Northeastern

Silicon Synapse Lab

MASTER'S PROJECT:

GOAL: Benchmarking RTAB-Map with LiDAR and Cloud Map Comparison for Enhanced Localization and Mapping.

MASTER'S PROJECT:

OBJECTIVES

- To benchmark the performance of LIO-SAM and RTAB-Map in terms of trajectory accuracy and point cloud quality in real-world environments.
- To develop a standardized experimental workflow that integrates advanced mapping, localization, and object detection method

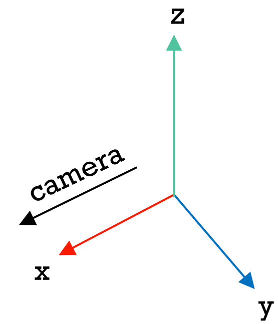
Milestones

- Understand and be able to run current LIOSAM
- Build a Testing rig to Run LIOSAM and Rtab-map for fair comparison simultaneously
- Run LIOSAM and Rtab-map with Yolo simultaneously on the cobra head and collect multiple datasets.
- Run complete analysis on Cloudcompare such as C2C and model comparison

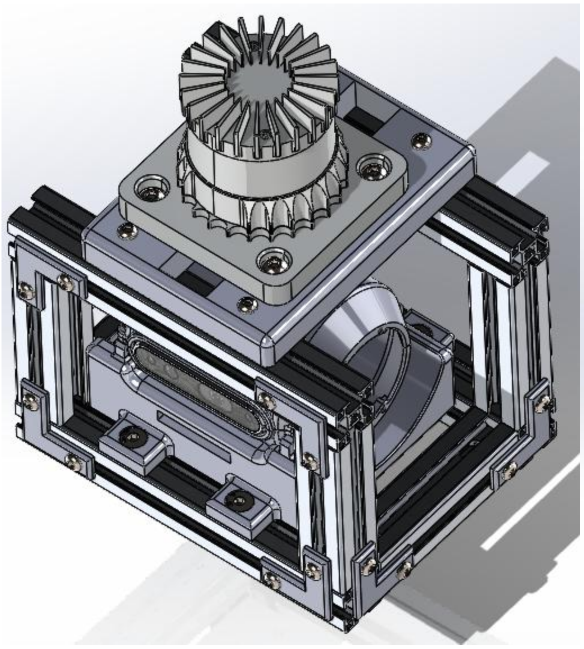
DEMO:

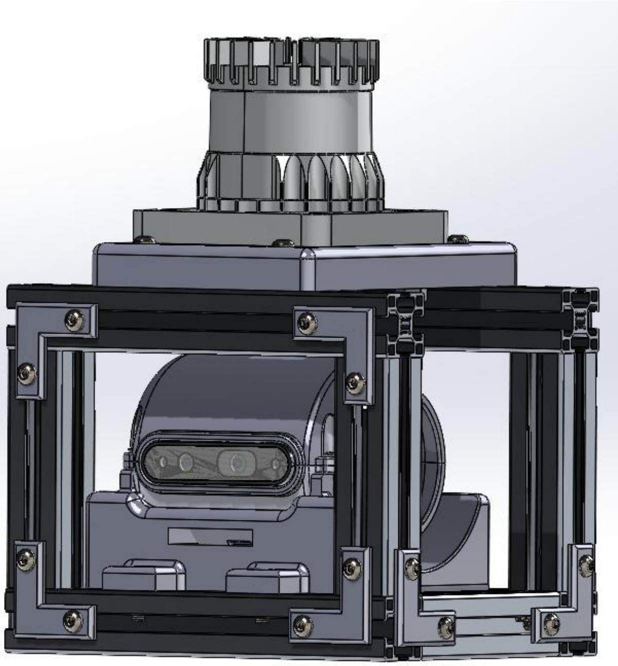
The demo will showcase the test rig with the Cobra robot's head running LIO-SAM, RTAB-Map, and YOLO simultaneously. Real-time outputs, including trajectories and point clouds, will be displayed alongside a comparative analysis of the mapping results in CloudCompare.

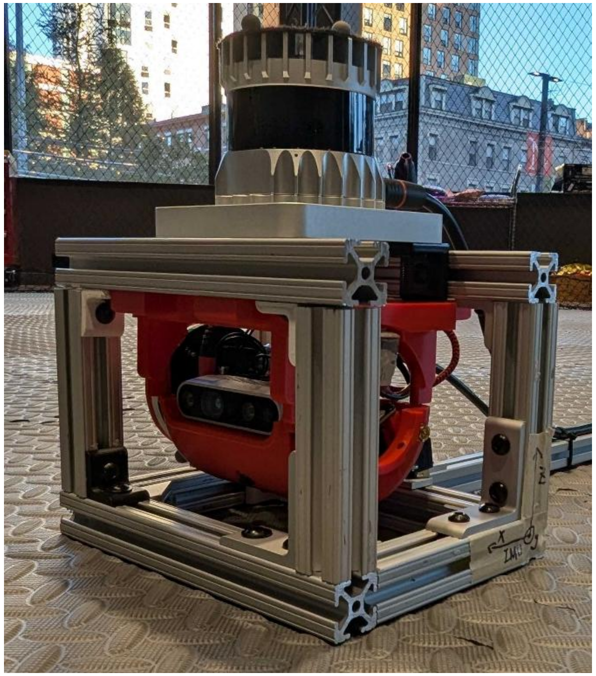
CAD Design And Assembly



- Design
  - Custom CAD model for a robust testing rig
  - Built using aluminum extrusions and 3D-printed mounts.
- Purpose
  - Ensures accurate alignment of Cobra head (with camera) and LiDAR for simultaneous benchmarking of LIO-SAM and RTAB-Map.

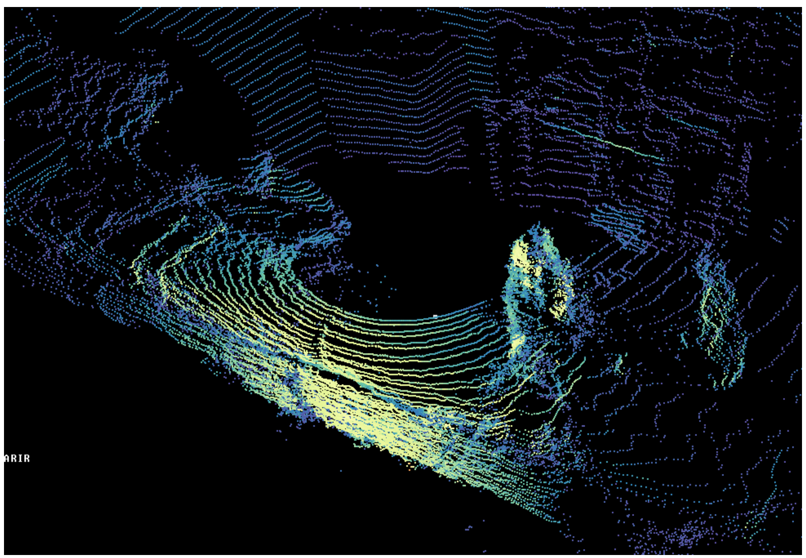






Data Collection and Initial Calibration

- Installed and configured Ouster LiDAR drivers to integrate with ROS/ROS2.
- Successfully set up and ran the LiDAR, verifying point cloud and IMU data output
- Calibrated IMU to resolve drifting in LIOSAM



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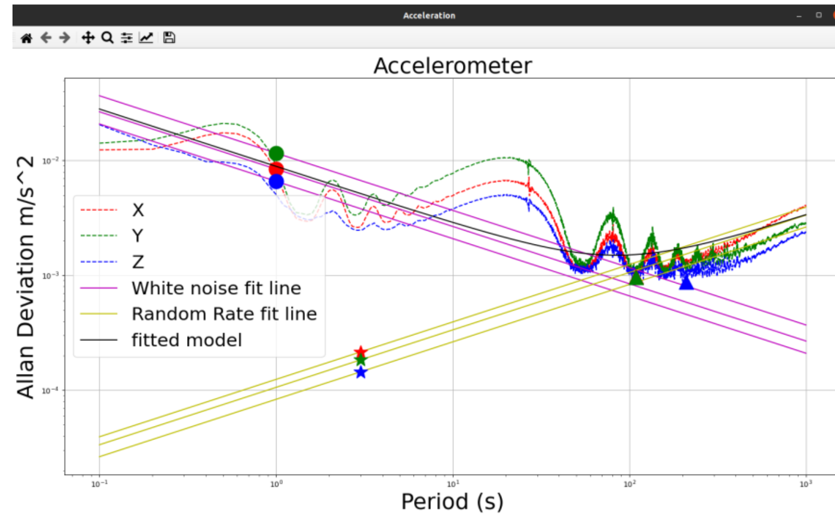
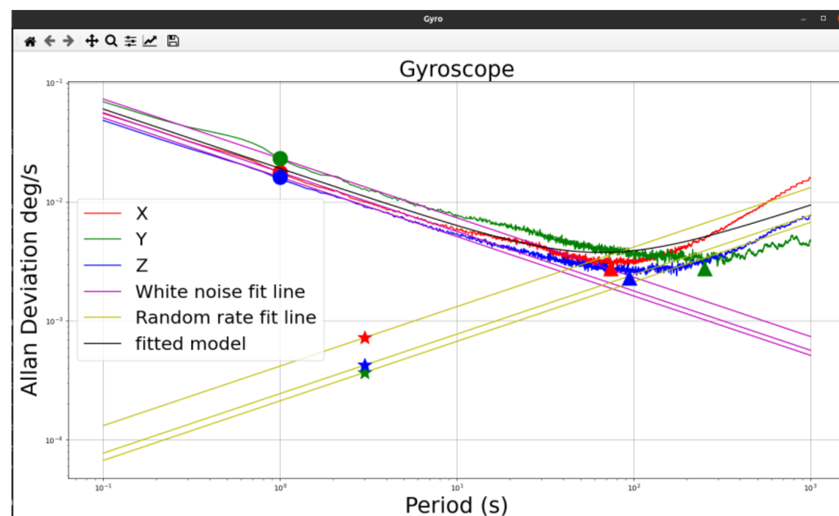
#Accelerometer
accelerometer_noise_density: 0.011611984885771755
accelerometer_random_walk: 0.0002152243898437869

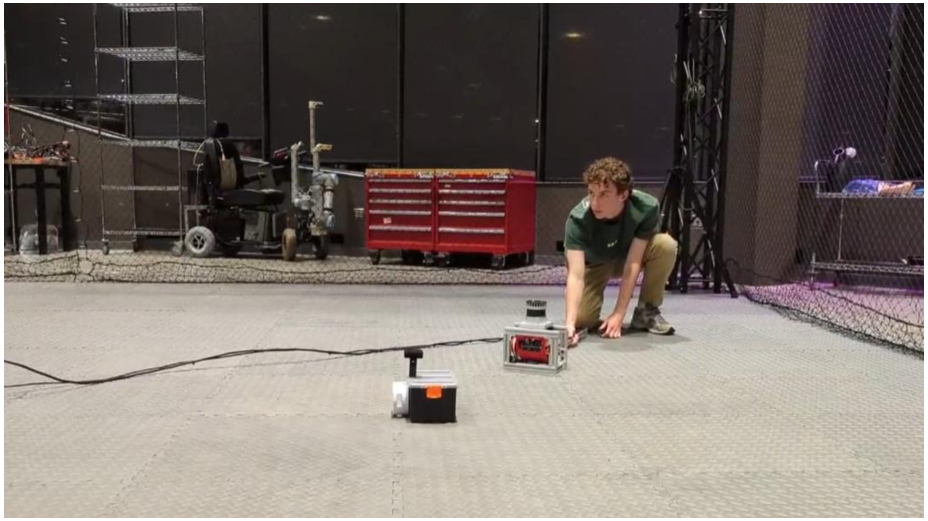
#Gyroscope
gyroscope_noise_density: 0.00040450326813224683
gyroscope_random_walk: 1.2601841519185798e-05
```

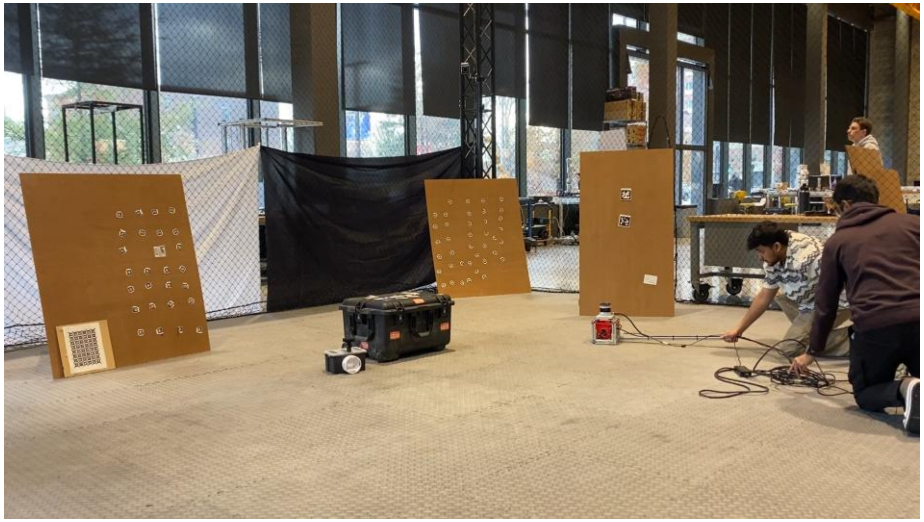




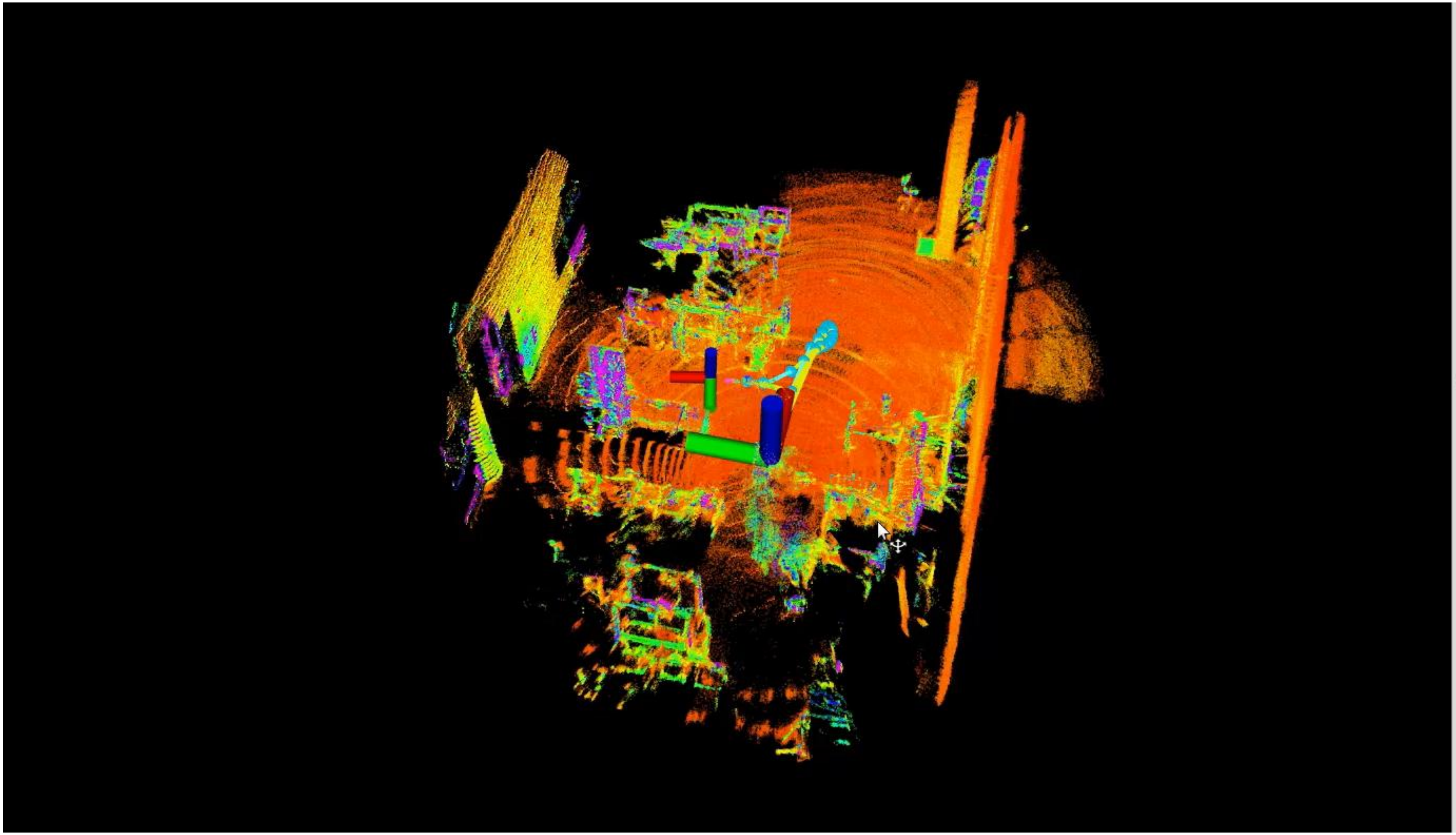
Data Collection

- Recorded videos on different Environmental setups
- Recorded in an open and empty cage to map the boundaries and walls of the cage
- Recorded with a box at the center to analyze the mapping of a singular object.
- Recorded with multiple planks in the front to compare occluded environment.
- Recorded with Rtabmap, LIOSAM, and YOLO object detection running simultaneously.





Running LIO-SAM



Challenges Faced and steps to Resolve:

- **IMU Drifting**

Issue: Drift in IMU data caused inaccuracies in pose estimation over time.

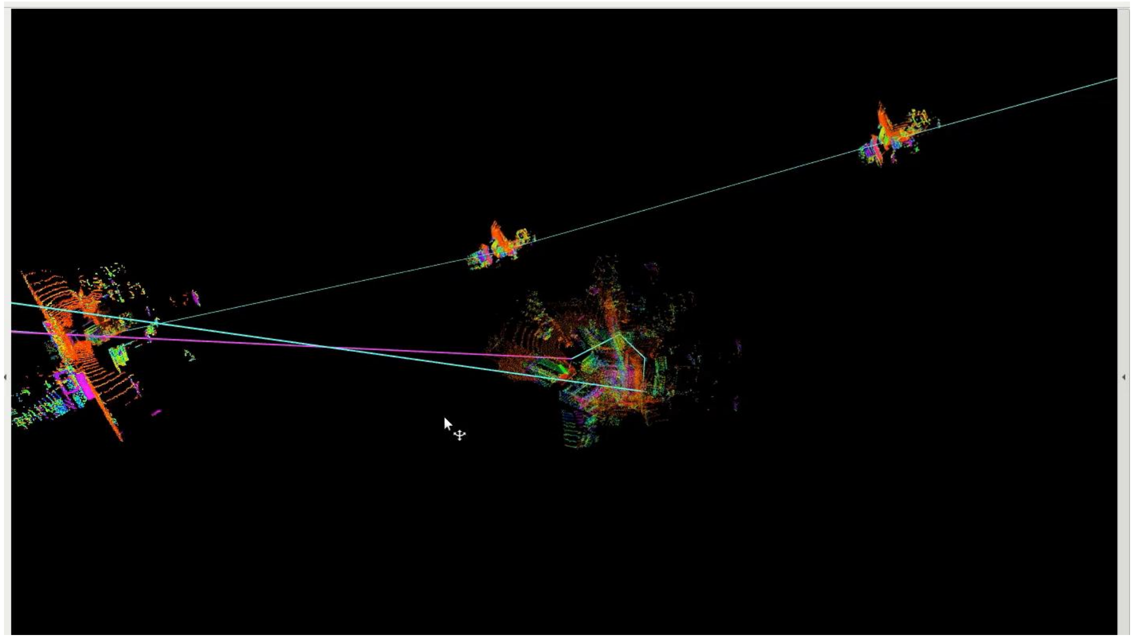
Resolution: Calibrated IMU parameters and fine-tuned pre-integration settings in LIO-SAM.

- **NAN Values parsed my lidar causing failure in Liosam mapping**

Issue: NAN values occurred when objects were too close to the LiDAR sensor.

Resolution: Adjusted voxel filter values to better handle close peripheral regions and filter invalid points.

Resolution: Adjust voxel size
Indoor Settings: 0.1 m to 0.2 m (10 cm to 20 cm).
Outdoor Settings (default): 0.4 m to 0.5 m (40 cm to 50 cm).



Challenges Faced and steps to Resolve:

- **High Computational Load on Jetson**

Issue: Unable to run both LIO-SAM and RTAB-Map simultaneously due to Jetson's limited processing power.
Resolution: Limited LiDAR range to 5 meters, reducing the number of points processed for mapping.
CPU consumption before went to 100% and crashed the system, while later it stayed stable up to 68-70 % after reducing the range.

- **Loop Closure in RTAB-Map**

Issue: RTAB-Map struggled with loop closure when moving too fast during dataset recording.
Resolution: Slowed down movement during dataset recording to improve loop closure consistency.

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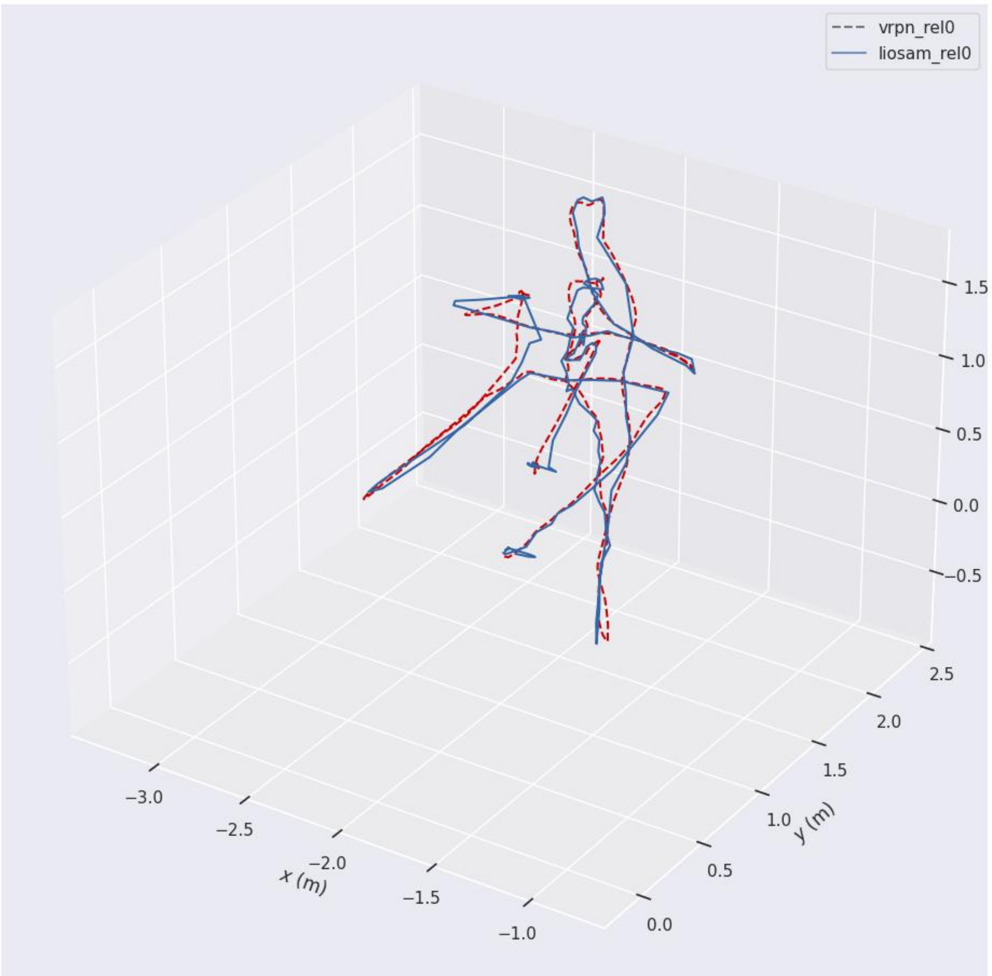
Trajectory Analysis

- OPTITRACK comparison




```
(with SE(3) Umeyama alignment)

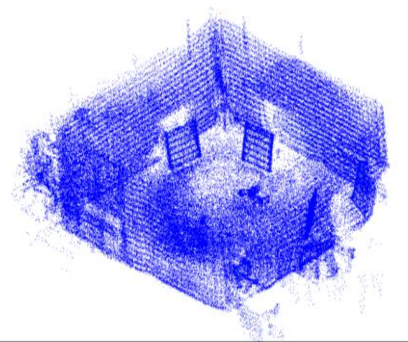
       max      0.390874
      mean      0.082998
    median      0.056467
       min      0.010571
      rmse      0.103716
       sse      2.656971
       std      0.062195
```

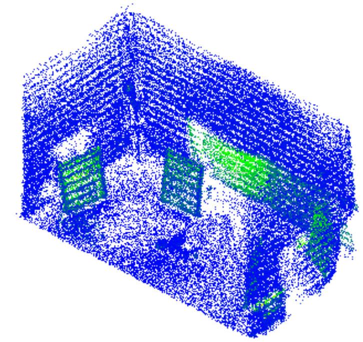
The results indicate that the estimated trajectory closely follows the ground truth, with a mean error of ~0.083 meters and an RMSE of ~0.10 meters. However, a few points have larger errors (up to ~0.39 meters). The trajectory alignment was performed using SE(3) Umeyama alignment to minimize these errors.

CLOUD COMPARE ANALYSIS

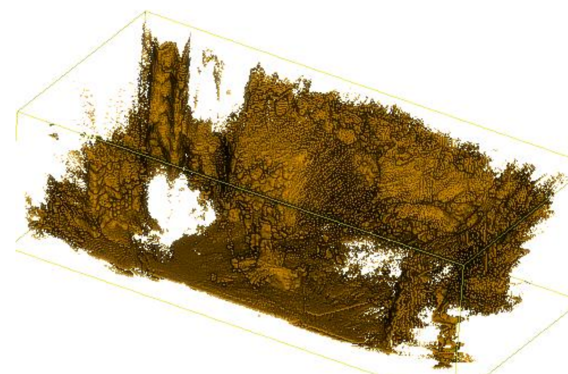
Preprocessing:

- **Segmentation:**

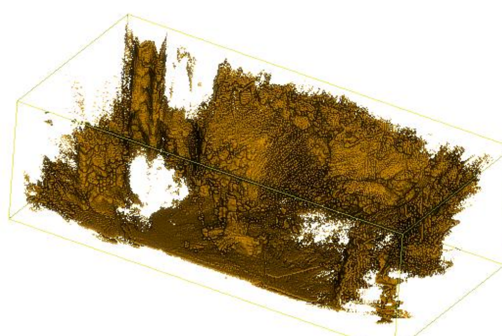


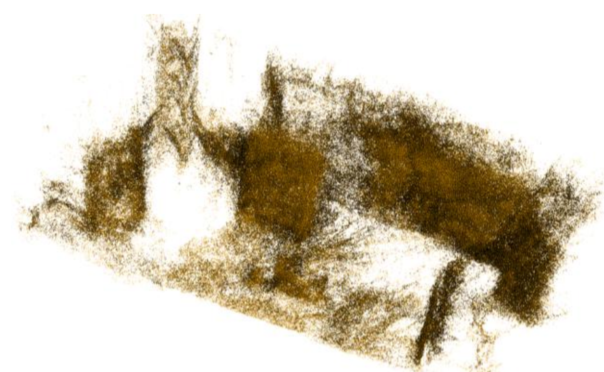


- **Colorization and shading**



- **Subsampling**
  - subsampled from **2070905** pts to **541292** pts (down-sampled **62%).**
  - Voxel-based subsampling by voxel size of **2.4cm**

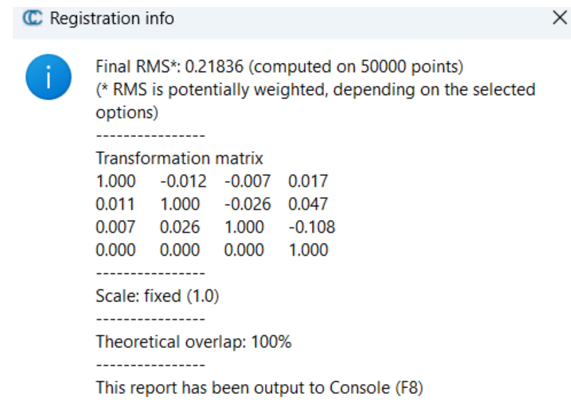




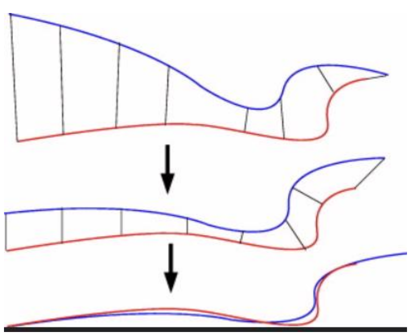
CLOUD COMPARE ANALYSIS

Alignment

- ICP is an algorithm to align 2-point clouds by minimizing their differences. It iteratively refines the transformation (rotation and translation) needed to align a "source" point cloud to a "target" point cloud.

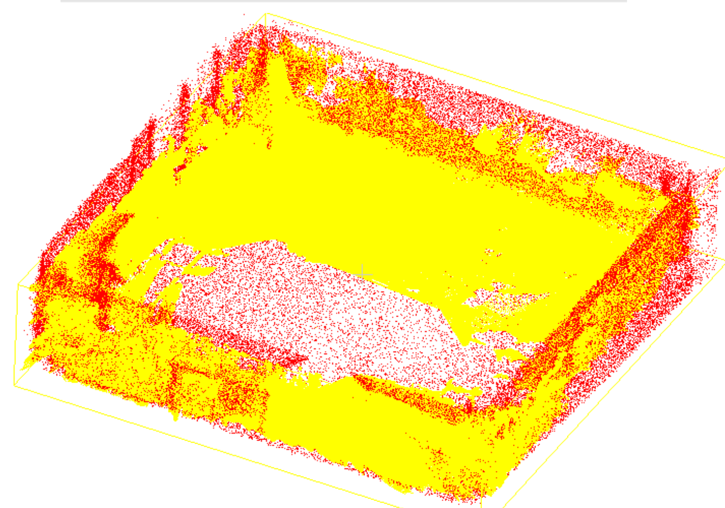


- **Find Correspondences**: Match the closest points in the target cloud to the source cloud.
- **Estimate Transformation**: Calculate the rotation and translation to align the matched points.
- **Apply Transformation**: Update the source cloud with the computed transformation.
- **Repeat**: Iterate until the alignment error is minimal or a set limit is reached.



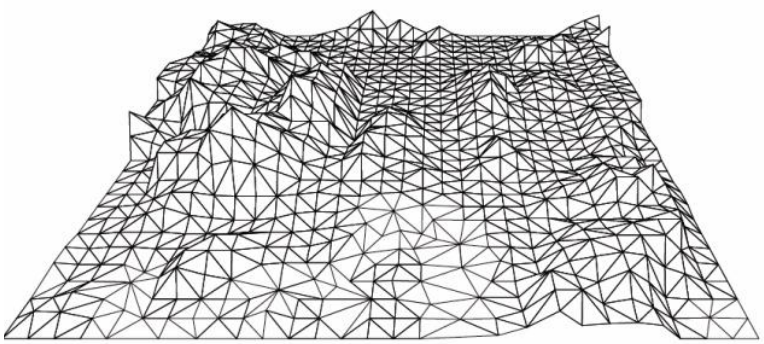
$$\min_{R,t} \sum_{i=1}^{N} \|R\mathbf{p}_i + t - \mathbf{q}_i\|^2$$

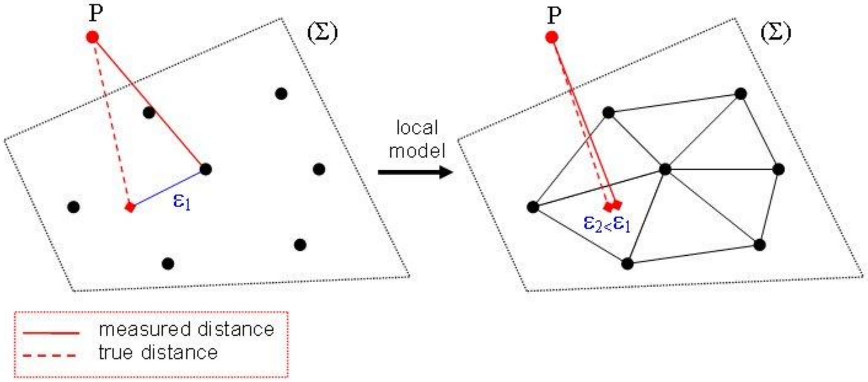
•R is the 3×3 rotation matrix.
•t is the 3×3 translation vector.
•Source point cloud {p}
•Target point cloud {Q}

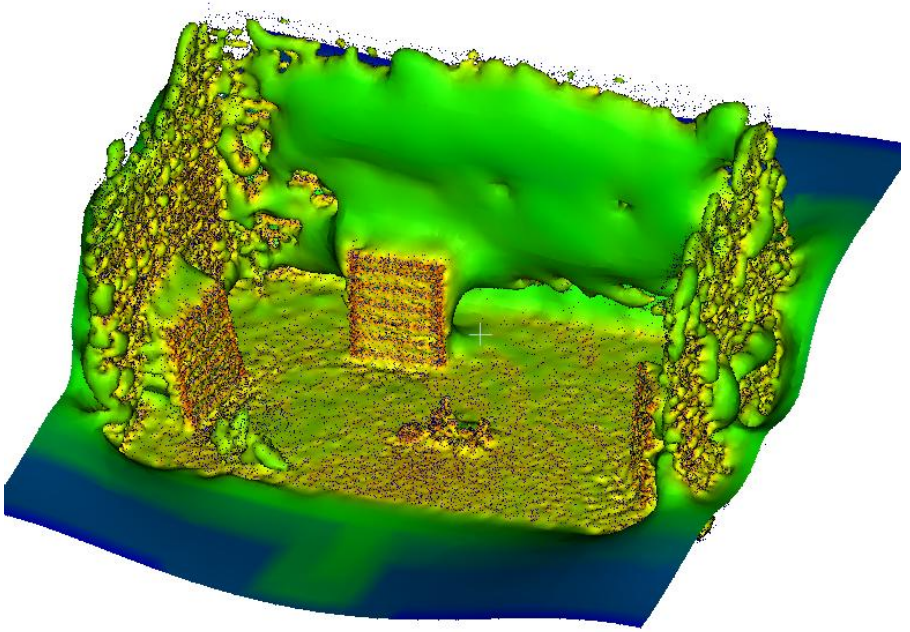


CLOUD COMPARE ANALYSIS

- **Cloud to cloud Distance Computation:**
- Cloud-to-cloud triangulation distance is computed by projecting each point from one cloud onto the triangular mesh surface of the other cloud and measuring the shortest perpendicular distance. This provides precise point-to-surface comparisons for alignment or error analysis.



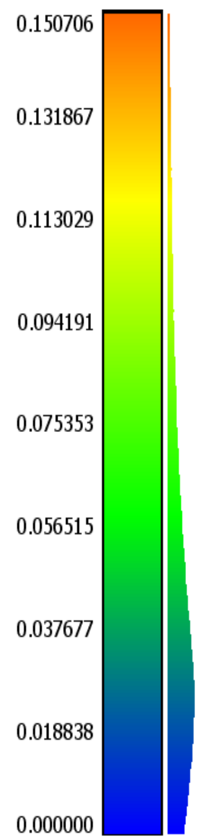


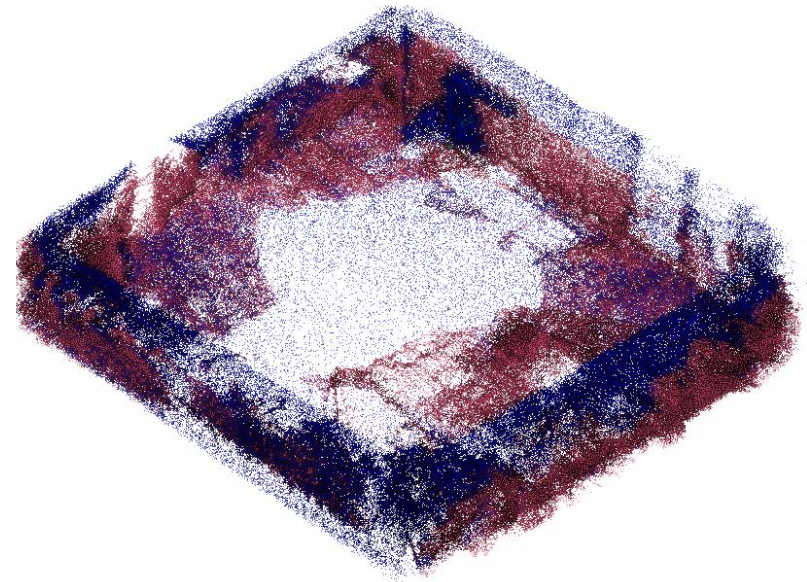


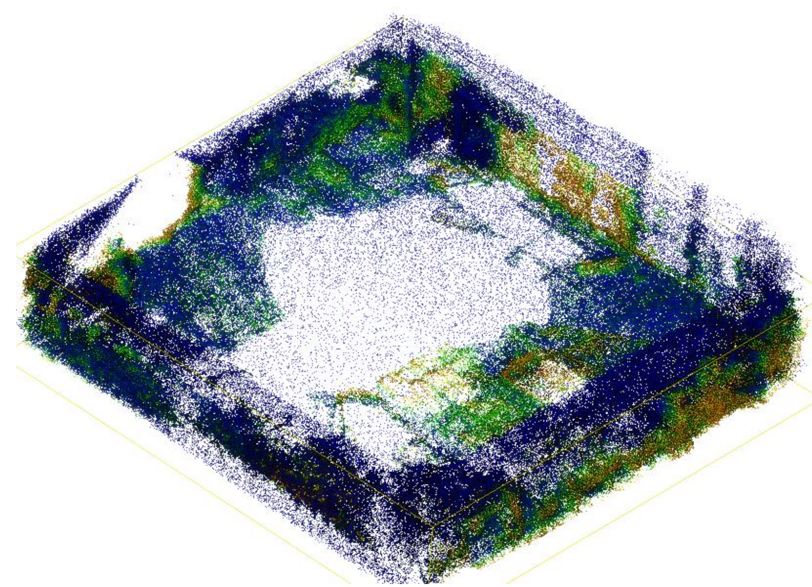
CLOUD COMPARE ANALYSIS

- C2C results for the whole map

  - Overall structure, boundaries and obstacles are mapped fairly accurate.
  - Areas behind objects and obstacles are distorted. Suggesting robot need to give extra attention to such scenarios while mapping.





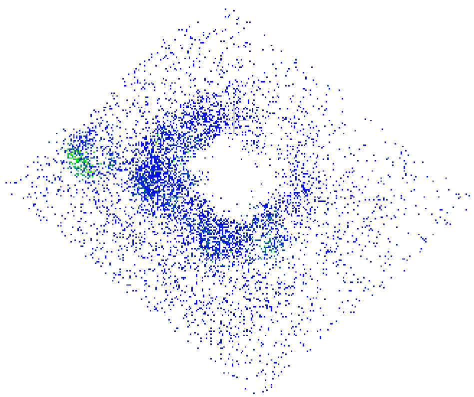


The histogram shows the proximity of points from the reference mesh. Red being the farthest which is 15.07 cms in this case and the range of blues represents closely aligning points which is 0 to 1.8 cms

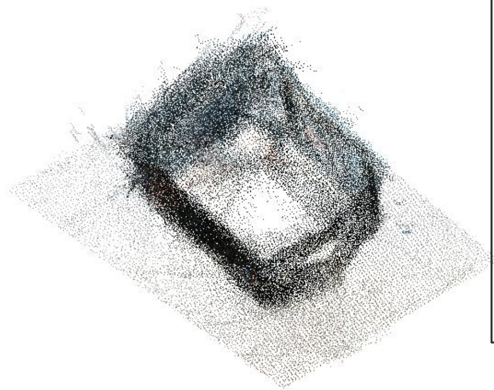
Mean distance = 0.0656596 / std deviation = 0.069039

CLOUD COMPARE ANALYSIS

- Isolated object comparison

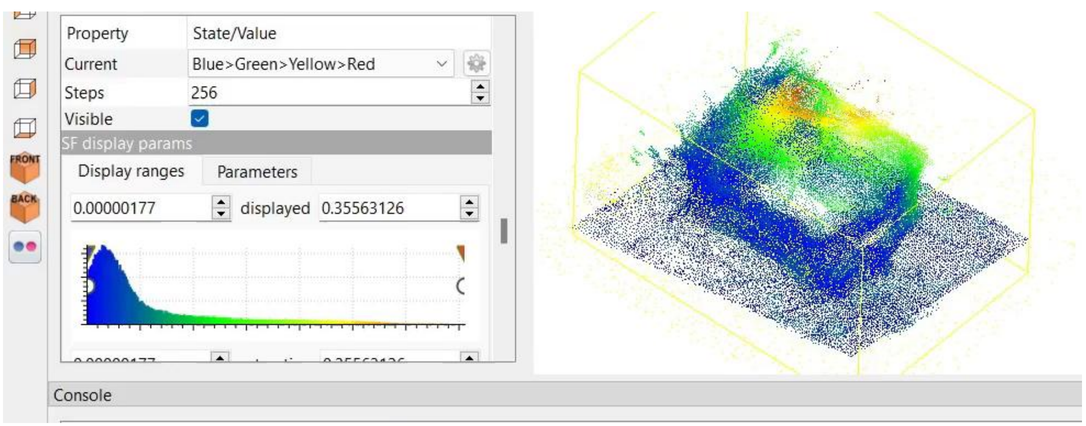


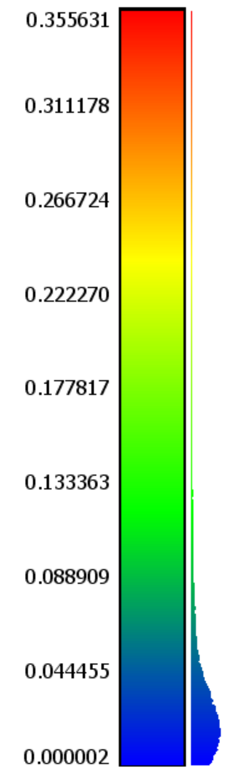
Lidar point cloud



Rtabmap cloud

- good estimate of the area covered by the object and dimensionality
- The front and the edges are fairly accurate
- Irregularities in the back, suggest insufficient mapping in the back of the object. Doesn't reflect the algorithm's flaw.



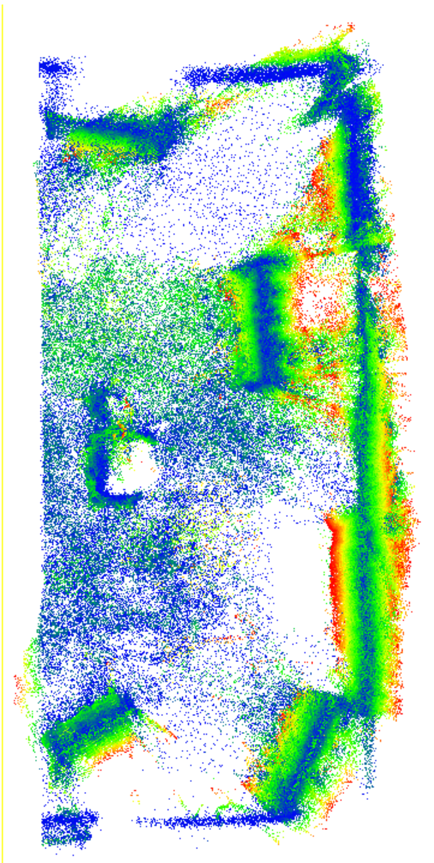


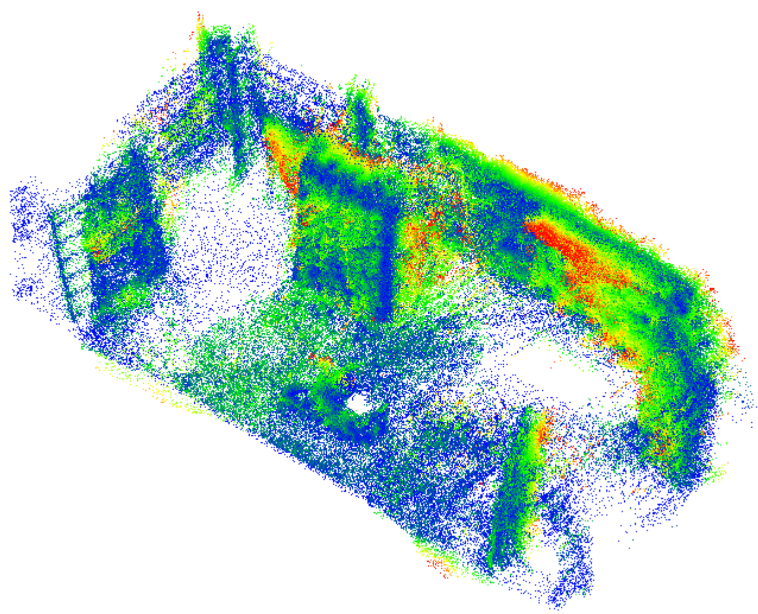
[20:03:18] [ComputeDistances] Mean distance = 0.058514 / std deviation = 0.0652436

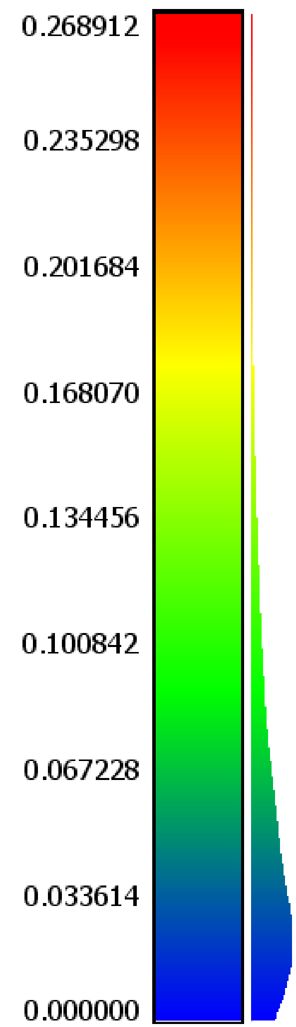
CLOUD COMPARE ANALYSIS

- C2C results

- Good estimation of the placements of the objects
- Good estimate of the peripheral boundaries
- Scattered points behind occlusions suggest irregular mapping in the sights where data is less.
- Rtab is seen performing poorly where overlapping of objects in the field of view but performs well where there is an unobstructed view of the scene.

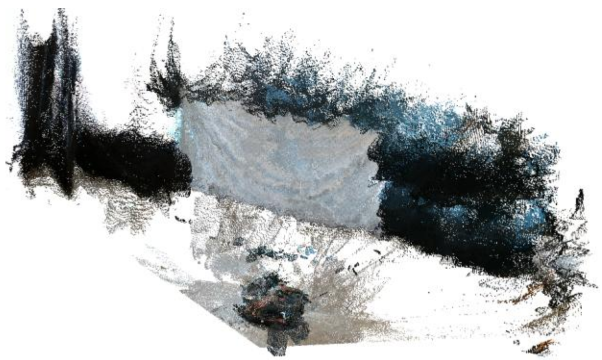


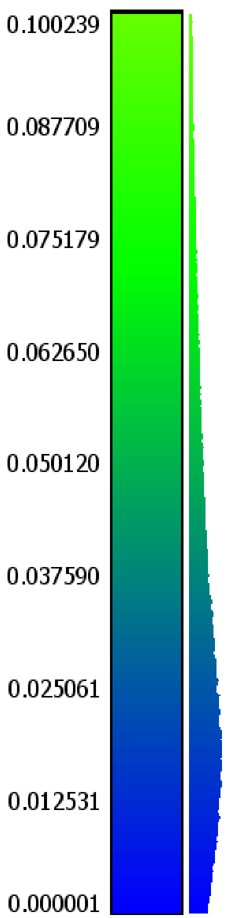


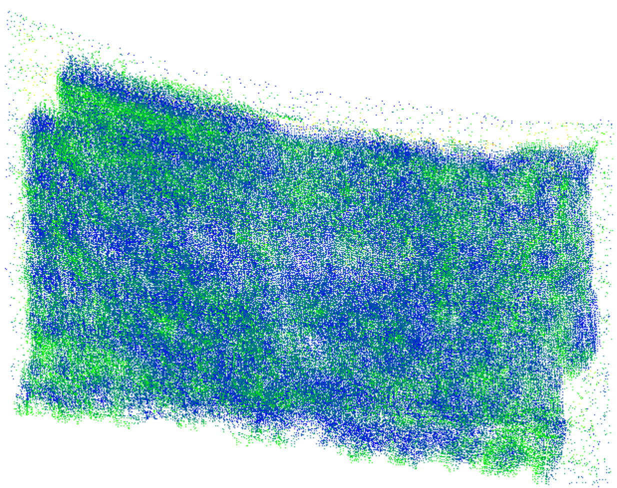


[22:46:44] [ComputeDistances] Mean distance = 0.0695916 / std deviation = 0.0671589

Planar Surface comparision







- Comparison done for pelted cloth as a planar surface with some features.
- Lowest error and deviation observed.
- 10 cm being the farthest and most points are within 0-2 cms.

[15:28:34] [ComputeDistances] Mean distance = 0.0390155 / std deviation = 0.0306445

Key findings

Conclusion

We successfully mapped the environment using **RTAB-Map** and benchmarked its performance using **LIO-SAM** as a reference. Comparative analysis of the generated point clouds in Cloud-Compare revealed the following:

1. RTAB-Map reliably reconstructed the environment and produced high-quality maps in most areas. However, it faced minor challenges in regions with significant occlusions and overlapping fields of view (FOV).

2. Performance: RTAB-Map is effective for visual SLAM and provides good results in static and moderately complex environments. While slightly slower than the reference, it remains a robust solution for many applications.

TEST SETUP	Standard deviation	Range of Blue(closely aligning points	Farthest point (max error)
Segmented object (BOX)	0.0652436	0 - 4 cms	35 cms
Occluded Area	0.0671589	0 - 3.3 cms	26 cms
Planar surfaces	0.0306445	0 – 2.5 cms	10 cms
peripheral map	0.0690390	0 – 2.1 cms	15 cms