LIO-SAM with SPOT

By Group - 7

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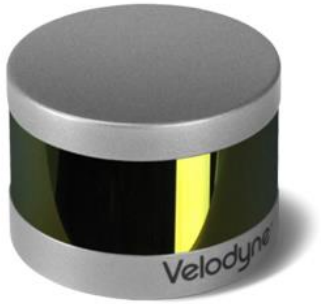
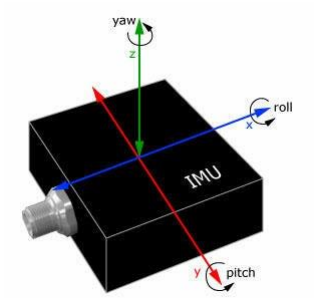
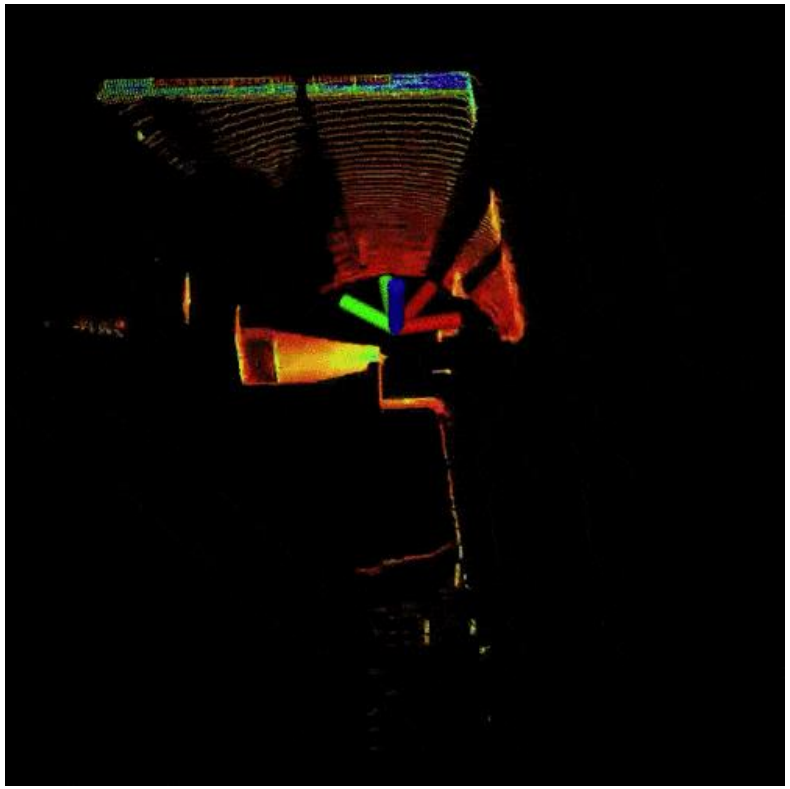






Northeastern University

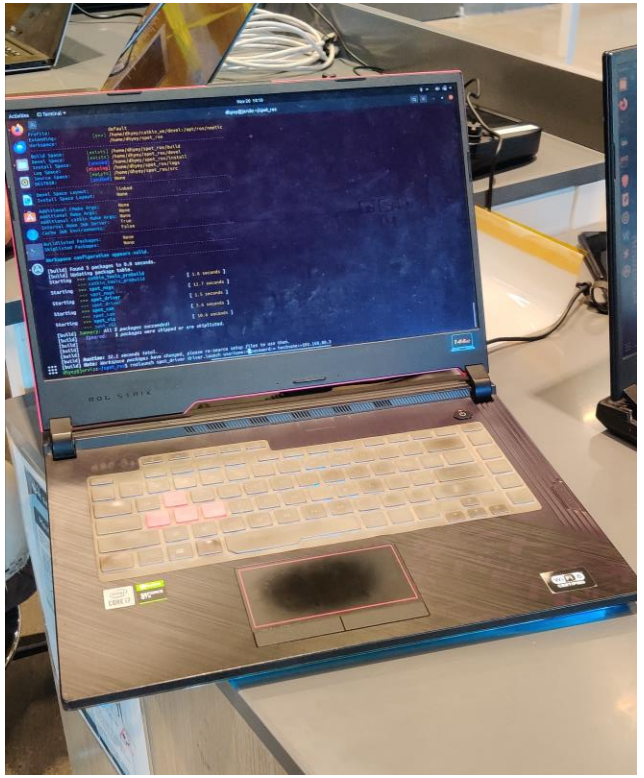
BostonDynamics

LIO-SAM with SPOT

A Journey of Challenges and Progress

We implemented the LIO-SAM (LiDAR-Inertial Odometry with Smoothing and Mapping) algorithm on data collected from the Spot robot, aiming to achieve high-precision 3D mapping and localization in a dynamic environment.

Although the project is still in progress, we have made substantial strides in understanding and implementing the algorithm and collecting the data.



Motivation

- Spot is changing how organizations monitor and operate their sites, ensure the safety of their teams, and make data-driven decisions.
- We can put Spot's unprecedented agility and advanced autonomy to work and extend the reach of industries.

What is LIO SAM

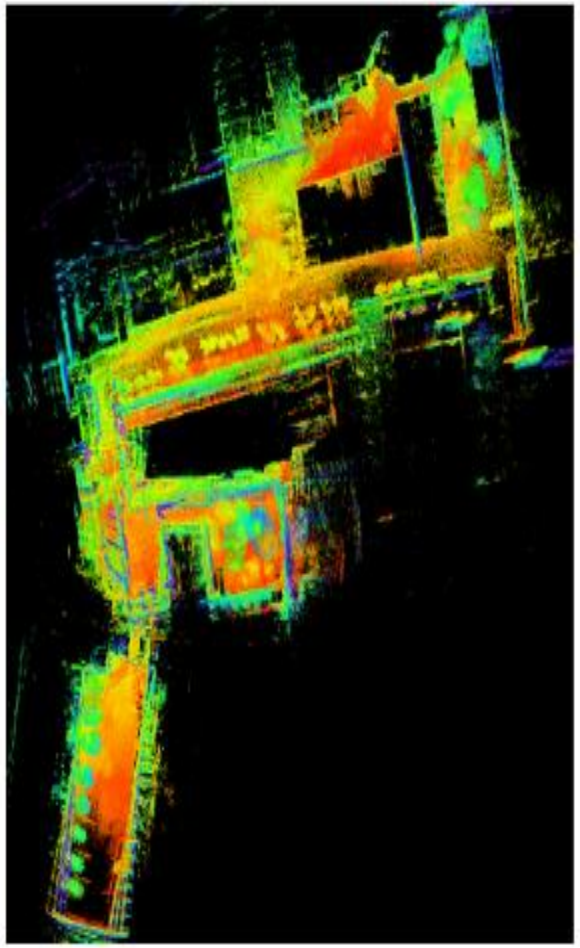
- **LIO-SAM (LiDAR-Inertial Odometry with Smoothing and Mapping)** is a state-of-the-art SLAM algorithm that combines data from LiDAR and IMU (Inertial Measurement Unit) sensors to achieve accurate and robust 3D mapping and localization. It is designed for real-time operation in dynamic and challenging environments.
- **Key Features:**
- **Tight Integration of LiDAR and IMU:**
  - Uses LiDAR for spatial accuracy and IMU for motion compensation, enabling precise localization and mapping in environments where GPS may not work.
- **Factor Graph Optimization:**
  - Builds a factor graph to optimize poses and trajectories, ensuring global consistency and minimizing drift.
- **Real-Time Performance:**
  - Capable of providing real-time odometry and mapping, suitable for mobile robotics applications.
- **Loop Closure:**
  - Detects when the robot revisits an area to correct drift and improve map consistency.

Why LIO SAM ?

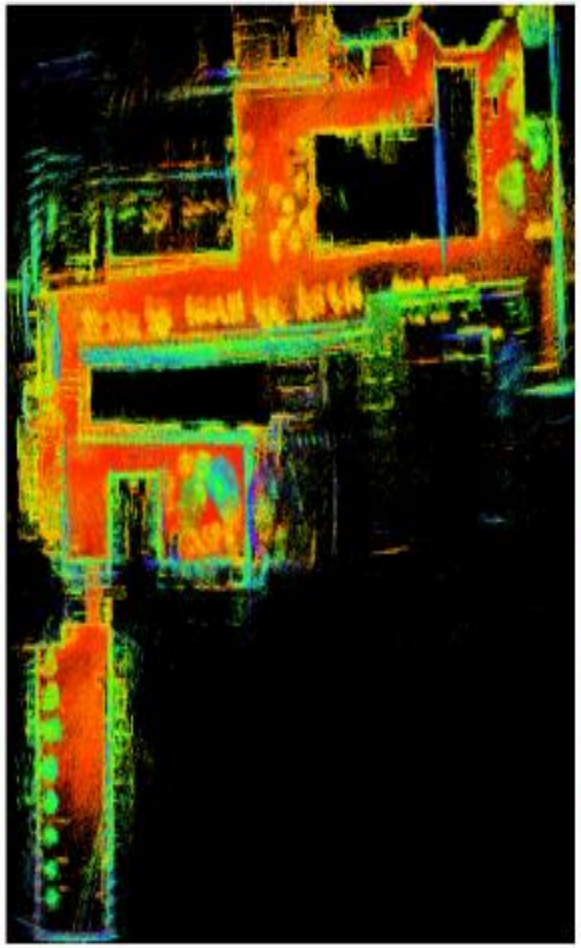
Feature	LOAM	LIOM	LIO-SAM
Sensor Fusion	Relies mostly on LiDAR	Loosely integrates LiDAR with IMU	Tightly integrates LiDAR and IMU
Optimization	No global smoothing (relies on ICP-like)	Loosely optimized over poses	Factor graph-based global smoothing
Real-time Capability	Efficient for real-time	Moderate real-time performance	High real-time performance
Accuracy	Good in LiDAR-dominant environments	Better than LOAM due to IMU use	Best, especially in dynamic motion
Robustness to Dynamics	Moderate	Better than LOAM	High robustness in fast/dynamic motions
Loop Closure Handling	Limited	Improved	Strong with backend optimization
Implementation	Computationally efficient but lacks smoothing	Computationally heavier	Balance of efficiency and accuracy

Why LIO-SAM

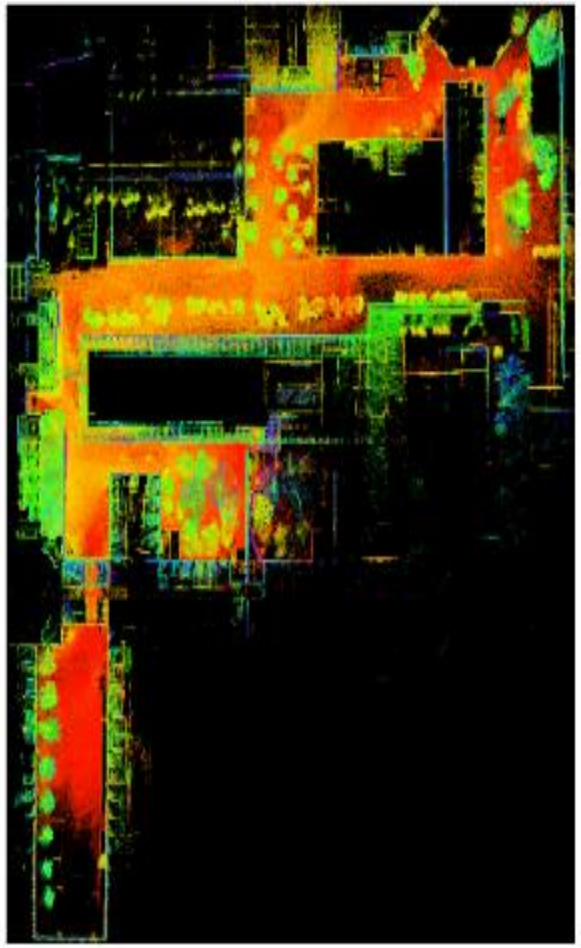
(a) Google Earth



(b) LOAM



(c) LIOM



(d) LIO-SAM

Algorithm

- **LIO-SAM Algorithm (Simplified)**
- **Input Sensors:**
  - **IMU:** Captures motion.
  - **LiDAR:** Provides 3D point clouds.
  - **GPS (Optional):** Adds global positioning.
- **Data Processing:**
  - **IMU Pre-integration:** Estimates motion.
  - **LiDAR Feature Extraction:** Identifies edges/planes.
- **Factor Graph Construction:**
  - Combines constraints from IMU, LiDAR, GPS, and loop closure.
- **Loop Closure:**
  - Detects revisited areas to reduce drift.
- **Optimization:**
  - Refines poses using factor graph optimization.
- **Output:**
  - Builds a consistent 3D map.

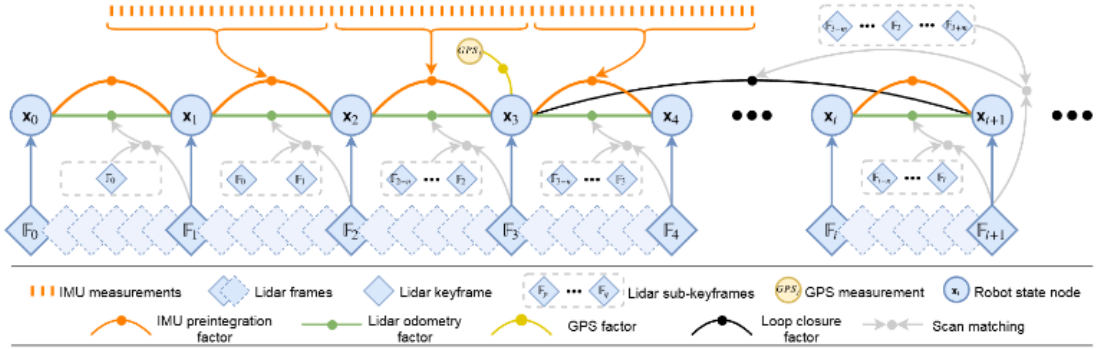
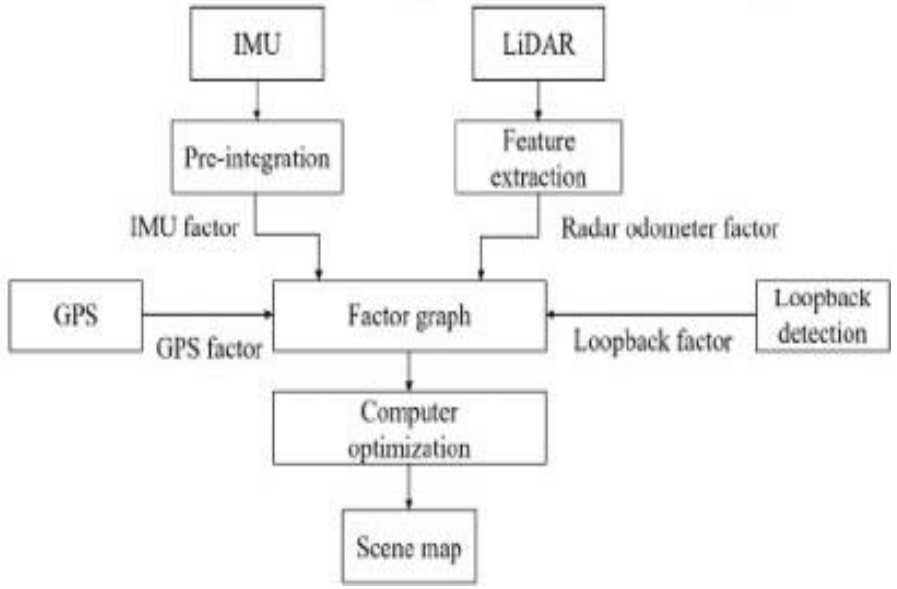


Fig. 1: The system structure of LIO-SAM. The system receives input from a 3D lidar, an IMU and optionally a GPS. Four types of factors are introduced to construct the factor graph.: (a) IMU preintegration factor, (b) lidar odometry factor, (c) GPS factor, and (d) loop closure factor. The generation of these factors is discussed in Section III.



Algorithm

$$\mathbf{x} = [\,\mathbf{R}^{\mathbf{T}},\ \mathbf{p}^{\mathbf{T}},\ \mathbf{v}^{\mathbf{T}},\ \mathbf{b}^{\mathbf{T}}\,]^{\mathbf{T}}, \tag{1}$$

$$\hat{\boldsymbol{\omega}}_t = \boldsymbol{\omega}_t + \mathbf{b}_t^{\boldsymbol{\omega}} + \mathbf{n}_t^{\boldsymbol{\omega}} \tag{2}$$

$$\hat{\mathbf{a}}_t = \mathbf{R}_t^{\mathbf{BW}}(\mathbf{a}_t - \mathbf{g}) + \mathbf{b}_t^{\mathbf{a}} + \mathbf{n}_t^{\mathbf{a}}, \tag{3}$$

We can now use the measurements from the IMU to infer the motion of the robot. The velocity, position and rotation of the robot at time $t + \Delta t$ can be computed as follows:

$$\mathbf{v}_{t+\Delta t} = \mathbf{v}_t + \mathbf{g}\Delta t + \mathbf{R}_t(\hat{\mathbf{a}}_t - \mathbf{b}_t^{\mathbf{a}} - \mathbf{n}_t^{\mathbf{a}})\Delta t \tag{4}$$

$$\begin{aligned}\mathbf{p}_{t+\Delta t} = \mathbf{p}_t + \mathbf{v}_t\Delta t + \frac{1}{2}\mathbf{g}\Delta t^2 \\ + \frac{1}{2}\mathbf{R}_t(\hat{\mathbf{a}}_t - \mathbf{b}_t^{\mathbf{a}} - \mathbf{n}_t^{\mathbf{a}})\Delta t^2\end{aligned} \tag{5}$$

$$\mathbf{R}_{t+\Delta t} = \mathbf{R}_t\,\mathbf{exp}((\hat{\boldsymbol{\omega}}_t - \mathbf{b}_t^{\boldsymbol{\omega}} - \mathbf{n}_t^{\boldsymbol{\omega}})\Delta t), \tag{6}$$

$$\Delta\mathbf{v}_{ij} = \mathbf{R}_i^{\mathsf{T}}(\mathbf{v}_j - \mathbf{v}_i - \mathbf{g}\Delta t_{ij}) \tag{7}$$

$$\Delta\mathbf{p}_{ij} = \mathbf{R}_i^{\mathsf{T}}(\mathbf{p}_j - \mathbf{p}_i - \mathbf{v}_i\Delta t_{ij} - \frac{1}{2}\mathbf{g}\Delta t_{ij}^2) \tag{8}$$

$$\Delta\mathbf{R}_{ij} = \mathbf{R}_i^{\mathsf{T}}\,\mathbf{R}_j. \tag{9}$$

$$\mathbf{d}_{e_k} = \frac{\left|(\mathbf{p}_{i+1,k}^e - \mathbf{p}_{i,u}^e) \times (\mathbf{p}_{i+1,k}^e - \mathbf{p}_{i,v}^e)\right|}{\left|\mathbf{p}_{i,u}^e - \mathbf{p}_{i,v}^e\right|} \tag{10}$$

$$\mathbf{d}_{p_k} = \frac{\left|\begin{matrix}(\mathbf{p}_{i+1,k}^p - \mathbf{p}_{i,u}^p) \\ (\mathbf{p}_{i,u}^p - \mathbf{p}_{i,v}^p) \times (\mathbf{p}_{i,u}^p - \mathbf{p}_{i,w}^p)\end{matrix}\right|}{\left|(\mathbf{p}_{i,u}^p - \mathbf{p}_{i,v}^p) \times (\mathbf{p}_{i,u}^p - \mathbf{p}_{i,w}^p)\right|}, \tag{11}$$

where k, u, v, and w are the feature indices in their corresponding sets. For an edge feature $\mathbf{p}_{i+1,k}^e$ in ${}'\mathbf{F}_{i+1}^e$, $\mathbf{p}_{i,u}^e$ and $\mathbf{p}_{i,v}^e$ are the points that form the corresponding edge line in $\mathbf{M}_i^e$. For a planar feature $\mathbf{p}_{i+1,k}^p$ in ${}'\mathbf{F}_{i+1}^p$, $\mathbf{p}_{i,u}^p$, $\mathbf{p}_{i,v}^p$, and $\mathbf{p}_{i,w}^p$ form the corresponding planar patch in $\mathbf{M}_i^p$. The Gauss–Newton method is then used to solve for the optimal transformation by minimizing:

$$\min_{\mathbf{T}_{i+1}} \left\{ \sum_{\mathbf{p}_{i+1,k}^e \in {}'\mathbf{F}_{i+1}^e} \mathbf{d}_{e_k} + \sum_{\mathbf{p}_{i+1,k}^p \in {}'\mathbf{F}_{i+1}^p} \mathbf{d}_{p_k} \right\}.$$

- ***2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) October 25-29, 2020, Las Vegas, NV, USA (Virtual)***
- Tixiao Shan, Brendan Englot, Drew Meyers, Wei Wang, Carlo Ratti, and Daniela Rus

Progress made so far

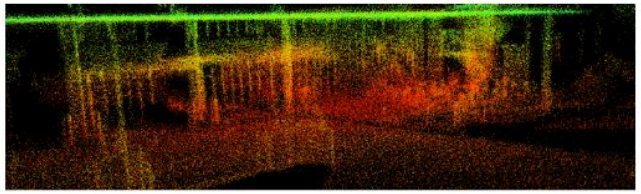
Research

- Reviewed the paper:

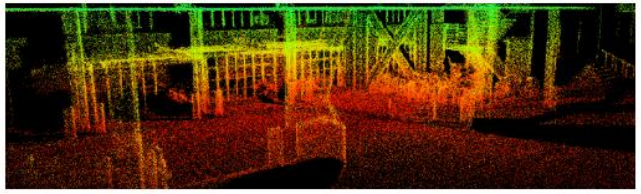
  LIO-SAM: Tightly-Coupled Lidar Inertial Odometry via Smoothing and Mapping

  (Authors: Tixiao Shan, Brendan Englot, Drew Meyers, Wei Wang, Carlo Ratti, and Daniela Rus)

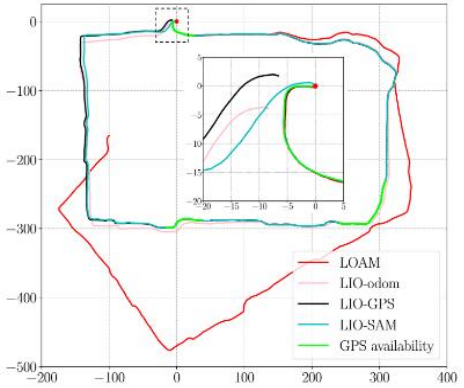
(a) Test environment



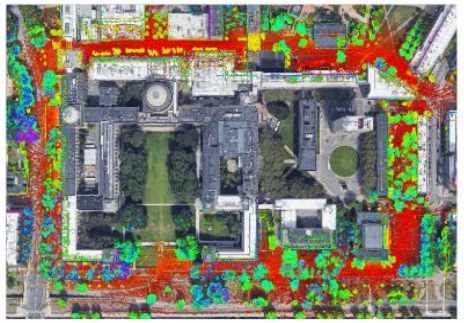
(b) LOAM



(c) LIO-SAM

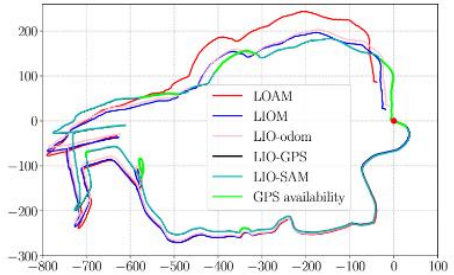


(a) Trajectory comparison

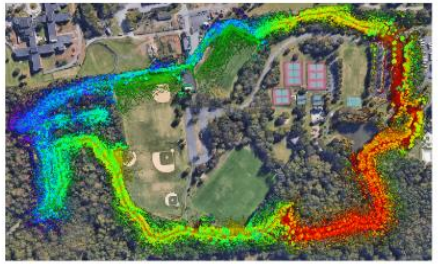


(b) LIO-SAM map aligned with Google Earth

Fig. 5: Results of various methods using the *Campus* dataset that is gathered on the MIT campus. The red dot indicates the start and end location. The trajectory direction is clock-wise. LIOM is not shown because it fails to produce meaningful results.



(a) Trajectory comparison



(b) LIO-SAM map aligned with Google Earth

Fig. 6: Results of various methods using the *Park* dataset that i gathered in Pleasant Valley Park, New Jersey. The red dot indicate the start and end location. The trajectory direction is clock-wise.

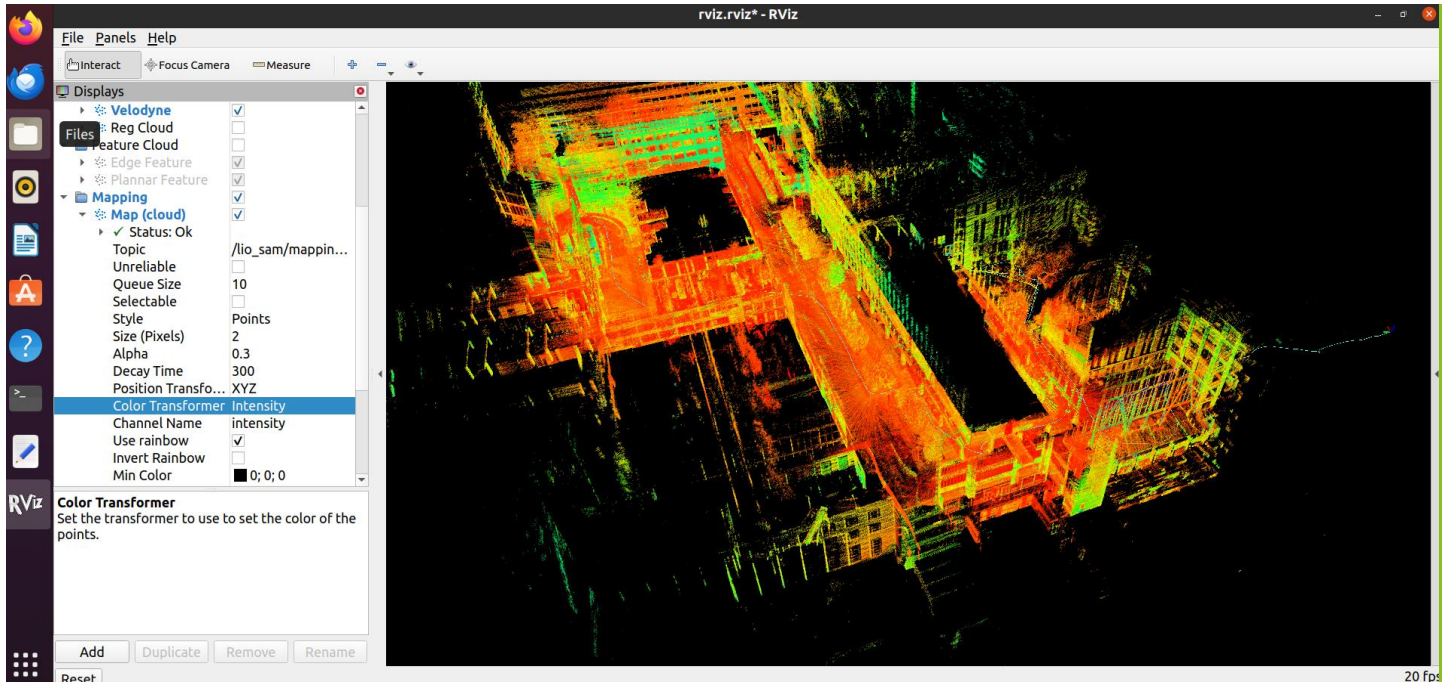
TABLE IV: Runtime of mapping for processing one scan (ms)

Dataset	LOAM	LIOM	LIO-SAM	Stress test
Rotation	83.6	Fail	41.9	13×
Walking	253.6	339.8	58.4	13×
Campus	244.9	Fail	97.8	10×
Park	266.4	245.2	100.5	9×
Amsterdam	Fail	Fail	79.3	11×

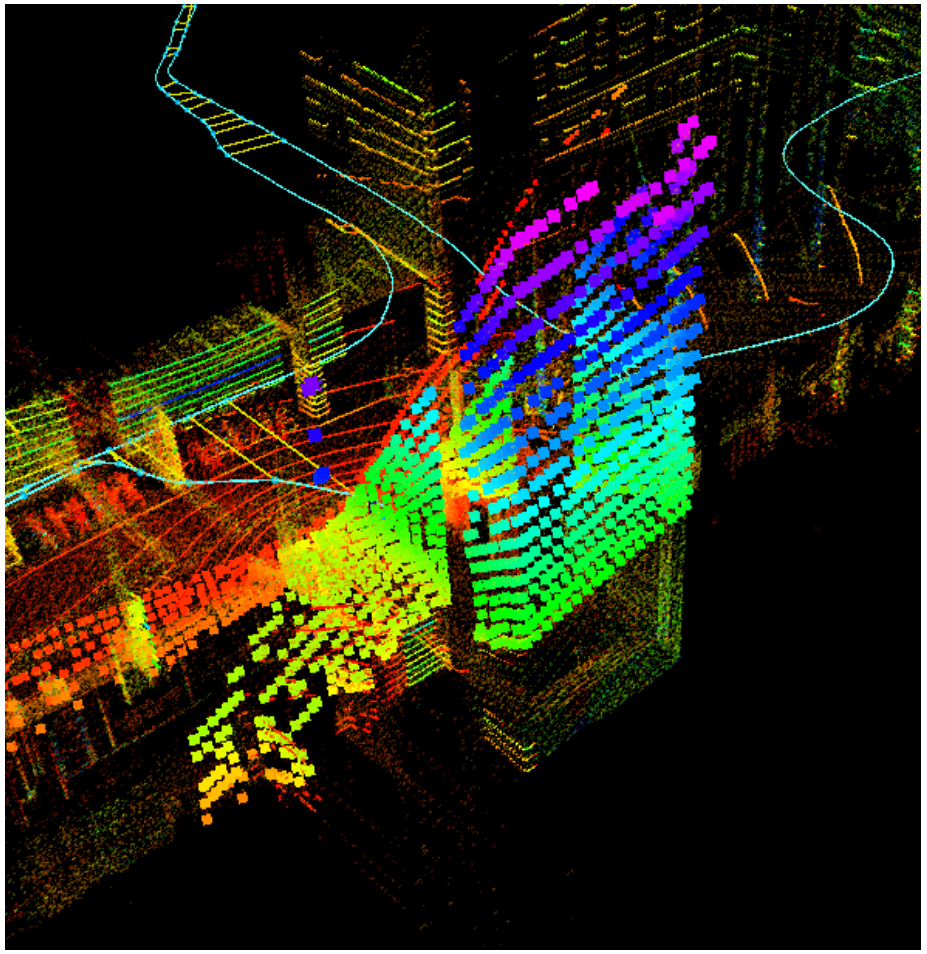
Progress made so far

Implementation

- Successfully implemented LIO-SAM for the KITTI dataset (*walking_data.bag*).
- Applied the loop closure.



Map of the MIT campus



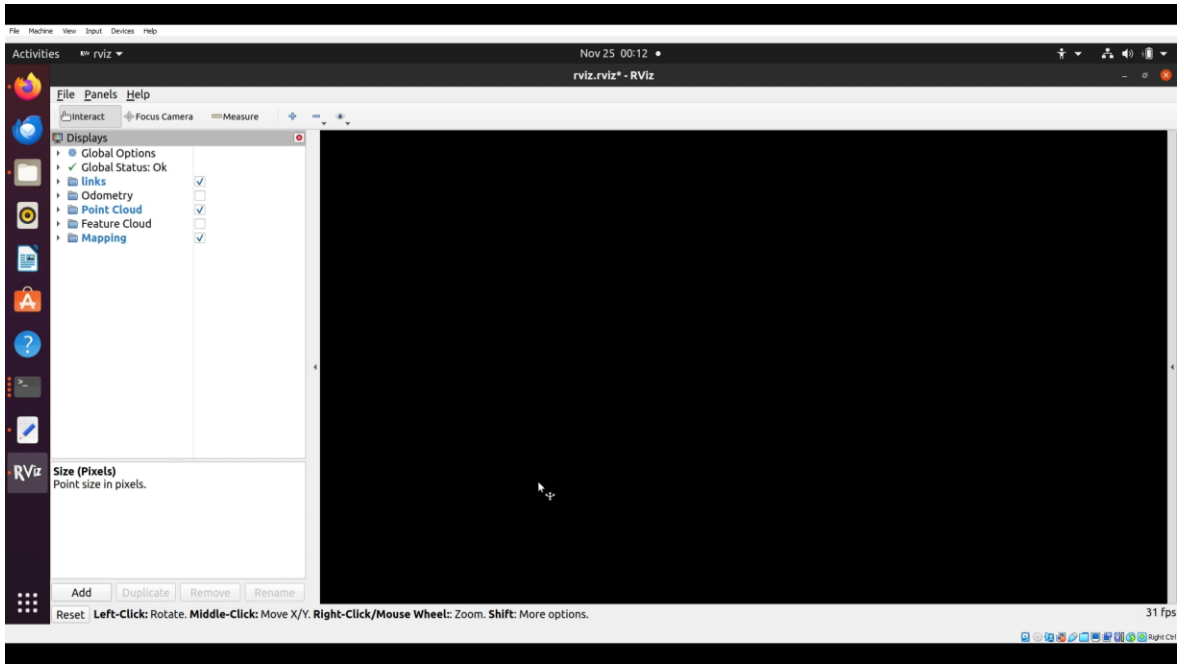
Loop closer and ICP working

Progress made so far

Data Collection

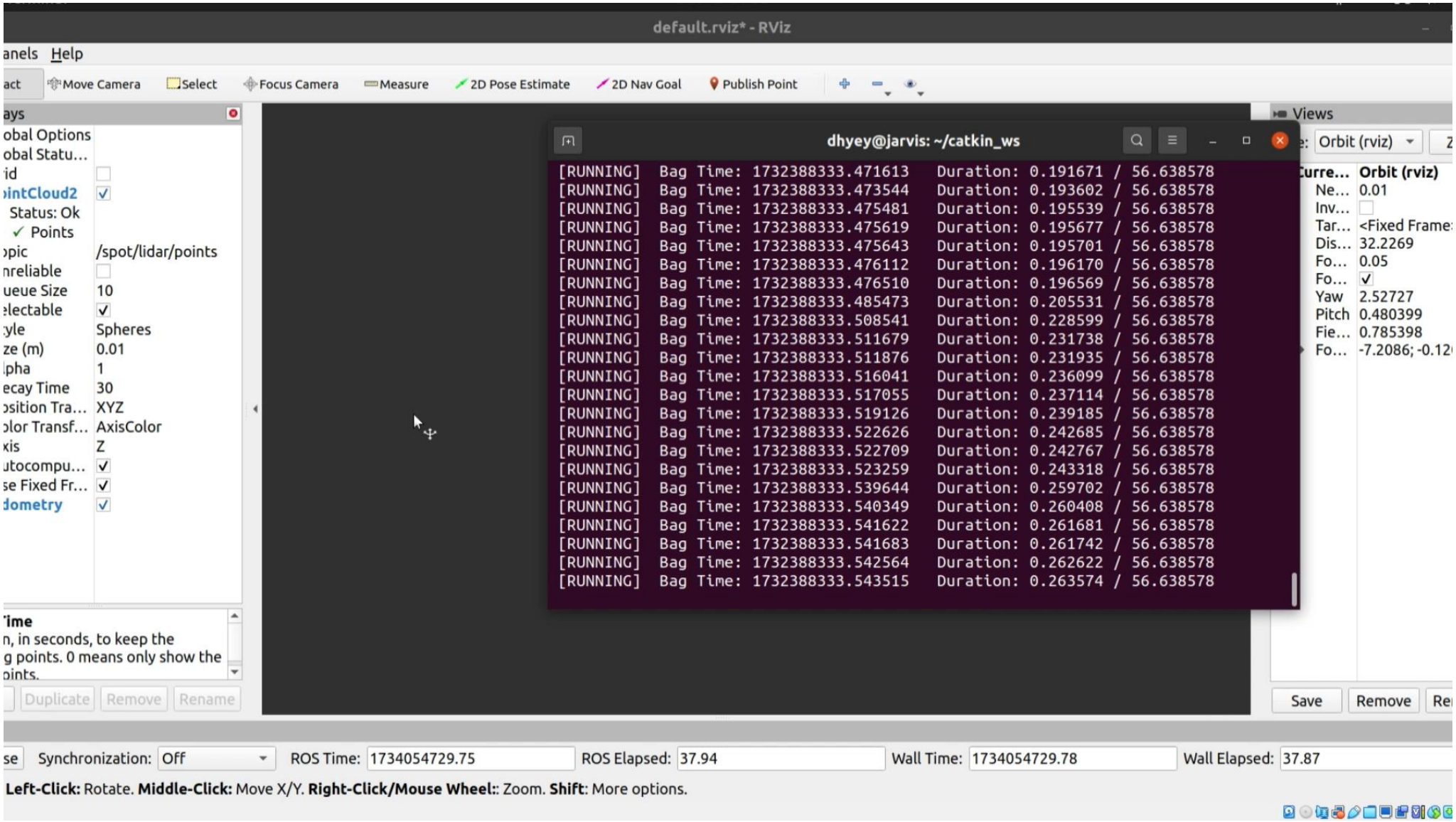
- Collected a trial dataset in the High Bay environment for further testing and validation.
- Got nice and clean point cloud data.

Mapping the High-bay with spot



Visualizing the map in Rviz

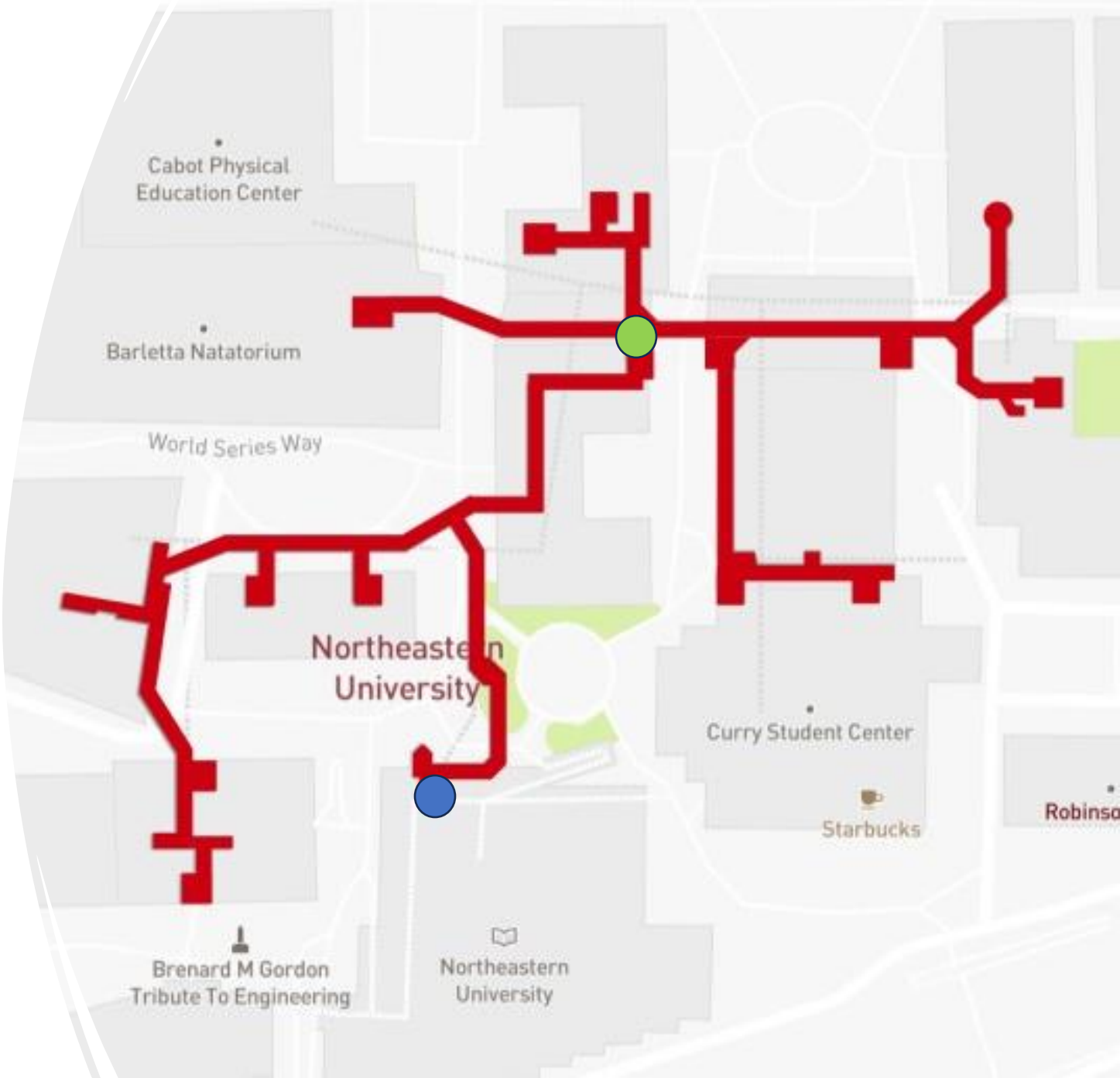
Progress made so far



[High-Bay Rviz Spot]

Future plan

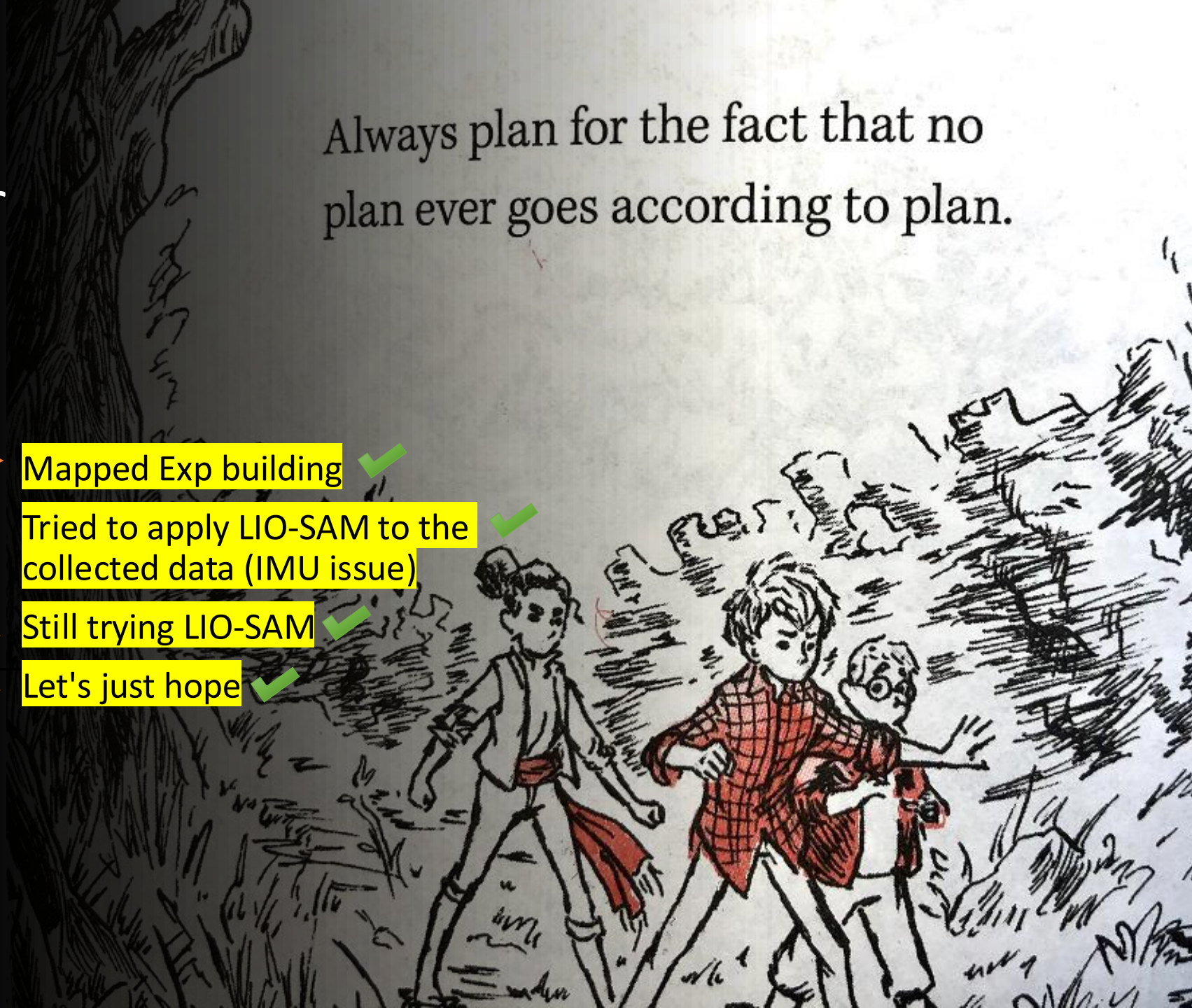
- Mapping NEU Tunnels
- Applying LIO-SAM to the collected data
- Applying Loop closer
- Trying multi floor mapping



Nothing went according to our Plan:

(It's part of learning)

- ~~Mapping NEU Tunnels~~ → Mapped Exp building ✔
- ~~Applying LIO-SAM to the collected data~~ → Tried to apply LIO-SAM to the collected data (IMU issue) ✔
- ~~Applying Loop closer~~ → Still trying LIO-SAM ✔
- ~~Trying multi floor mapping~~ → Let's just hope ✔



Further progress, Challenges and Outcomes:

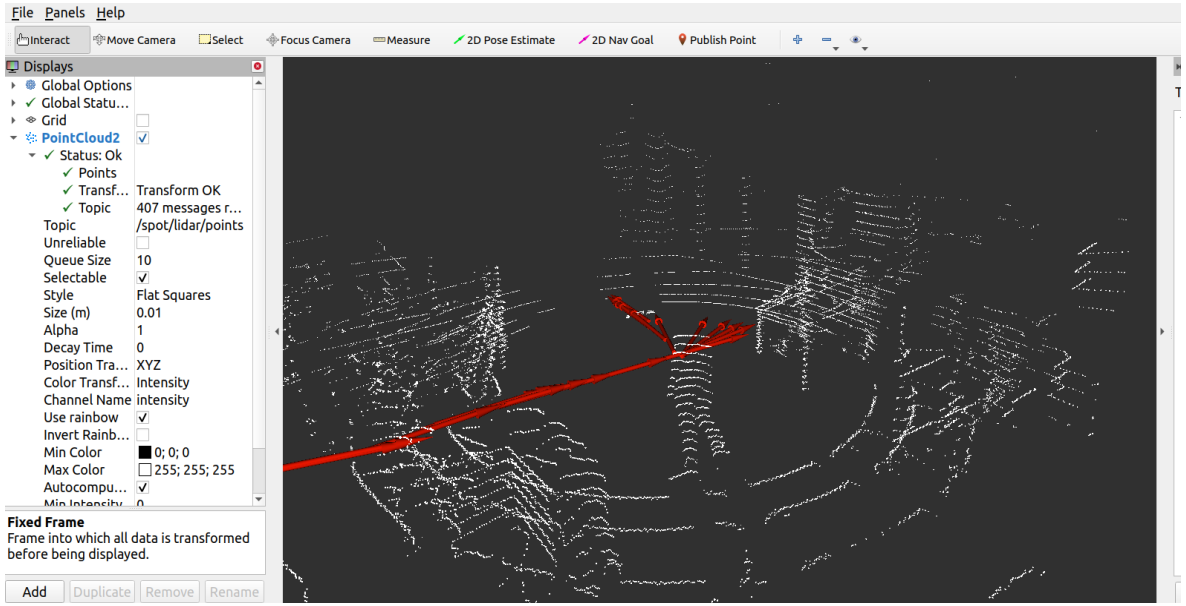
1. **Improved Understanding of LIO-SAM**:

   - We tried to dig in the algorithm code to find a workaround of IMU.

   - Also Tried to take the quaternions and modify it for our use.

```
/spot/depth/right/depth_in_visual/camera_info
/spot/dock/status
/spot/lidar/points
/spot/motion_or_idle_body_pose/status
/spot/navigate_route/status
/spot/navigate_to/status
/spot/odometry
/spot/odometry/twist
/spot/odometry_corrected
/spot/status/battery_states
/spot/status/behavior_faults
/spot/status/estop
/spot/status/feedback
/spot/status/feet
/spot/status/leases
/spot/status/metrics
/spot/status/mobility_params
/spot/status/motion_allowed
/spot/status/power_state
/spot/status/system_faults
/spot/status/wifi
/spot/trajectory/status
/spot/world_objects
/tf
/tf_static
dhyey@jarvis:~/catkin_ws$ s
```

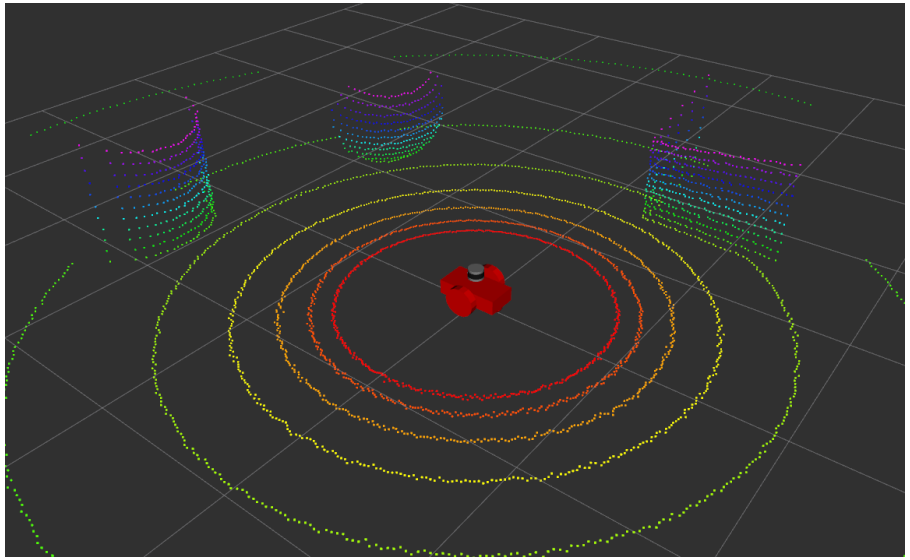
```
dhyey@jarvis:~/catkin_ws$ rosmsg info nav_msgs/Odometry
std_msgs/Header header
  uint32 seq
  time stamp
  string frame_id
string child_frame_id
geometry_msgs/PoseWithCovariance pose
  geometry_msgs/Pose pose
    geometry_msgs/Point position
      float64 x
      float64 y
      float64 z
    geometry_msgs/Quaternion orientation
      float64 x
      float64 y
      float64 z
      float64 w
  float64[36] covariance
geometry_msgs/TwistWithCovariance twist
  geometry_msgs/Twist twist
    geometry_msgs/Vector3 linear
      float64 x
      float64 y
      float64 z
    geometry_msgs/Vector3 angular
      float64 x
      float64 y
      float64 z
  float64[36] covariance
```



Challenges and Outcomes:

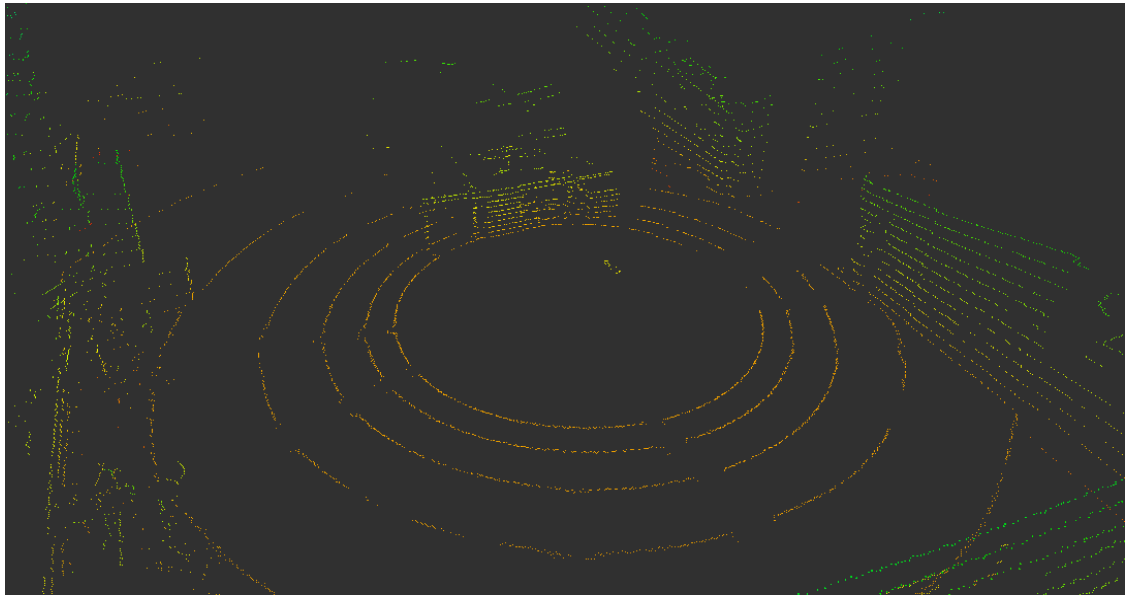
- Time_stamp issue (in our own custom driver).

- The ring and intensity data not present in the SPOT_IMU msg. (even though the rings were visible in rviz, Bottom RIGHT IMAGE)



```
dhyey@jarvis:~/catkin_ws$ rosmsg info sensor_msgs/PointCloud2
std_msgs/Header header
  uint32 seq
  time stamp
  string frame_id
uint32 height
uint32 width
sensor_msgs/PointField[] fields
  uint8 INT8=1
  uint8 UINT8=2
  uint8 INT16=3
  uint8 UINT16=4
  uint8 INT32=5
  uint8 UINT32=6
  uint8 FLOAT32=7
  uint8 FLOAT64=8
  string name
  uint32 offset
  uint8 datatype
  uint32 count
bool is_bigendian
uint32 point_step
uint32 row_step
uint8[] data
bool is_dense

dhyey@jarvis:~/catkin_ws$
```

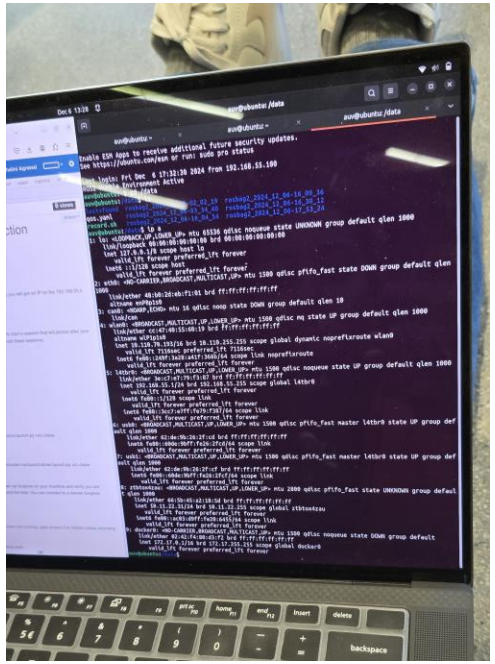


Further progress, Challenges and Outcomes:

2. Collected new Data with spot: (with new rig)

- We used new rig attached on spot with a separate jetson nano, lidar and vector nav IMU.

- We then took spot for a walk around the EXP building from High-Bay to a left & right loop, around and back.



EXP Spot Data Rec

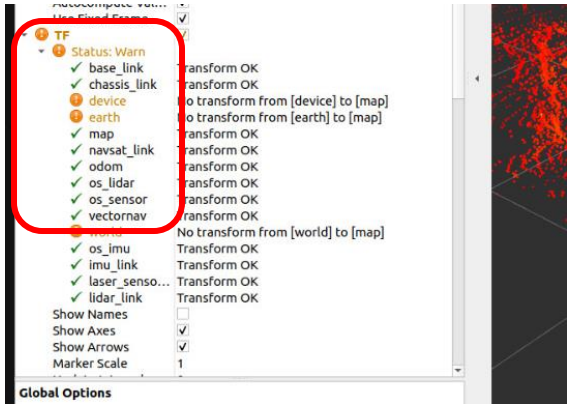
Challenges and Outcomes:

-Initially we were not able to convert ros2bag that was recorded to ros1bag for our LIO-SAM algorithm, but later we found the ros2 support of the LIO-SAM for ubuntu 22.04 ROS2 – Humble.

-We are getting errors in device and earth TF.

-The world and device TF is looping in itself.

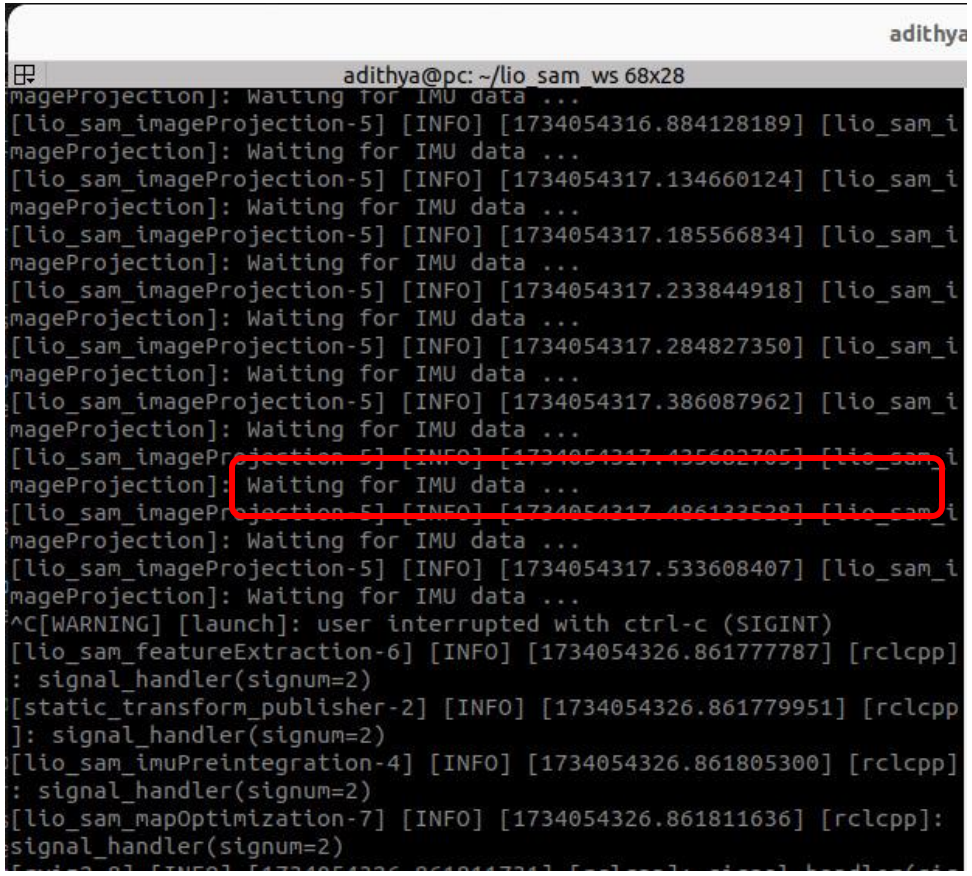
```
earth
└── map
    └── odom
        └── base_link
            ├── os_sensor
            │   ├── os_lidar
            │   └── os_imu
            ├── chassis_link
            │   ├── vectornav
            │   ├── navsat_link
            │   └── imu_link
            │       └── laser_sensor_frame
            └── lidar_link
```

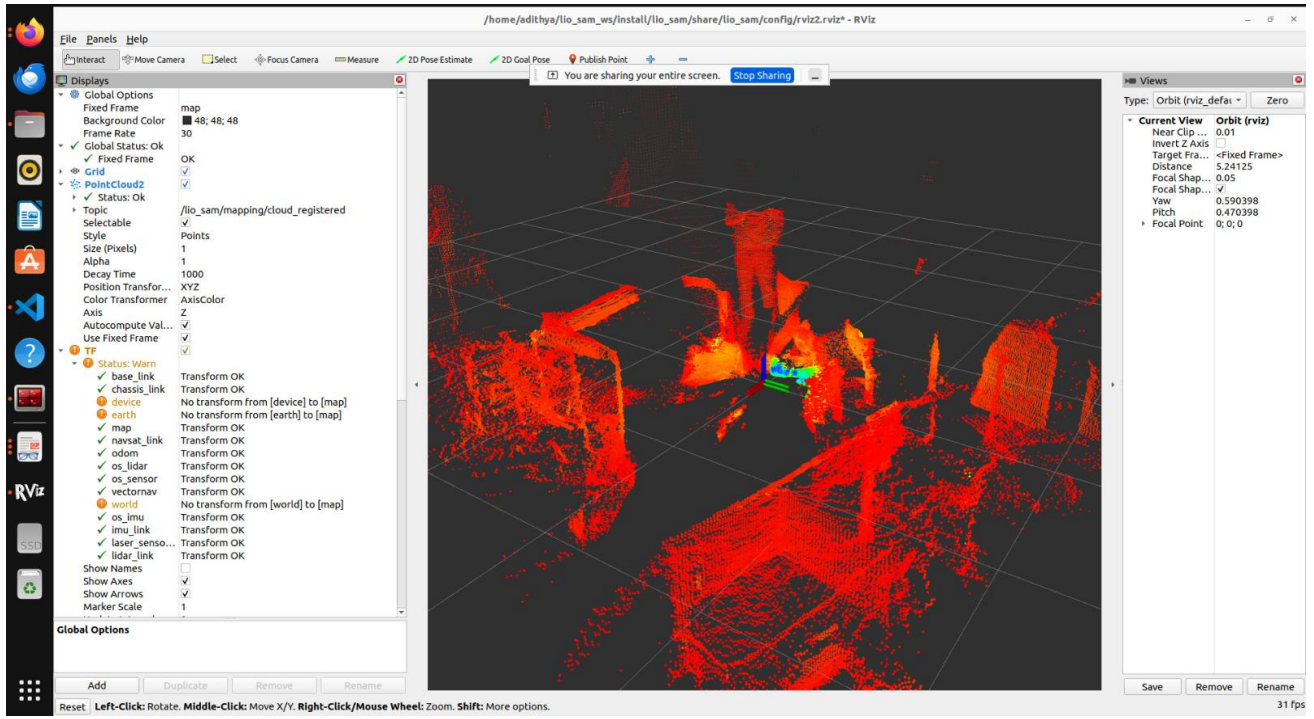


Challenges and Outcomes:

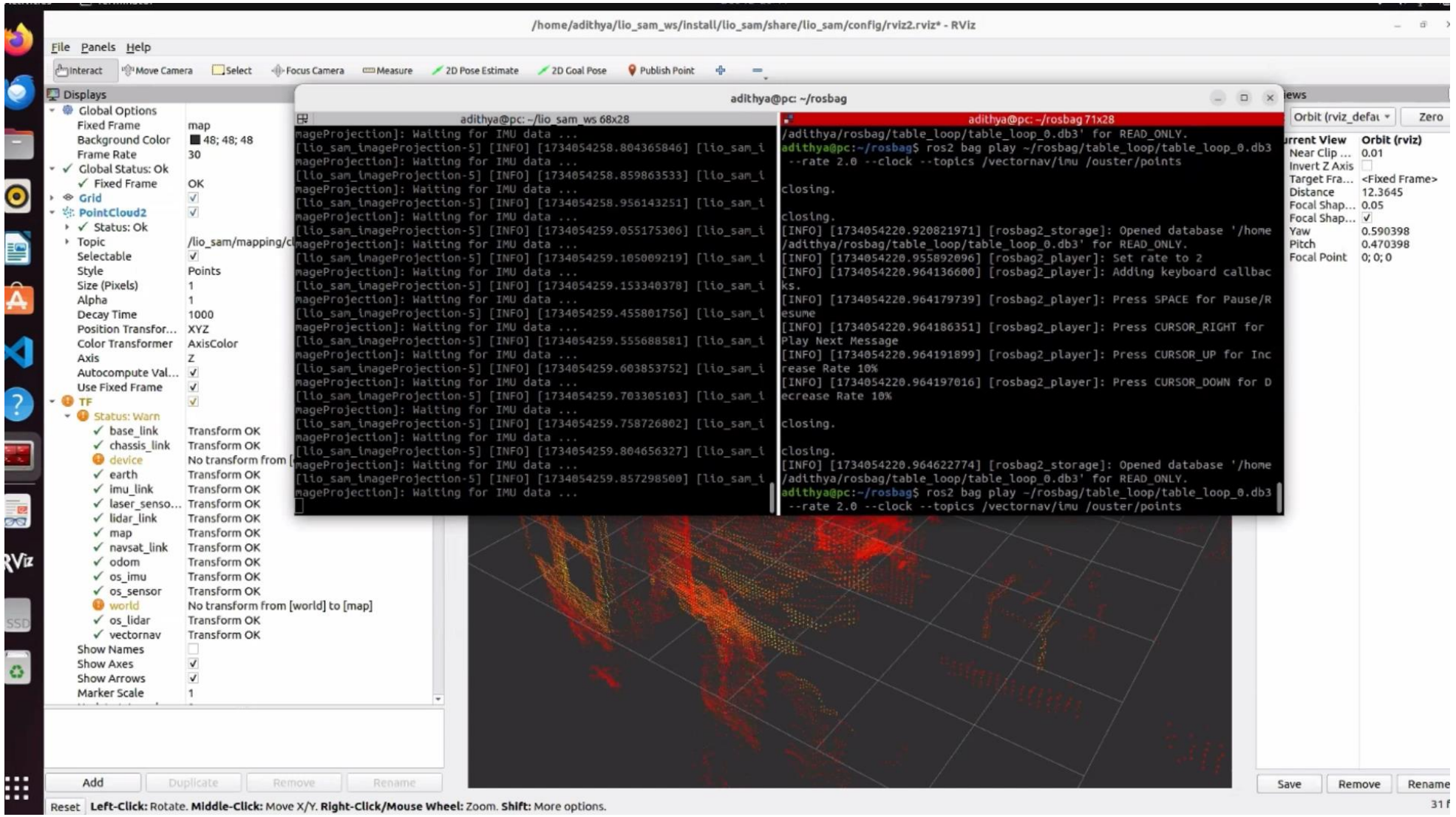
- Since the LIO-SAM is been tested in Microstrain IMUs since we are using vectornav the LIO-SAM package is not able to receive the data properly

- On the left image it can be seen that, there is no IMU data, and it shows "waiting for IMU data … "





Challenges and Outcomes:

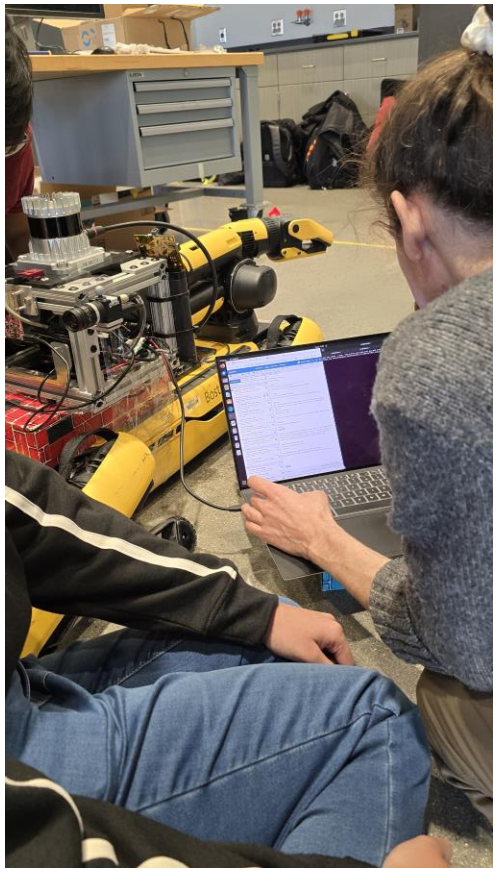


[Spot new Test rig Data Rviz - ROS2]

Results and Discussion:

- Successfully implemented the LIO-SAM algorithm on the KITTI dataset of MIT buildings, demonstrating functional loop closure and mapping capabilities.
- Conducted data collection in the High Bay environment, producing high-quality point cloud data visualized effectively in Rviz.
- Resolved initial issues with converting ROS2 bags to ROS1 compatibility by utilizing LIO-SAM support on Ubuntu 22.04 with ROS2-Humble.
- Integrated a new rig on the Spot robot featuring a separate Jetson Nano, LiDAR, and VectorNav IMU. The system enabled thorough data collection across the EXP building and dynamic loops.

- Exploring the algorithm's internals improved the team's grasp of LIO-SAM's intricacies, including factor graph optimization and IMU integration.
- Modifications to quaternions for custom use cases demonstrated adaptability in problem-solving.
- The reliance on specific sensor configurations limits LIO-SAM's flexibility across diverse platforms. Future work could explore making the algorithm sensor-agnostic.
- Expanding tests to multi-floor and tunnel environments is necessary to validate real-world applicability.
- Despite the challenges, this work highlights the robustness and potential of LIO-SAM for dynamic, GPS-denied environments, paving the way for refined 3D localization and mapping solutions.



Any questions?

References:

- https://github.com/TixiaoShan/LIO-SAM?tab=readme-ov-file
- T. Shan, B. Englot, D. Meyers, W. Wang, C. Ratti, and D. Rus, "LIO-SAM: Tightly-coupled Lidar Inertial Odometry via Smoothing and Mapping"
- https://drive.google.com/drive/folders/1ofWXLbhqu4m_-7foQu_30O7dn41ErS4w?usp=sharing

(The above link is our drive link for Spot data)

Northeastern University

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