J., Artuñedo, A., & Villagra, J. (2021). Ground segmentation algorithm for sloped terrain and sparse LiDAR point cloud. *IEEE Access*, *9*, 132914-132927.

[15] Rey, R., Cobano, J. A., Corzetto, M., Merino, L., Alvito, P., Caballero, F. (2021). A novel robot co-worker system for paint factories without the need of existing robotic infrastructure. *Robotics and Computer-Integrated Manufacturing*, *70*, 102122.

[16] Nguyen, T. P., Nguyen, H., Ngo, H. Q. T. (2023). Visual application of navigation framework in cyber-physical system for mobile robot to prevent disease. *International Journal of Advanced Robotic Systems*, *20*(2), 17298806231162202.

[17] Abbasi, R., Bashir, A. K., Alyamani, H. J., Amin, F., Doh, J., Chen, J. (2022). Lidar point cloud compression, processing and learning for autonomous driving. *IEEE Transactions on Intelligent Transportation Systems*, *24*(1), 962-979.

[18] Liu, R., He, Y., Yuen, C., Lau, B. P. L., Ali, R., Fu, W., Cao, Z. (2021). Cost-effective mapping of mobile robot based on the fusion of UWB and short-range 2-D LiDAR. *IEEE/ASME Transactions on Mechatronics*, *27*(3), 1321-1331.

[19] Ranđelović, D. M., Vorotović, G. S., Bengin, A. Č., Petrović, P. N. (2021). Quadcopter Altitude Estimation Using Low-Cost Barometric, Infrared, Ultrasonic and LIDAR Sensors. *FME Transactions*, *49*(1).

[20] Yao, Q. Y., Chen, P. L., Chen, T. S. (2023). Human Activity Recognition Using 2-D LiDAR and Deep Learning Technology. *IEEE Sensors Letters*, *7*(10), 1-4.

[21] Ngo, H. Q. T., Le, V. N., Thien, V. D. N., Nguyen, T. P., Nguyen, H. (2020). Develop the socially human-aware navigation system using dynamic window approach and optimize cost function for autonomous medical robot. *Advances in Mechanical Engineering*, *12*(12), 1687814020979430.

[22] Nuha, H., Mohandes, M., Rehman, S., A-Shaikhi, A. (2022). Vertical Wind Speed Extrapolation Using Regularized Extreme Learning Machine. *FME Transactions*, *50*(3).

[23] Koide, K., Yokozuka, M., Oishi, S., Banno, A. (2021). Globally consistent 3D LiDAR mapping with GPU-accelerated GICP matching cost factors. *IEEE Robotics and Automation Letters*, *6*(4), 8591-8598.

[24] Yin, H., Lin, Z., Yeoh, J. K. (2023). Semantic localization on BIM-generated maps using a 3D LiDAR sensor. *Automation in Construction*, *146*, 104641.

[25] Shao, W., Bouazizi, M., Meng, X., Ohtsuki, T. (2024). People identification in private car using 3D LiDAR with generative image inpainting and YOLOv5. *IEEE Access*, *12*, 38258-38274.

[26] Wang, J., Xu, M., Zhao, G., Chen, Z. (2023). 3-D LiDAR localization based on novel nonlinear optimization method for autonomous ground robot. *IEEE Transactions on Industrial Electronics*, *71*(3), 2758-2768.

[27] Wang, Y., Li, X., Zhang, J., Li, S., Xu, Z., Zhou, X. (2021). Review of wheeled mobile robot collision avoidance under unknown environment. *Science Progress*, *104*(3), 00368504211037771.

[28] Liu, L.et al. (2023). Path planning techniques for mobile robots: Review and prospect. *Expert Systems with Applications*, *227*, 120254.

[29] Saleem, Z., Gustafsson, F., Furey, E., McAfee, M., Huq, S. (2025). A review of external sensors for human detection in a human robot collaborative environment. *Journal of Intelligent Manufacturing*, *36*(4), 2255-2279.

[30] Wang, X., Zhou, X., Xia, Z., Gu, X. (2021). A survey of welding robot intelligent path optimization. *Journal of Manufacturing Pro–cesses*, *63*, 14-23.

[31] Sousa, R. B., Sobreira, H. M., Moreira, A. P. (2023). A systematic literature review on long-term localization and mapping for mobile robots. *Journal of Field Robotics*, *40*(5), 1245-1322.

[32] Zhao, L., Deng, X., Li, R., Gui, X., Sun, J., Li, T., Zhang, B. (2023). Graph-based robust localization of object-level map for mobile robotic navigation. *IEEE Transactions on Industrial Electronics*, *71*(1), 697-707.

[33] Weerakoon, L., Herr, G. S., Blunt, J., Yu, M., Chopra, N. (2022). Cartographer_glass: 2D graph SLAM framework using LiDAR for glass environ–ments. *arXiv preprint arXiv:2212.08633*.

[34] Fasiolo, D. T., Scalera, L., Maset, E. (2023). Com–paring LiDAR and IMU-based SLAM approaches for 3D robotic mapping. *Robotica*, *41*(9), 2588-2604.

[35] Hroob, I., Polvara, R., Molina, S., Cielniak, G., Hanheide, M. (2021). Benchmark of visual and 3D lidar SLAM systems in simulation environment for vineyards. In *Towards Autonomous Robotic Sys–tems: 22nd Annual Conference, TAROS 2021, Lin–coln, UK, September 8–10, 2021, Proceedings 22* (pp. 168-177). Springer International Publishing.

[36] Li, S., He, R., Guan, H., Shen, Y., Ma, X., Liu, H. (2024). A 3D LiDAR-Inertial Tightly-Coupled SLAM for Mobile Robots on Indoor Environment. *IEEE Access*.

[37] Gómez, J., Aycard, O., Baber, J. (2023). Efficient detection and tracking of human using 3D LiDAR sensor. *Sensors*, *23*(10), 4720.

[38] Zeng, J., Mitra, D., Chen, M., Zhang, E., Chomal, S., Tharmarasa, R. (2024). Camera-Assisted Radar Detection Clustering for Extended Target Trac–king. *IEEE Transactions on Instrumentation and Measurement*.

[39] Kunjumon, R., Sangeetha Gopan, G. S. (2021). Sensor fusion of camera and LiDAR using Kalman filter. In *Intelligent Systems: Proceedings of SCIS 2021* (pp. 327-343). Springer Singapore.

[40] Bozorgi, H., Truong, X. T., Ngo, T. D. (2022). Re–liable, robust, accurate and real-time 2d lidar hu–man tracking in cluttered environment: A social dynamic filtering approach. *IEEE Robotics and Automation Letters*, *7*(4), 11689-11696.

[41] Wang, J. et al. (2023). 3-D LiDAR localization based on novel nonlinear opti–mization method for autonomous ground robot. *IEEE Transactions on Industrial Electronics*, *71*(3), 2758-2768.

[42] Ngo, H. Q. T., Le, V. N., Thien, V. D. N., Nguyen, T. P., Nguyen, H. (2020). Develop the socially hu–man-aware navigation system using dynamic window approach and optimize cost function for autonomous medical robot. *Advances in Mechani–cal Engineering*, *12*(12), 1687814020979430.

[43] Banisetty, S. B., Forer, S., Yliniemi, L., Nicolescu, M., Feil-Seifer, D. (2021). Socially aware naviga–tion: A non-linear multi-objective optimization ap–proach. *ACM Transactions on Interactive Intelli–gent Systems (TiiS)*, *11*(2), 1-26.

[44] Cai, K., Chen, W., Wang, C., Song, S., Meng, M. Q. H. (2022). Human-aware path planning with improved virtual doppler method in highly dynamic environments. *IEEE Transactions on Automation Science and Engineering*, *20*(2), 1304-1321.

КОМПАРАТИВНА СТУДИЈА 2Д И 3Д ЛИДАР ТЕХНОЛОГИЈА У ИНДУСТРИЈСКИМ ПРИМЕНАМА АУТОНОМНЕ НАВИГАЦИЈЕ

Х.К.Т. Нго, Т.Ф. Нгујен

У области роботике, четири задатка аутономних робота, као што су навигација, локализација, пра–ћење објеката и планирање кретања, играју кључну улогу у осигуравању аутономије и интелигенције система у сложеном и разноврсном окружењу. Све његово функционисање ослања се на радну способност ласерског скенера или ЛиДАР (детек–ција и одређивање удаљености светлости) сензора, који постаје обећавајући алат за ове задатке због прецизног мерења удаљености и широког видног поља. Циљ овог рада је да се процене и упореде радне перформансе између 2Д и 3Д ЛиДАР сензора у специфичним задацима. У различитим применама, 2Д ЛиДАР сензор скенира у једној равни, док 3Д користи ласере за снимање прецизних 3Д података објеката и окружења. Серија експеримената из стварног света спроведена је у лабораторијском окружењу, фокусирајући се на три главна задатка: детекцију и праћење објеката, могућности мапирања и планирање кретања. Захваљујући овим практич–ним тестовима, резултати истичу предности и сла–бости и 2Д и 3Д ЛиДАР сензора у таквим задацима. Експериментални резултати показују да, у поређењу са 2Д ЛиДАР-ом, 3Д ЛиДАР смањује грешку ме–рења до 59% на Y-оси, побољшава тачност људске детекције за 28,8% у условима оклузије и елими–нише навигационе колизије изазване планарним слепим тачкама, иако по цену ниже брзине кадрова.