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Low-Cost Static LiDAR–IMU Based Real-Time Object Detection for Indoor Environments

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ABSTRACT

Reliable detection and tracking of moving objects is essential for indoor robotics and smart environments. This paper presents a real-time 2D object detection and tracking system that uses a fixed planar LiDAR sensor combined with an inertial measurement unit (IMU), all implemented on a Raspberry Pi. The LiDAR is set up in a stationary position, which allows for continuous monitoring of a specific area and helps separate moving objects from static background structures based on motion. Unlike mobile sensing systems, this approach does not require estimating ego-motion. Instead, the IMU identifies and reduces measurement errors caused by mechanical vibrations and slight changes in orientation that can impact fixed LiDAR setups. Moving objects are detected by analysing consecutive range scans over time, grouped spatially using lightweight clustering, and tracked in the 2D plane with an efficient state model. While the system can cater to human-centric applications, it does not impose any object-specific shape or learning-based assumptions. This flexibility allows the framework to apply to a variety of moving objects. Experimental results in indoor settings show stable real-time performance even with limited computational resources. These findings confirm that low-cost LiDAR and IMU sensing is suitable for general object detection and tracking.

KEYWORDS

2D object detection, LiDAR sensing, IMU integration, Raspberry Pi, Real-time tracking.

1. Introduction

Reliable detection and tracking of moving objects is a core requirement for robotic systems operating in indoor environments. Applications such as service robotics, surveillance, autonomous monitoring, and human–robot interaction depend on the ability to observe motion reliably in real time. Early studies demonstrated that laser range scanners can detect and track moving objects by exploiting temporal differences between consecutive scans, even when the sensor itself is mounted on a moving platform [1], [2]. These results established the feasibility of motion-based perception using range-only data. While vision-based approaches dominate object detection research, they are often sensitive to illumination changes, occlusions, and privacy constraints, and typically require significant computational resources. Planar LiDAR sensors provide a practical alternative by delivering direct geometric measurements that are largely independent of lighting conditions. Prior work has shown that 2D LiDAR data can support object detection and tracking through scan differencing, clustering, and probabilistic estimation techniques [1], [3], [4], making LiDAR suitable for real-time processing on embedded systems

Much of the existing LiDAR-based tracking literature assumes a mobile sensing platform, where object detection is closely coupled with ego-motion estimation and localization. Probabilistic filtering methods, including Kalman filtering [5] and particle filtering with statistical data association [3], are commonly used to handle uncertainty and multi-target tracking. Although effective, these approaches rely on accurate motion estimation and often introduce considerable computational

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overhead, limiting their applicability on low-cost embedded hardware.

Static LiDAR installations represent a practically important but comparatively less explored configuration. When the sensor is fixed, stationary background structures can be identified through temporal consistency, simplifying the separation of moving objects from static elements. However, static setups remain susceptible to false motion caused by mechanical vibrations, mounting imperfections, or small orientation changes. Similar challenges related to distinguishing true object motion from observer-induced effects have been discussed in earlier tracking work [6]. IMUs are traditionally used for ego-motion estimation on mobile robots, but their potential role in static LiDAR-based perception has received limited attention. In fixed installations, IMU measurements can provide useful information about sensor stability, enabling suppression of vibration-induced artifacts without requiring full motion estimation. This observation motivates the integration of inertial sensing to improve robustness in static LiDAR systems. Previous studies have also explored human-aware perception and learning-based motion models for improved tracking and prediction [7] [8] [9]. While these methods achieve strong performance, they typically demand higher computational resources or longer observation periods, making them less suitable for lightweight embedded implementations.

In this context, this paper presents a real-time 2D object detection and tracking framework using a static LiDAR–IMU system implemented on a Raspberry Pi. The proposed approach relies on temporal analysis of LiDAR scans for motion detection, spatial clustering to form object hypotheses, and lightweight tracking to maintain object identities over time. IMU measurements are used to monitor sensor stability and reduce false detections caused by non-environmental disturbances. Unlike object-specific or learning-based methods [7], [10], the framework makes no assumptions about object category or shape, allowing it to generalize to a wide range of moving objects while remaining computationally efficient.

2. System Architecture

The proposed system is designed as a lightweight perception pipeline for real-time 2D object detection and tracking using a static LiDAR–IMU configuration on embedded hardware. The architecture emphasizes deterministic execution, low computational overhead, and robustness to sensor-induced disturbances, while avoiding dependencies on localization, mapping, or external computation.

2.1 Hardware and software architecture

The system consists of three primary hardware components: a planar 2D LiDAR sensor, an inertial measurement unit (IMU), and a Raspberry Pi serving as the central processing unit. All sensing and computation are performed locally on the Raspberry Pi, enabling standalone operation without reliance on external servers, GPUs, or network connectivity. The LiDAR and IMU are rigidly mounted on a fixed structure, ensuring a constant spatial relationship between the sensors throughout operation as shown in figure 1. From a software perspective, processing is organized as a sequential pipeline operating on streamed sensor data. The main stages include data acquisition, preprocessing, motion-based object detection, tracking, and optional visualization or logging. Each stage is designed to execute within a bounded time budget to guarantee consistent real-time performance on embedded hardware.

2.2 Static Sensing Model and Motion-Based Detection

Unlike mobile robot perception systems, the proposed architecture assumes that the LiDAR sensor remains stationary during operation. Consequently, ego-motion estimation, odometry integration, and simultaneous localization and mapping are not required. This assumption simplifies the processing pipeline and avoids cumulative errors associated with scan alignment. The static sensing model allows the system to exploit temporal consistency in LiDAR measurements. Range returns from stationary background structures remain stable across scans, while moving objects introduce temporal variations. This distinction forms the basis of the motion-based detection strategy employed in the system, enabling separation of dynamic objects from static elements without explicit environment modeling.

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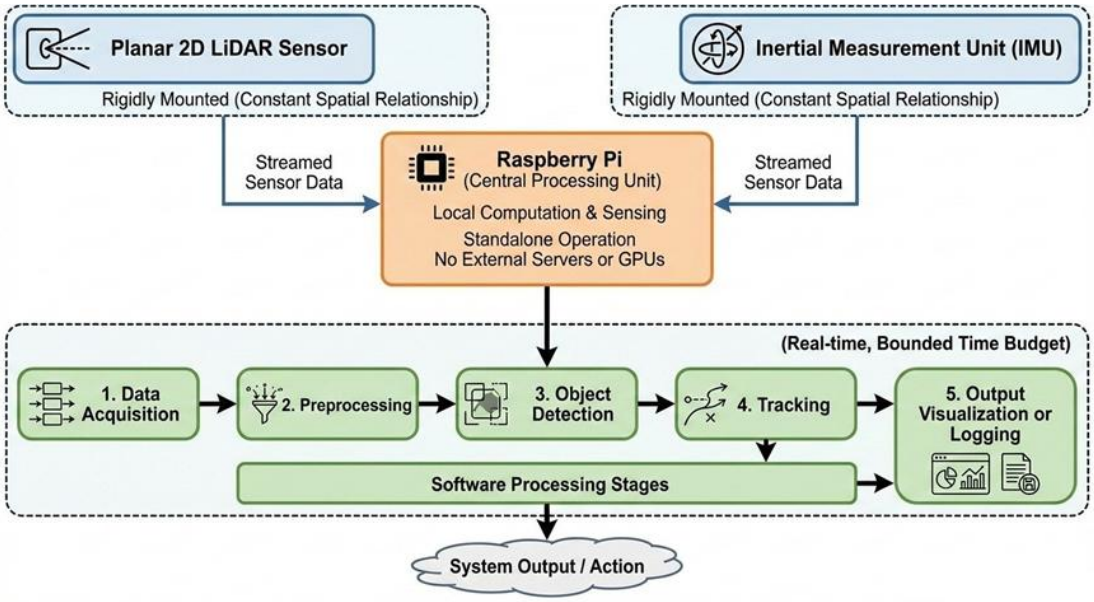

Figure 1. System Diagram illustrating the Hardware integration of LiDAR and IMU sensors with the Sequential Real-Time software processing in Raspberry PI.

2.3 Role of the IMU and Embedded Design Considerations

The IMU is integrated into the system not for motion estimation, but for sensor stability monitoring. Even in static installations, LiDAR measurements can be affected by mechanical vibrations, minor tilts, or environmental disturbances. IMU data is monitored to detect abnormal inertial events, such as sudden linear or angular accelerations, that may indicate sensor instability. When such events are detected, the corresponding LiDAR scans can be flagged or down-weighted during motion analysis, reducing false detections with minimal computational cost. LiDAR and IMU data streams are synchronized and processed in real time. Raw LiDAR scans are filtered, converted into a Cartesian representation, and passed to the detection and tracking stages, while IMU-derived stability information influences how motion evidence is interpreted. The overall architecture is intentionally designed for embedded deployment. Memory usage, floating-point operations, and algorithmic complexity are kept low, and no learning-based models or large-scale optimization routines are employed. These design choices allow the system to sustain stable real-time operation on a Raspberry Pi while maintaining reliable object detection and tracking performance in static indoor environments.

3. Sensor setup and Data Acquisition

This section describes the physical sensor configuration and the data acquisition process used in the proposed system. The setup is designed for continuous indoor monitoring while operating within the computational limitations of an embedded platform.

3.1 LiDAR and IMU Configuration

A planar 2D LiDAR sensor, shown in figure 2, is mounted at a fixed location overlooking the monitored area and operates in a horizontal scanning plane. The mounting height and orientation are chosen such that the scan plane intersects typical object cross-sections, enabling reliable detection of moving objects without the need for multiple sensing layers. The LiDAR provides range measurements in polar coordinates at a constant scan rate, which are streamed to the Raspberry Pi through a serial or USB interface.

An inertial measurement unit (IMU) is rigidly attached to the LiDAR mounting structure to ensure that inertial measurements accurately reflect the physical state of the sensor assembly as shown in figure 3. The IMU provides linear acceleration and angular velocity measurements at a higher sampling rate than the LiDAR and is interfaced with the Raspberry Pi using a standard digital communication protocol. Timestamping is used to align inertial measurements with corresponding LiDAR scans.

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Figure 2. 2D LiDAR used for detecting the object during the experiment.

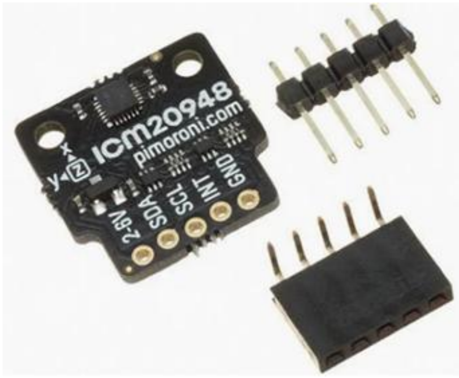

Figure 3. Inertial Measuring Unit used for Mechanical Correction of Error during the experiment.

Table 1. Sample data storage format of .csv file by lidar sensor

Angle (Radian)	Range (mm)
0.75	1340
1.50	1322
2.25	1351
-0.50	1005
-1.56	1225
-2.93	1237

3.2 Data Acquisition and Preprocessing

Sensor data acquisition is implemented as a continuous streaming process on the Raspberry Pi. LiDAR scans are read sequentially and validated to remove invalid or out-of-range measurements. Each validated scan is stored in a comma separated values (.csv) format, where individual laser beam measurements are recorded as shown in Table 1. The polar range measurements are subsequently converted into Cartesian coordinates within a fixed reference frame, which simplifies later spatial processing and clustering operations. IMU data is acquired in parallel with LiDAR measurements and filtered to suppress high-frequency noise while preserving transient events associated with mechanical disturbances. Threshold-based checks are applied to identify abnormal inertial activity, which is later used to suppress spurious motion artifacts in LiDAR data during object detection and tracking.

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3.3 Temporal Management and Practical Considerations

To support motion-based detection, the system maintains a short temporal history of recent LiDAR scans. This enables direct comparison of consecutive measurements and facilitates identification of dynamic points based on temporal variation. The size of the temporal window is selected to balance motion sensitivity, memory usage, and processing latency. All data processing is performed online, and no long-term storage is required during normal operation. The rigid mounting of the LiDAR–IMU assembly, combined with inertial monitoring, improves robustness to common indoor disturbances such as minor vibrations or structural noise. This configuration allows the system to operate reliably as a standalone object detection and tracking module in static indoor environments.

4. Methodology and Experimental setup

This section describes the object detection and tracking methodology used in the proposed system together with the experimental conditions under which it was evaluated. The overall design targets a static LiDAR installation and favors motion-based reasoning, simple geometric operations, and predictable execution suitable for embedded platforms.

4.1 Motion-Based Detection and Tracking Pipeline

Since the LiDAR sensor remains stationary during operation, range measurements corresponding to static structures are expected to remain stable over time. This property is used to construct a background model by observing range consistency at each angular index across a short temporal window. Measurements that remain within a predefined tolerance band are classified as background and excluded from further processing. This allows static clutter to be suppressed without requiring explicit scene mapping or prior knowledge of the environment. After background removal, remaining points are treated as candidates for dynamic objects. Motion is detected using temporal differencing between consecutive LiDAR scans. Points whose range variation exceeds a noise-based threshold are classified as dynamic. This approach avoids scan matching or iterative optimization, keeping computational cost low. To reduce noise, isolated points that do not persist across multiple frames are discarded. Dynamic points are then grouped into object-level hypotheses using Euclidean distance-based clustering. Clusters below a minimum size are treated as noise, while remaining clusters are tracked over time using a lightweight constant-velocity model defined in the 2D plane. Data association is based on spatial proximity, allowing multiple objects to be tracked simultaneously with bounded execution time.

4.2 IMU-Assisted Stability Handling

Although the LiDAR sensor is static, mechanical vibrations and minor mounting disturbances can introduce apparent motion in range measurements. To address this, IMU data is continuously monitored for abnormal inertial activity, such as sudden linear or angular acceleration spikes. These events indicate periods during which LiDAR measurements may be unreliable. LiDAR scans acquired during such intervals are down weighted or ignored during motion analysis. This simple gating mechanism reduces spurious detections caused by sensor movement rather than environmental motion. Importantly, the approach does not require full sensor fusion or motion compensation, preserving the simplicity and efficiency of the overall pipeline.

4.3 Experimental Setup and Runtime Characteristics

Experiments were conducted in indoor environments such as offices and laboratories containing both static structures and moving objects. The LiDAR–IMU assembly was mounted at a fixed location, and all sensor data processing was performed in real time on a Raspberry Pi. Evaluated scenarios included single-object motion, multiple objects with intersecting trajectories, and controlled vibration events introduced near the sensor mount. System performance was assessed based on detection consistency, track stability, and processing latency. Across all experimental runs, the system operated continuously in real time without frame drops. Key runtime characteristics, including scan rate, CPU utilization, memory usage, and system startup behavior, are summarized in Table 2, confirming that the complete pipeline remains within the computational limits of the embedded platform.

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5. Result and Analysis

5.1 Object Detection and Tracking Performance

Across all experimental scenarios, the system consistently detected moving objects within the LiDAR field of view after background suppression. Stationary structures were effectively filtered out, resulting in minimal static clutter. Objects entering the monitored area were typically detected within a few consecutive scans, indicating that the temporal differencing approach provided sufficient sensitivity to motion. False detections were uncommon under normal conditions and mainly occurred during sudden environmental disturbances. Enabling IMU-assisted stability handling significantly reduced such spurious detections, confirming the usefulness of inertial monitoring for static LiDAR installations. The tracking module maintained stable trajectories over time, including scenarios with multiple moving objects. Tracks remained consistent through moderate occlusions and short measurement dropouts, provided that objects reappeared within a limited temporal window. In situations involving intersecting paths or prolonged close proximity, occasional identity switches were observed, highlighting the limitations of lightweight spatial data association under dense conditions. Representative trajectory plots are shown in Figure 4 and Figure 5. Quantitative distance measurements obtained from the LiDAR were compared against known reference distances, as summarized in Table III, showing low average error across tested ranges.

Table 2. System parameter for performance analysis.

Metric	Value
Average Scan Rate	7.5 Hz
First Scan Start Time	5 seconds post boot
CPU Load	41 - 47% (1 core)
RAM Usage	260 MB

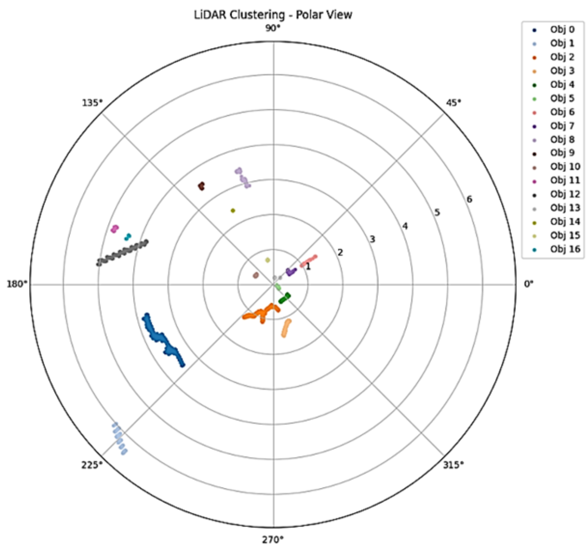

Figure 4. Clustered LiDAR Data points into a Polar plot view

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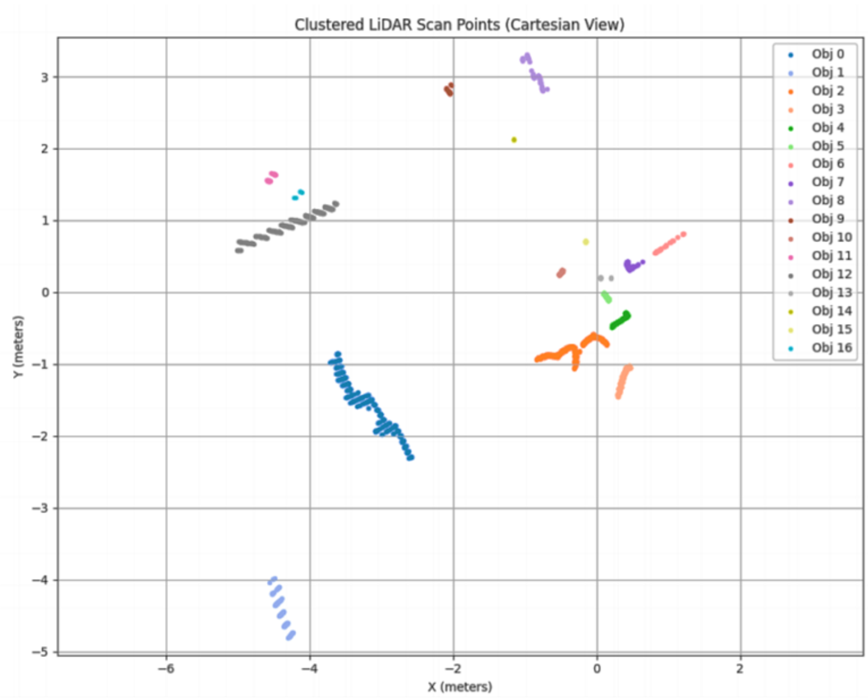

Figure 5. Clustered LiDAR Data points into a Cartesian plot view

Table 3. Comparison of object's distance measured for lidar sensor and actual data (data is in cm.)

Known distance	Measured average	Error	Error (%)
50	50.8	+0.8	1.6
100	99.4	-0.6	0.6
150	200.9	+0.9	0.45
200	299.2	-0.8	0.27

5.2 Effect of IMU-Assisted Stability Handling

Controlled vibration experiments demonstrated the impact of IMU integration on detection robustness. Without inertial gating, mechanical disturbances produced widespread apparent motion in the LiDAR scans, leading to false detections. When IMU-based gating was applied, affected scans were suppressed, preventing false object hypotheses from propagating into the tracking stage. These results indicate that IMU data provides valuable contextual information in static configurations, improving reliability without requiring complex sensor fusion or motion compensation.

5.3 Computational Performance and Limitations

The complete detection and tracking pipeline operated in real time on the Raspberry Pi throughout all experiments. Per-scan processing latency remained well below the LiDAR scan period, and memory usage remained stable over extended operation. The absence of learning-based models and iterative optimization contributed significantly to computational efficiency. Some limitations were observed in highly crowded scenes, where tracking accuracy degraded due to ambiguous data association. Very slow-moving objects occasionally blended into the background model, resulting in delayed detection. These behaviors reflect deliberate design trade-offs favoring simplicity and real-time performance over more complex modeling. Overall, the results demonstrate that reliable 2D object detection and tracking can be achieved using a static LiDAR–IMU configuration on low-cost embedded hardware, with a practical balance between robustness and computational efficiency.

6. Conclusion and Future Work

The experimental results indicate that a static 2D LiDAR system, when combined with lightweight processing and IMU based stability monitoring, can support reliable real-time object detection and tracking on embedded hardware such as the Raspberry Pi. The design prioritizes robustness and predictable execution while operating under tight computational constraints. A key design decision is the use of motion-based detection instead of object-specific models. This keeps the framework general and reduces computational load, allowing it to operate efficiently on low-cost hardware. The trade-off is limited semantic information, as the system does not attempt object classification or higher-level behavior analysis. The static LiDAR configuration simplifies the perception pipeline by eliminating ego-motion estimation, scan matching, and mapping. This contributes to stable real-time performance but introduces sensitivity to mechanical disturbances. IMU assisted stability monitoring mitigates this issue by suppressing vibration-induced artifacts without increasing algorithmic complexity.

Tracking performance is reliable at moderate object densities but degrades in crowded scenes due to simplified data association. More advanced tracking methods could address this limitation but would increase computational cost. Very slow-moving objects may also be absorbed into the background model, reflecting an inherent balance between noise suppression and motion sensitivity. Overall, the observed limitations result from deliberate design choices aimed at maintaining real-time performance on embedded platforms. Within these constraints, the proposed system provides a practical solution for static LiDAR-based object detection and tracking in indoor environments.

This paper presented a real-time 2D object detection and tracking framework based on a static LiDAR–IMU configuration implemented on a Raspberry Pi. By exploiting temporal consistency in LiDAR range measurements, the system separates moving objects from static background structures without relying on ego-motion estimation, scan matching, or learning based models. IMU-based stability monitoring addresses measurement artifacts caused by vibrations and minor disturbances, which are common in static LiDAR installations. Experimental evaluation in indoor environments showed that the system can reliably detect and track multiple moving objects in real time under embedded computational constraints. The results demonstrate that effective geometric perception can be achieved on low-cost hardware when the sensing setup and processing pipeline are carefully designed. The motion-based formulation allows the approach to generalize beyond human tracking to a broad range of dynamic objects, supporting applications such as indoor monitoring and service robotics.

The observed limitations stem from deliberate design trade-offs. Tracking accuracy decreases in highly crowded scenes due to simplified data association, and very slow-moving objects may be absorbed into the background model. These effects reflect a focus on computational efficiency and deterministic execution rather than semantic interpretation or long-term prediction. Future work will focus on extending the framework while preserving its embedded-friendly nature. Planned improvements include adaptive background modeling for slow motion, improved data association in dense environments, and selective use of lightweight learning-based components. Additional extensions may consider multi-LiDAR setups or integration with higher-level decision modules. Overall, the proposed system provides a practical foundation for low-cost, real-time object detection and tracking using static LiDAR sensing.

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