# ROS2 LIDAR AUTO-CALIBRATION AND SLAM

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# DECLARATION

I declare that the project work contained in this report is original and was done by me, under the guidance of my project guide.

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Date: Signature

# CERTIFICATE

This is to certify that ADEGOKE JAMIU OLALEKAN, bearing BU22EECE0100484, has satisfactorily completed the Mini Project entitled in partial fulfilment of the requirements as prescribed by the University for the VIIth semester, Bachelor of Technology in "Electrical, Electronics and Communication Engineering" and submitted this report during the academic year 2025-2026.

[Signature of the Guide] [Signature of HOD]

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# Chapter 1: Introduction

## 1.1 Overview of the problem statement

In Virya Autonomous Technologies' fleet of AMRs, accurate sensor calibration is foundational to robust localization and perception. Among these, the extrinsic calibration between the 3D LIDAR and the robot base frame is especially critical, as even small misalignments can propagate errors in sensor fusion and navigation pipelines.

Given operational realities, LIDAR units may be frequently removed for servicing, rotation across platforms, or reuse in manufacturing and subsequently remounted. This introduces the need for a systematic, repeatable calibration process that ensures consistent pose estimation despite such changes.

**The challenge is two-fold:**

- Guarantee intra-robot repeatability (same robot, different mount events)
- Ensure inter-robot consistency (same model, different units)

This project aims to develop a marker-based LIDAR calibration methodology that is both field executable and suitable for production environments, optionally incorporating IMU data for refinement

## 1.2 Objectives and goals

❖ Calibration Framework Design

Develop a LIDAR calibration workflow that uses visual markers (eg: AprilTags, ArUco, checkerboards to determine the extrinsic transform between the LIDAR and robot frame.

❖ Repeatability Validation

Quantitatively assess how well the procedure maintains calibration accuracy across:

- Multiple remounting cycles on the same robot
- Multiple instances of the same robot model

❖ Toolchain & Workflow Integration

Ensuring the calibration system is easy to execute by production or field technicians and integrates cleanly with Virya's existing ROS 2-based sensor fusion stack.

# Chapter 2: Literature Review

## 1. CaLiV: LiDAR-to-Vehicle Calibration of Arbitrary Sensor Setups

Tahiraj et al. addressed the critical task of extrinsic calibration in sensor fusion systems for autonomous vehicles, specifically the calibration between LiDAR sensors and the vehicle base frame and among LiDAR sensors themselves. They recognise the limitations of existing methods, particularly in scenarios involving multi-LiDAR setups with non-overlapping fields of view common in large vehicles such as buses or trains, where current calibration frameworks either require overlapping sensor fields, rely heavily on external sensing devices, or are sensitive to environmental richness.

Their primary contribution is the introduction of CaLiV. a novel target-based calibration framework that does not require overlapping fields of view or external devices and works for arbitrary multi-LiDAR vehicle setups. The method combines motion-induced field-of-view overlap, pose estimation via an Unscented Kalman Filter, and a Gaussian mixture model-based registration algorithm (GMMCalib) to initially align point clouds in a shared calibration frame. It then formulates and solves a minimisation problem to recover both translational and rotational calibration parameters, achieving accurate sensor-to-sensor (S2S) and sensor-to-vehicle (S2V) calibration.

Experimental validation was carried out in both simulation (using CARLA) and real-world conditions. Their results demonstrated that CaLiV outperforms the state-of-the-art, targetless, and target-based calibration frameworks in terms of accuracy, especially in the challenging scenario of non-overlapping and oppositely oriented LiDAR setups. The approach was shown to deliver low rotation and translation errors, with quantitative comparisons to other open-source algorithms included.

They also discussed practical considerations such as trajectory design for observability, real-world implementation filters, and offline (non-real-time) computation constraints. Notably, the method prioritises rotational over translational accuracy due to the impact of angular error on safety-critical perception and planning in autonomous vehicles.

## 2. CalTag: Robust calibration of mmWave Radar and LiDAR using backscatter tags

Xu *et al.* (2024) addressed a critical challenge in robotic perception and autonomous vehicles: accurate and reliable extrinsic calibration between mmWave radar and LiDAR sensors in cluttered, real-world environments. Traditional calibration methods commonly rely on corner reflectors as radar fiducials, but these face limitations in environments with significant clutter, leading to poor calibration accuracy and increased risk of false detection.

Their primary contribution is the introduction of CalTag, a novel fiducial system for mmWave radar based on backscatter technology. Unlike conventional corner reflectors, CalTag employs artificial frequency shifts to generate highly distinctive radar signatures, making it robust to environmental clutter and interference. The calibration procedure involves placing CalTag at multiple locations, capturing corresponding point clouds with both radar and LiDAR, and estimating the extrinsic transformation using clustering and the Kabsch algorithm for optimal matching.

Their experimental results clearly demonstrate CalTag's superiority over corner reflectors in both qualitative and quantitative metrics. Across environments ranging from low to heavy clutter, CalTag maintains low root-mean-square error (RMSE) in calibration, while the corner reflector's performance degrades severely as clutter increases. Furthermore, CalTag's effectiveness is validated in scenarios involving significant rotation between radar and LiDAR sensors, ensuring reliable calibration in non-ideal, real-world deployments.

They also provided a detailed analysis of the trade-offs in radar signal processing parameters and highlighted the importance of precision in fiducial detection. Notably, CalTag eliminates the need for manual coarse calibration steps required by corner reflector-based methods, thereby reducing error and setup complexity. They suggested future directions in enabling real-time or fully autonomous calibration and extending the approach to 3D, six-degree-of-freedom cases using advanced radar systems.

## 3. Static Extrinsic Calibration of a Vehicle-Mounted LiDAR Using Spherical Targets

The thesis by Philip Sandstrom tackles the problem of extrinsic calibration of a static vehicle-mounted LiDAR sensor in a static environment, which is crucial for accurate mapping and autonomous vehicle perception systems. Unlike many dynamic calibration approaches, this work focuses on static setups typical of factory or controlled indoor environments.

Their main contribution lies in developing a calibration method using three known spherical targets whose centres act as reference points to estimate the LiDAR's position relative to the vehicle. A simulation environment using the CARLA autonomous driving simulator is established to generate 3D LiDAR point clouds reflective of real measurements in such scenarios. The calibration algorithm includes preprocessing of point clouds, clustering to isolate individual spheres, fitting spheres to the clusters to estimate centers, and applying the Iterative Closest Point (ICP) algorithm for aligning detected centers with the known reference points.

Extensive experimentation involving 1,000 randomised LiDAR poses indicates high accuracy, with root mean square errors (RMSE) on the order of sub-millimetres for point alignments and low translation and rotation parameter errors. The study also investigates the effects of noise, target size, point cloud density, and laser channel drop-offs, providing insights into the robustness and sensitivity of the method under non-ideal conditions.

Their work acknowledges limitations, including assumptions about perfect target manufacturing and detection, the impact of noise and simulation environment fidelity, and the challenge of translating simulation results into real-world calibration tools. Nevertheless, the method offers a fast and accurate candidate approach for extrinsic calibration in static environments, with the developed simulation tool providing a reusable platform for further research or industrial adaptation.

## 4. Extrinsic Calibration between a Camera and a 2D LiDAR using a Photogrammetric Control Field

The paperwork by Huang *et al. (2019)* tackles the challenge of extrinsic calibration between a camera and a 2D laser rangefinder (LRF), a critical step in enabling sensor fusion for robotics, mapping, and autonomous navigation applications. It focuses on overcoming limitations of previous approaches that require multiple shots, suffer from degenerate cases, or produce ambiguous solutions.

The key contribution is proposing a robust, accurate calibration scheme using a photogrammetric control field, uniquely enabling the entire calibration process with just a single observation. The control field consists of numerous precisely surveyed control points distributed in a 3D space, serving as a common reference for both the camera and LRF calibration. This approach decouples the calibration into two separate parts: calibrating the LRF to the control field using intersections of laser scanning planes with the edges of a room corner (modelled as a trirectangular trihedron), and calibrating the camera to the control field using control point correspondences and direct linear transformation techniques.

The methodology leverages the geometry of the room corner to produce a simplified, unique solution to the perspective-three-point (P3P) problem for the LRF calibration, avoiding classical P3P ambiguities and degeneracies. For the camera, distortion rectification and redundant control point observations enable precise estimation of intrinsic and extrinsic parameters. The extrinsic parameters between the camera and LRF are then obtained via coordinate transformations through the control field reference frame.

Extensive simulations and real-world experiments verify the scheme's performance. The calibration proved robust against varying levels of image noise, range noise, and outliers, maintaining low rotation and translation errors. Comparisons with state-of-the-art methods demonstrated superior accuracy and precision, with qualitative validations through the projection of LRF points onto camera images in both indoor and outdoor scenes. The scheme also requires only a single shot of the control field, significantly simplifying practical data collection

## 5. Robot self-calibration using actuated 3D sensors

Peters and Knoll present a novel framework for fully autonomous calibration of robot manipulators using only an arbitrary eye-in-hand 3D sensor, without reliance on external calibration objects, markers, or reference devices. This research significantly advances robot calibration methodologies by framing the problem as an offline SLAM-like optimization, leveraging multiple 3D scans of an arbitrary static scene acquired during robot motion.

The primary contribution involves extending the Iterative Closest Point (ICP) algorithm into a bundle adjustment framework that optimizes complex kinematic parameters of the entire robotic arm and the hand-to-eye transformation using only spatial point cloud data. This approach calibrates the complete kinematic chain, including revolute and prismatic joints, and supports different types of 3D sensors such as single-beam LiDARs, triangulation-based line scanners, and depth cameras.

The methodology incorporates the Modified Complete and Parametrically Continuous (MCPC) model for kinematic chain representation, offering comprehensive and continuous pose parameters. The process begins by recording multiple scans during robot actuation in a static environment, projecting all sensor data into a fixed coordinate frame using the robot's kinematic model. The ICP-based optimisation iteratively minimizes point-to-plane distances across overlapping scans, accounting for normal consistency and filtering out noise and outliers.

Experimental validation is conducted on a KUKA LBR iiwa R840 robot with a diverse suite of sensors ranging from consumer-grade depth cameras to highly precise industrial-grade scanners. Results exhibit calibration precision comparable to that achieved by a dedicated external optical tracking system, even outperforming it occasionally in some scenarios.

# Chapter 3: Strategic Analysis and Problem Definition

## 3.1 SWOT Analysis

# 3.2 Project Plan - GANTT Chart

| | Task | Assigned To | Start | End | Dur | 2025 Jul | Aug | Sep | Oct | Nov | Dec | 2026 Jan | Feb | Mar | Apr |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Design Project | | 26/7/25 | 21/4/26 | 192 | | | | | | | | | | |
| 1 | Requirement/Resource Gathering | | 26/7/25 | 22/11/25 | 84.5 | | | | | | | | | | |
| 2 | Research Survey and Project review | | 26/7/25 | 12/8/25 | 12 | | | | | | | | | | |
| 3 | Cloud point preprocessing | | 5/9/25 | 25/9/25 | 15 | | | | | | | | | | |
| 4 | Cloud point registration | | 12/9/25 | 22/10/25 | 29 | | | | | | | | | | |
| 5 | First model Test and Evaluation | | 22/10/25 | 22/11/25 | 23 | | | | | | | | | | |
| 6 | Second Model Test | | 15/1/26 | 15/1/26 | 1 | | | | | | | | | | |
| 7 | Project Continuation-Completion | | 20/2/26 | 21/4/26 | 43 | | | | | | | | | | |

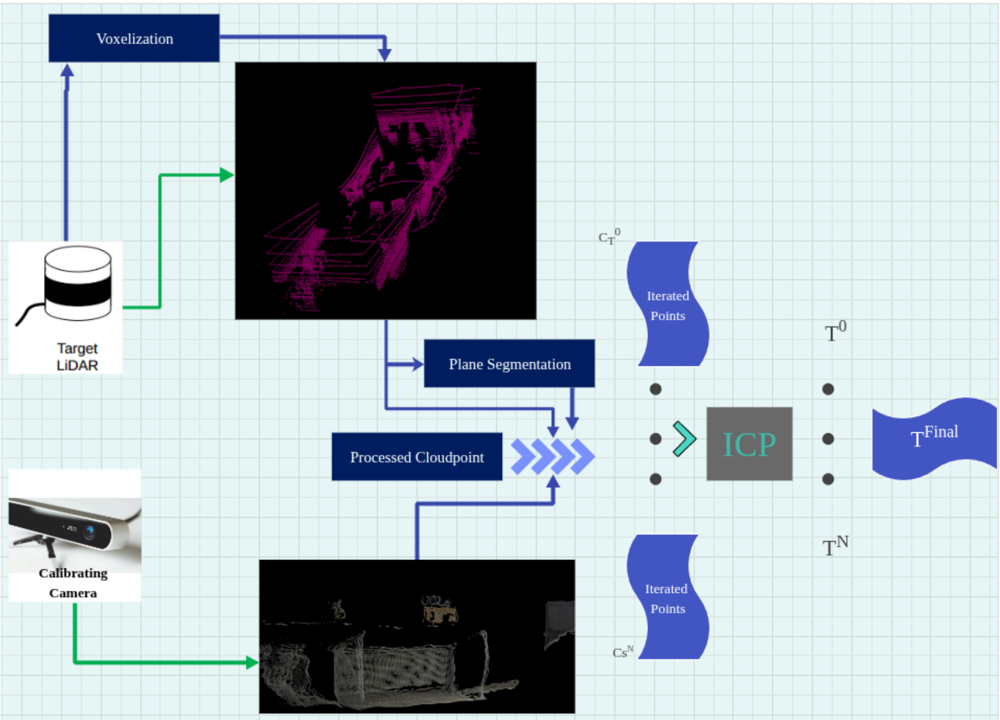
# 3.3 Problem statement

In Virya Autonomous Technologies' fleet of Autonomous Mobile Robots (AMRs), accurate and repeatable sensor calibration is critical to ensuring reliable localization and perception. Among the various sensors, the 3D LIDAR plays a pivotal role in mapping and navigation, making its extrinsic calibration with respect to the robot's base frame a fundamental requirement. However, in practical operations, LIDAR units are often removed and remounted for maintenance, rotation across different robots, or reuse in production environments. These frequent mount/dismount cycles introduce small but significant alignment variations that can lead to compounded localization and navigation errors. Consequently, there is a pressing need for a systematic, repeatable calibration methodology that can guarantee both intra-robot repeatability (consistency across multiple mountings on the same robot) and inter-robot consistency (uniform calibration across identical robot models). This project seeks to develop a marker-based calibration framework, optionally refined using IMU data, that can be easily executed by field technicians, integrated seamlessly into Virya's ROS 2-based sensor fusion stack, and validated for accuracy, repeatability, and production readiness.

# Chapter 4: Methodology

## 4.1 Description of the approach

### Architectural Diagram




## 4.1a **System Architecture Analysis: LIDAR–Camera Calibration Framework**

The above diagram represents the **camera-LiDAR to LiDAR-Vehicle extrinsic calibration pipeline** that leverages **3D point cloud registration** using the **Iterative Closest Point (ICP)** algorithm.
This proposed architecture demonstrates how raw data from both the **LIDAR** and the **camera** are preprocessed, segmented, and aligned to compute the final **transformation matrix ($T^{final}$)**, which defines the spatial relationship between the two sensors.

**1. Data Acquisition**

**(a) Target LIDAR**

- The **LIDAR sensor** captures a detailed **3D point cloud** of the calibration scene or environment, which will be placed on a frame with proper transformation for stable data collection.

- This point cloud contains geometric information (depth, distance, surface features).
- Before processing, it undergoes a **voxelization step**, which downsamples the dense cloud into smaller uniform cubes (voxels) to reduce computational load while preserving structural details.

**(b) Calibrating Camera**

- The **camera** simultaneously captures a corresponding **point cloud** or **depth image** of the same scene.
- The camera's perspective provides complementary information, often color or intensity-based, to assist in identifying corresponding features.

**3. Preprocessing and Segmentation**

- Both LIDAR and camera data streams are **preprocessed and unified** into a common representation called the **Processed Cloudpoint**.

- This step includes:
  - **Plane segmentation:** isolating dominant planar surfaces (such as floors, walls, or calibration boards) using algorithms like RANSAC.
  - **Noise filtering:** removing outliers and irrelevant background points.
  - **Coordinate normalization:** aligning both datasets in a consistent reference frame for subsequent processing.

**4. Feature Extraction and Correspondence**

- After segmentation, the system extracts **interest points** (denoted as $C^{I}_{T}$ to $C^{N}_{T}$ for camera and $L^{I}_{T}$ to $L^{N}_{T}$ for LIDAR) from both processed point clouds.
- These interest points represent geometric correspondences or key features visible to both sensors.
- The matching of these features is critical to initializing the **ICP** alignment step.

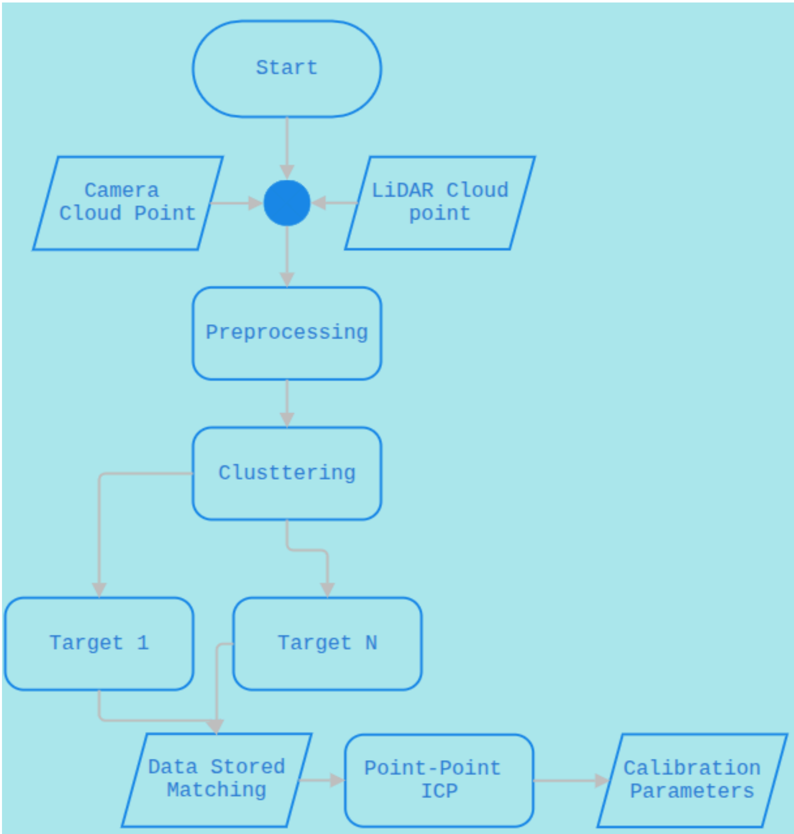
**5. Iterative Closest Point (ICP) Registration**

- The **ICP algorithm** iteratively refines the transformation between the LIDAR and camera point clouds.
- It works by minimizing the distance between matched points across iterations $T^0$, $T^1$, …, $T^{N,}$ progressively improving alignment accuracy.
- Each iteration updates the transformation estimate until the convergence criteria (e.g., minimal error threshold or max iterations) are met.

**6. Calibration Output**

- After convergence, the system produces the **final transformation matrix ($T^{final}$)**.
- $T^{final}$ defines the **extrinsic calibration parameters**, specifying the rotation (R) and translation (T) that map the LIDAR coordinate frame to the camera coordinate frame.
- This calibration data can then be used within the robot's perception stack to fuse LIDAR and camera data accurately for localization, mapping, or obstacle detection.

FlowChart




## 4.1b Process of Operation: LIDAR–Camera Calibration Workflow

The calibration process begins with initializing both sensor systems, the **camera** and the **LIDAR**, to capture synchronized 3D data for calibration.

1. **Data Acquisition (Camera Cloud Point & LIDAR Cloud Point)**

- ○ The **camera** generates a *3D point cloud* of the scene, often using depth estimation or structured light techniques.
- ○ Simultaneously, the **LIDAR** collects a *point cloud* of the same environment using laser range data.

These two datasets represent the same physical scene from different sensor perspectives.

2. **Preprocessing**
Raw data from both sensors undergoes **filtering and normalization** to remove noise, outliers, and irrelevant points.
Typical preprocessing steps include:

  ○ Down-sampling (voxel grid filtering)

  ○ Noise removal (statistical or radius filtering)

  ○ Coordinate frame normalization

3. **Clustering**
The preprocessed point clouds are **segmented** into distinct clusters to isolate meaningful objects or calibration targets (e.g., checkerboards, spheres, or AprilTag boards).
This step helps to associate the corresponding regions between the camera and the LIDAR data.

4. **Target Identification (Target 1 … Target N)**
Each detected cluster or calibration object is treated as a **target**.
Multiple targets are extracted to provide spatial diversity for more accurate transformation estimation.

5. **Data Stored Matching**
The features or coordinates of each identified target from the camera and LIDAR data are **matched and stored** for later processing.
This establishes initial correspondences between the two sensor frames.

6. **Point-to-Point ICP (Iterative Closest Point Alignment)**
The **Iterative Closest Point (ICP)** algorithm is then applied to minimize alignment error between matched points from the LIDAR and camera clouds.

  ○ The ICP iteratively adjusts the rotation and translation between the two datasets.

  ○ The goal is to find the **optimal extrinsic transformation matrix** that aligns both point clouds in a common coordinate frame.

7. **Calibration Parameter Computation**
The final output of the ICP stage yields the **calibration parameters** — typically a 4×4 transformation matrix comprising:

  ○ **Rotation (R):** Orientation of the LIDAR relative to the camera (or robot base).

  ○ **Translation (T):** Positional offset between the two sensors.
These parameters define the **extrinsic calibration** and can be stored in standard formats (e.g., YAML, URDF, or tf static transforms) for integration into ROS 2 pipelines.

## 4.2 Tools and techniques utilised

- Tools
  - ❖ Velodyne HL-32 3D LiDAR
  - ❖ Zed20 Stereo Camera
  - ❖ Python
  - ❖ Open3D
  - ❖ ROS2
  - ❖ RViz
- Techniques
  - ❖ ICP
  - ❖ Voxelization
  - ❖ Plane Segmentation

## 4.3 Design considerations

# Chapter 5: Implementation

## 5.1 Description of how the project was executed

## 5.2 Challenges faced and solutions implemented

# Chapter 6: Results

## 6.1 outcomes

## 6.2 Interpretation of results

## 6.3 Comparison with existing literature or technologies

# Chapter 7: Conclusion

Here, write Suggestions for further research or development, and Potential improvements or extensions

# Chapter 8: Future Work

Here write Suggestions for further research or development, Potential improvements or extensions.

# References

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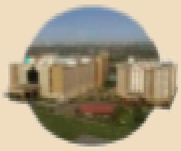

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