Sensor-Based Spatial Intelligence

Comparison of Low-Cost Odometry for Mobile Robot in Various Indoor Environments

SF4

INDEX

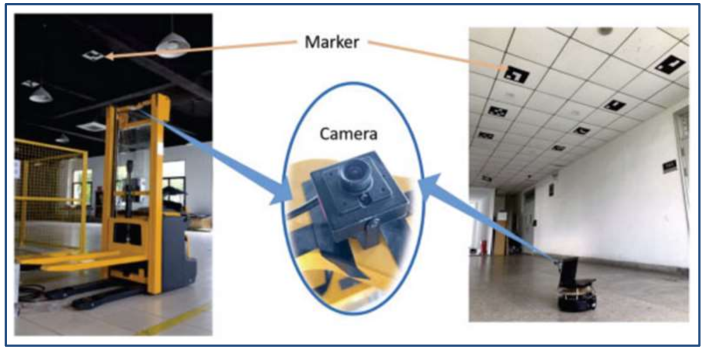
Our contents

1. Introduction

How about indoor SLAM???

We can't use GPS in the indoor environment.

What could replace GPS for high-accuracy pose estimation in the indoor environment?



Ceiling Markers

Magnetic Guide

→ **high-cost and difficult to maintain**

1. Introduction

What's the most reasonable solution?

low-cost sensors

various indoor environments

1. Introduction

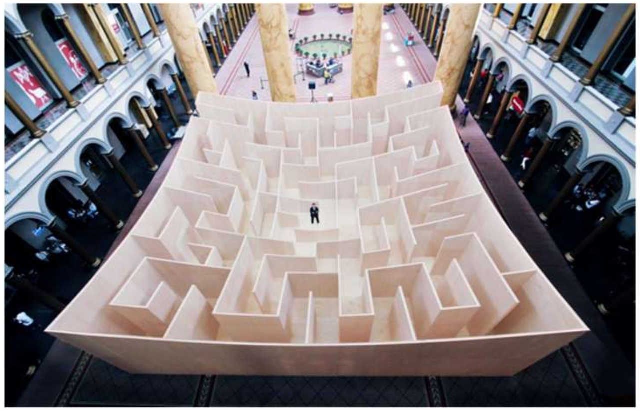
Combinations for Low-cost Sensor Fusion

- Wheel Encoder Only
- RGB-D Camera Only
- Monocular Camera Only
- 2D LiDAR Only
- 2D LiDAR + IMU
- Wheel Encoder + IMU
- Wheel Encoder + IMU + 2D LiDAR
- Wheel Encoder + IMU + RGB-D Camera
- Wheel Encoder + IMU + 2D LiDAR + RGB-D Camera

What sensor combination has the highest performance about cost-effectiveness in a given environment?

1. Introduction

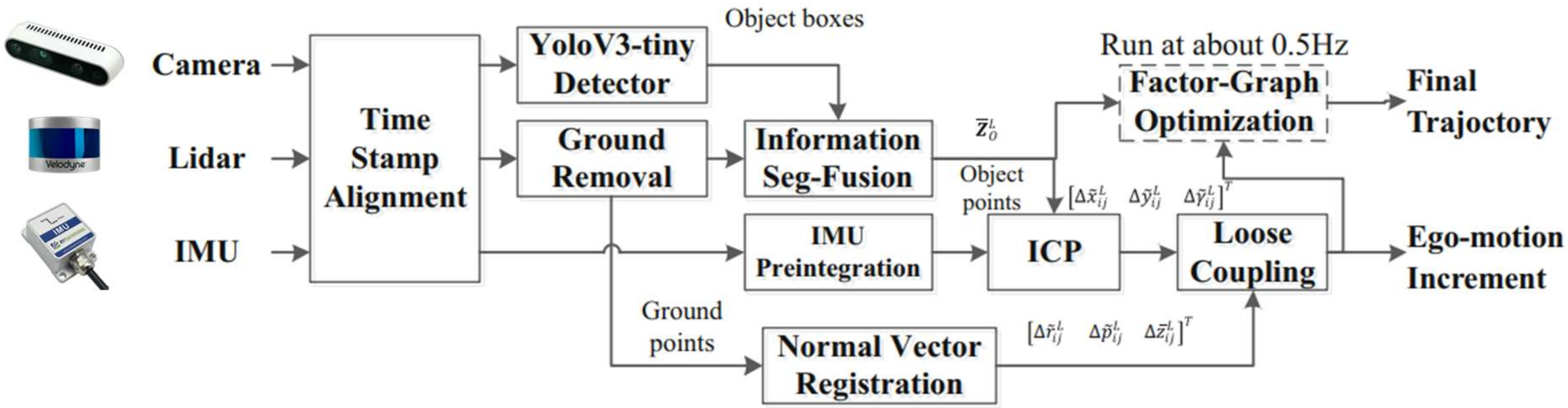
Multiple environments for experiments

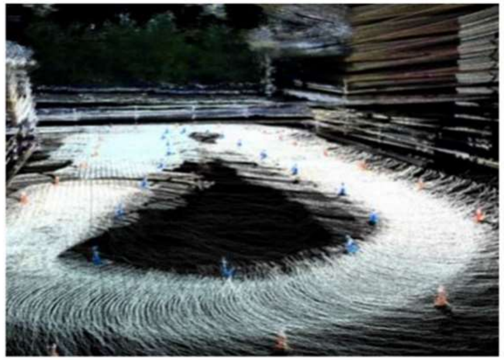


1. Introduction

Related Work1

Good performance , but high-cost odometry



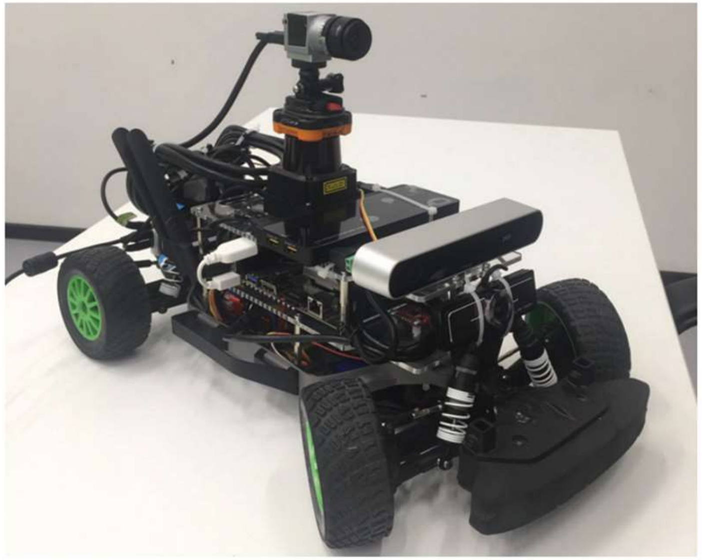


[1] W. Peng, Y. Ao, J. He, and P. Wang, "Vehicle Odometry with CameraLidar-IMU Information Fusion and Factor-Graph Optimization," Journal of Intelligent Robotic Systems, vol. 101, no. 4, Apr. 2021.

1. Introduction

Related Work2

PARAMETERS	CONFIGURATION
Chassi	4WD Traxxas #74076
Hardware	Jetson TX1
Processor	Quad ARM A57
GPU	NVIDIA Maxwell
RAM	4 GB
Sensors	
Lidar	Hokuyo UTM-30LX
Camera	Basler acA1300-200uc
Stereo camera	ZED camera
Software	
JetPack	3.1
OS	Ubuntu 16.04
ROS	Kinetic Kame



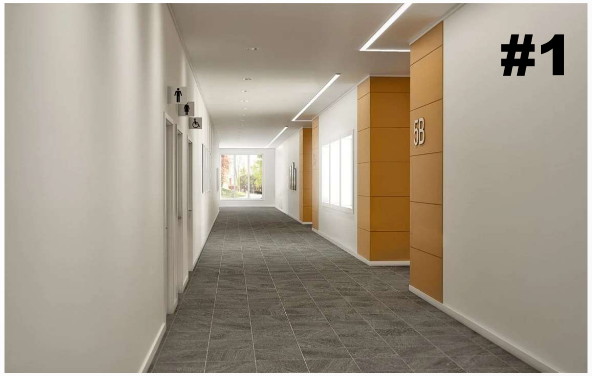
Comparison of results in the same environment. However, we compare in various environments.

[2] M. Filipenko and I. Afanasyev, "Comparison of Various SLAM Systems for Mobile Robot in an Indoor Environment," in 2018 International Conference on Intelligent Systems (IS), 2018.

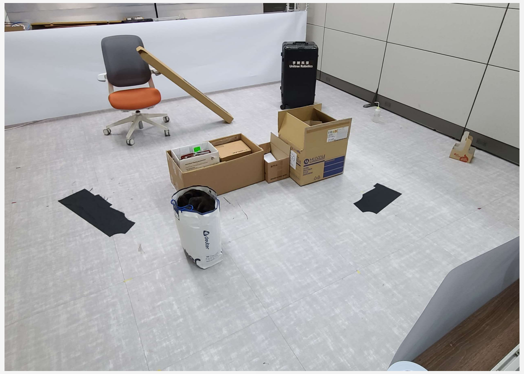
2. Methodology

Consideration factor

- Number of features



Not Many Feature!



Many Feature!

2. Methodology

Consideration factor

- Presence of the moving person (dynamic or static object)

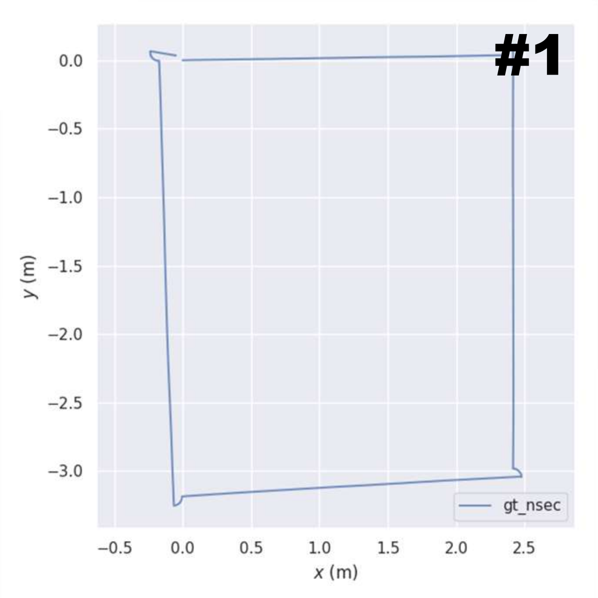
With Static Object

With Dynamic Object

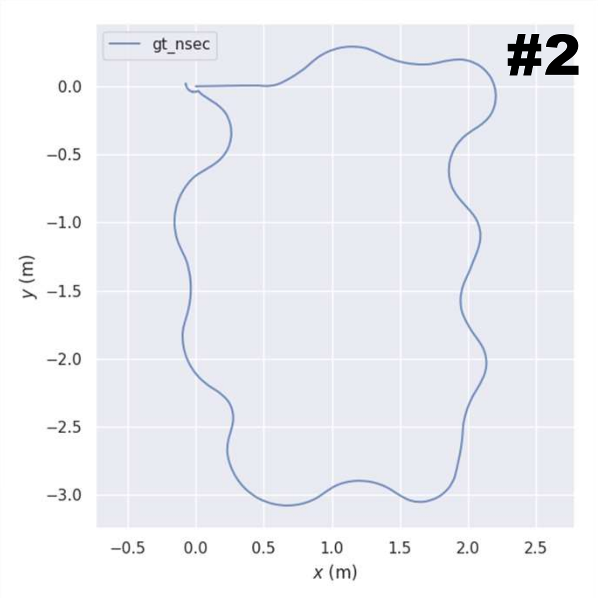
2. Methodology

Consideration factor

- Straight / Zig-Zag trajectory



Straight



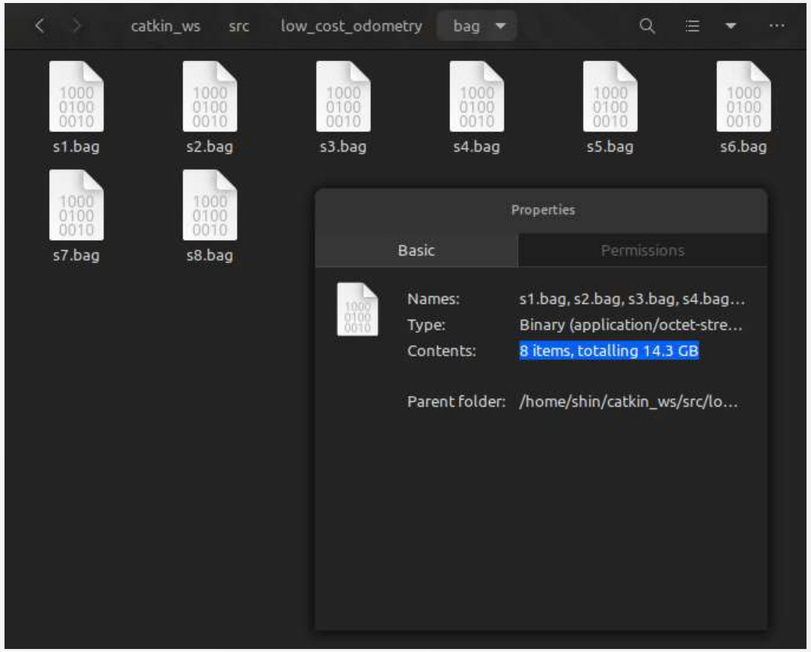
Zig-Zag

2. Methodology

8 Indoor Environment Scenarios

Office (not many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**

Living Room (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**
S5	**S6**	**S7**	**S8**



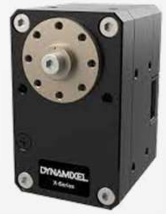
Our Dataset

2. Methodology

Mobile robot platform

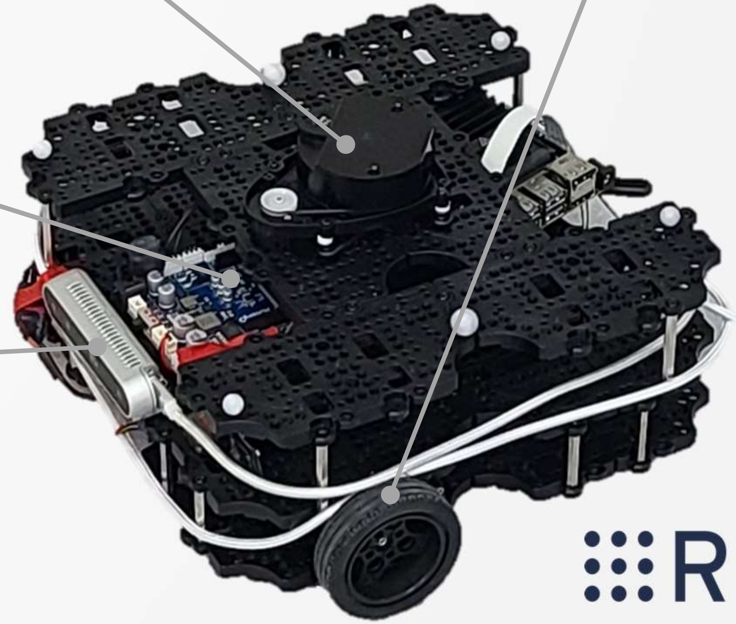
IMU
MPU9250

2D LiDAR sensor
LDS-01



Encoder
XM430-W210

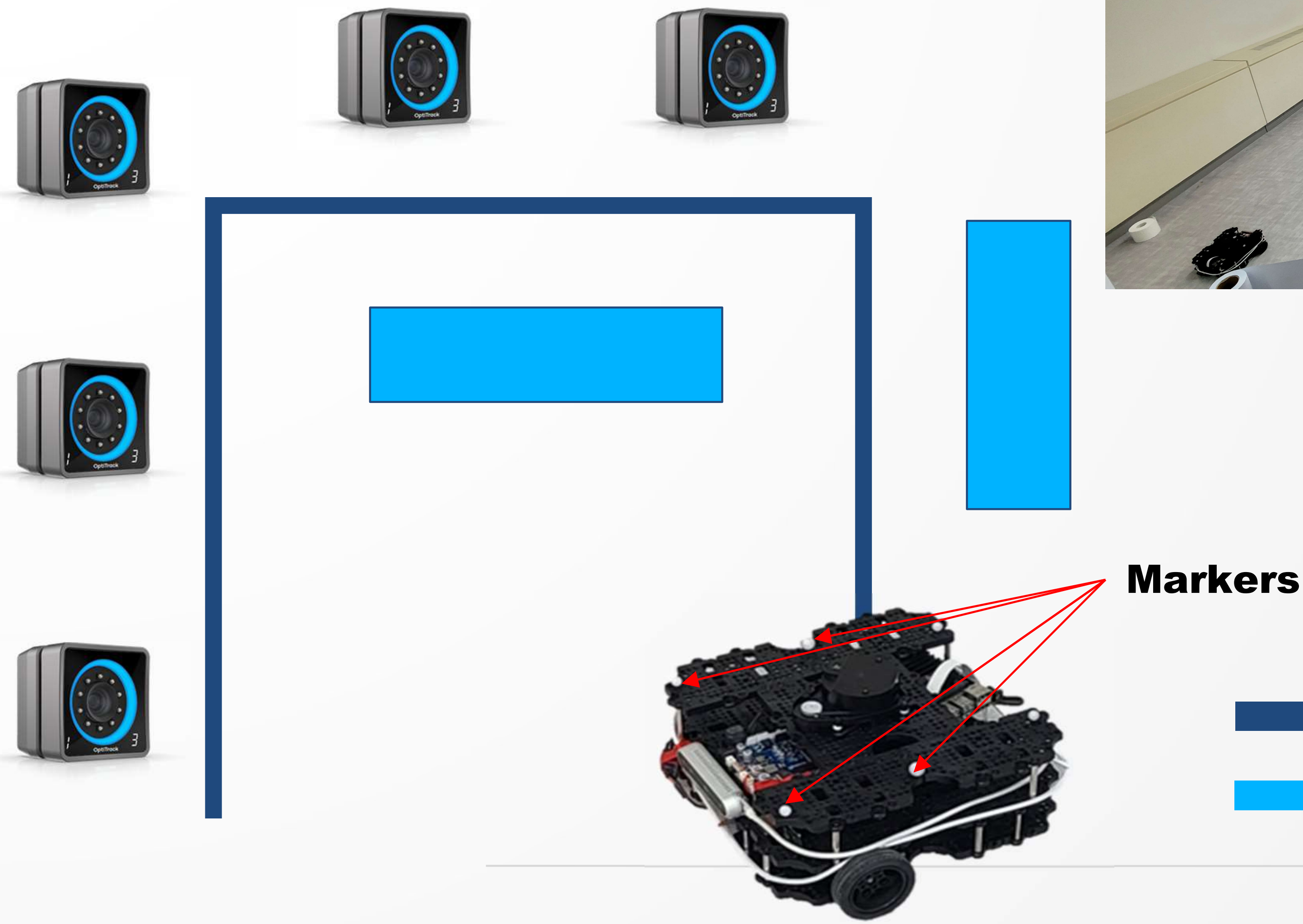
RGB-D camera
RealSense D415



ROS

TurtleBot 3 Waffle Pi

2. Methodology

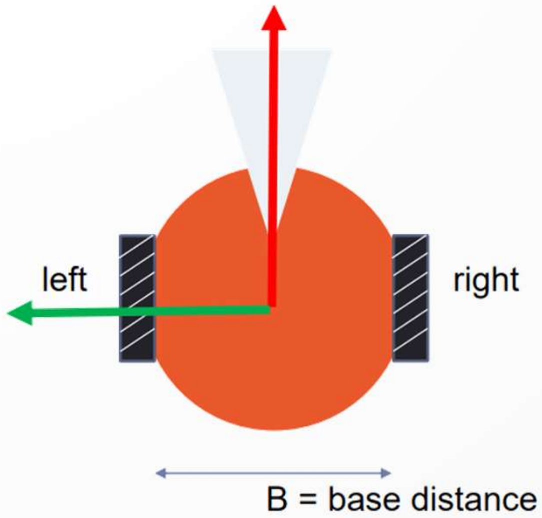



Test environment

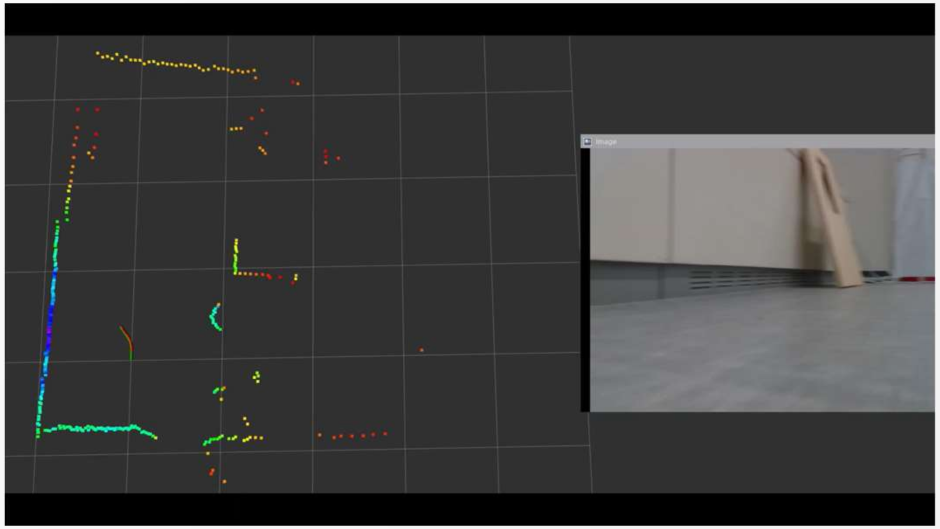
2. Methodology

Wheel Odometry Only

- Distance from each wheel d_R, d_L



$$\begin{aligned}\Delta x &= \frac{d_R + d_L}{2} \\ \Delta\theta &= \frac{d_R - d_L}{B}\end{aligned}$$



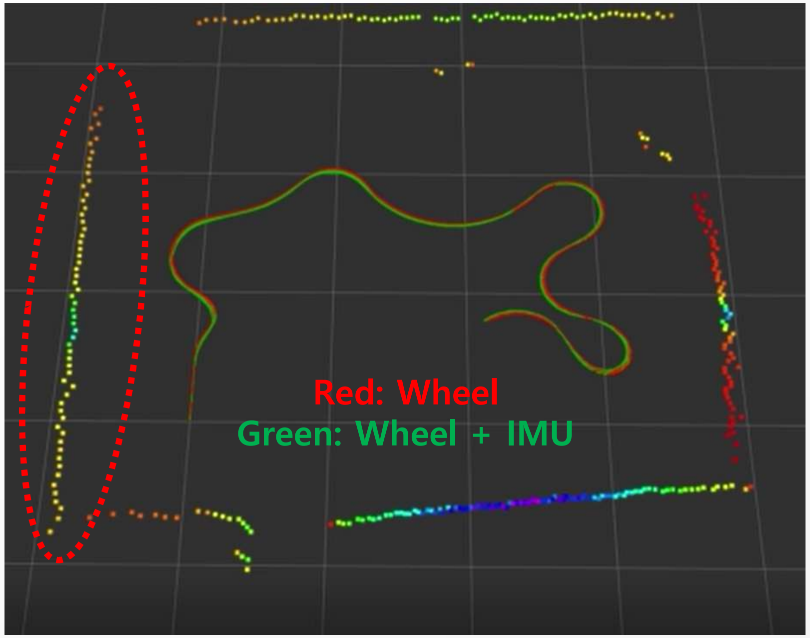
Odometry of two-wheeled robot from wheel encoder (Diagram in prof. Ayoung Kim's lecture note)

2. Methodology

EKF (Wheel + IMU, Wheel)

- ✓ `ekf_localization_node` in ROS package `robot_localization`
- ✓ Combining wheel odometry and IMU sensor data using extended Kalman filter (EKF)

LiDAR sensor data
(not used in this method)

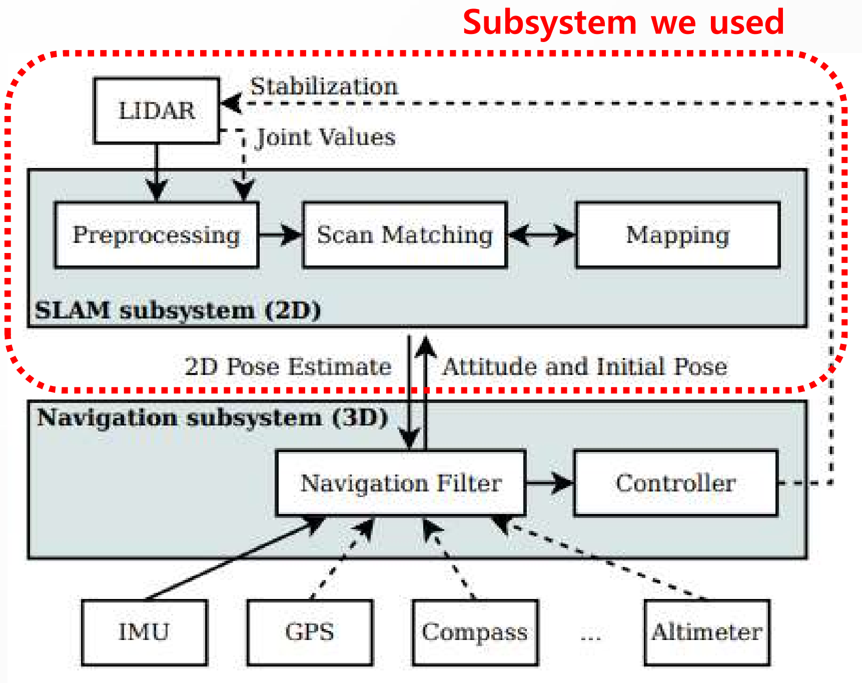


Visualization of wheel odometry and EKF result using rviz

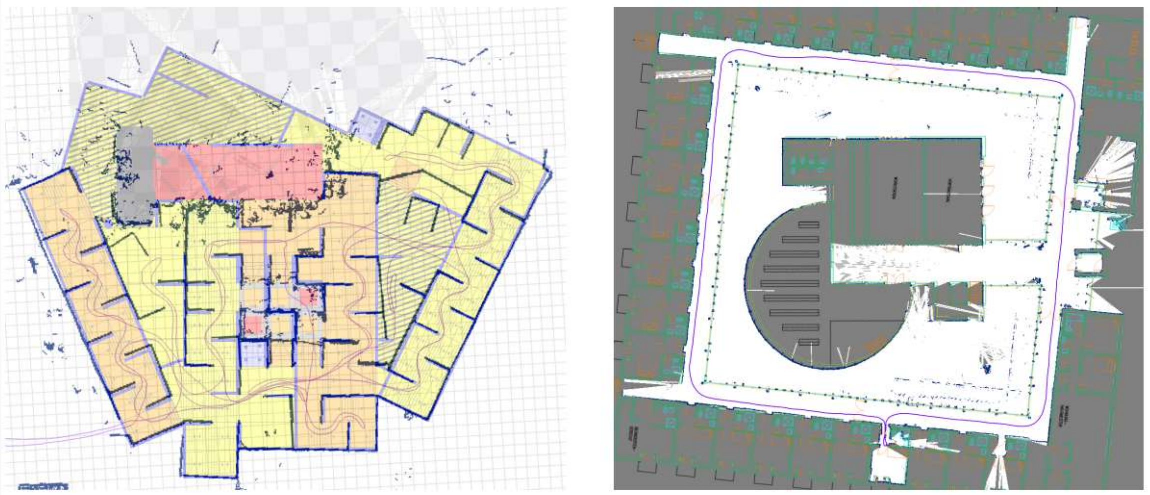
http://docs.ros.org/en/noetic/api/robot_localization/html/index.html

2. Methodology

Hector SLAM (LiDAR only)



Overview of SLAM and navigation system described in the paper



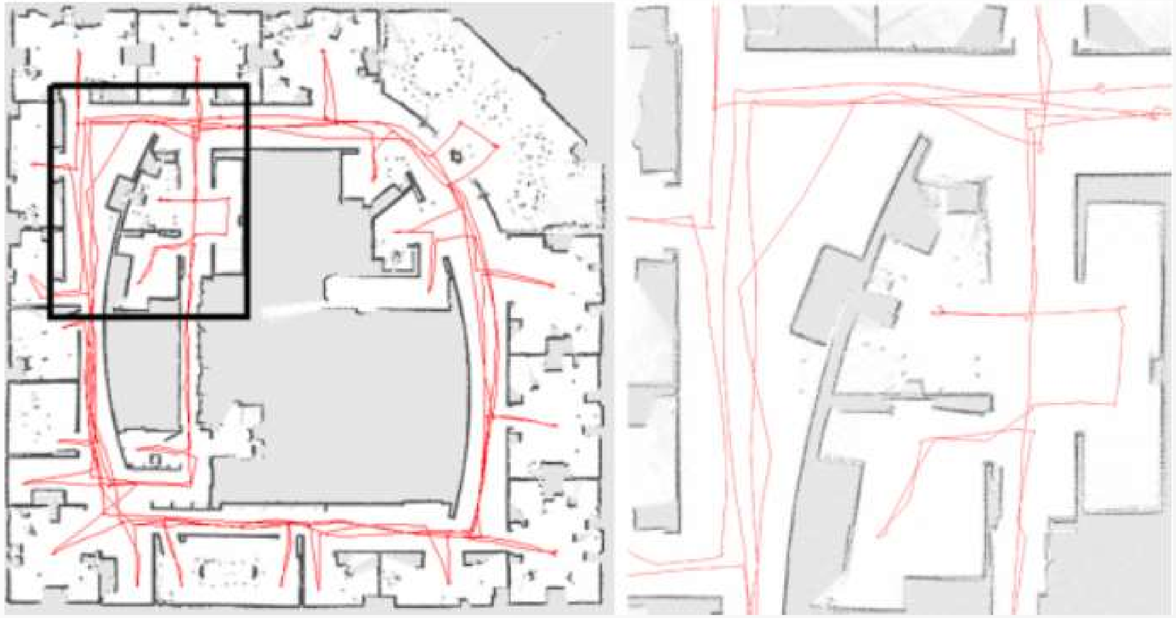
Learned map overlaid with ground truth

S. Kohlbrecher, O. von Stryk, J. Meyer and U. Klingauf, *2011 IEEE International Symposium on Safety, Security, and Rescue Robotics*, 2011, pp. 155-160

2. Methodology

Gmapping (Wheel + IMU + LiDAR)

- ✓ Build a grid map from 2D LiDAR scans with Rao-Blackwellized particle filter (RBPF)
- ✓ Effective sample size N_{eff} drops when loop closure detected (and resampling carried)



Gmapping experiment at the Intel Research Lab

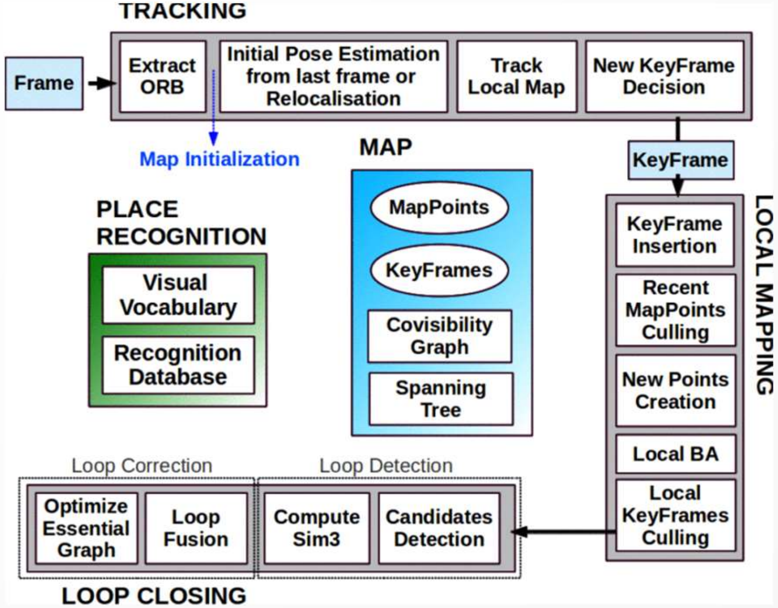
$$N_{\text{eff}} = \frac{1}{\sum_{i=1}^{N} \left(\tilde{w}^{(i)}\right)^2}$$

Definition of N_{eff}

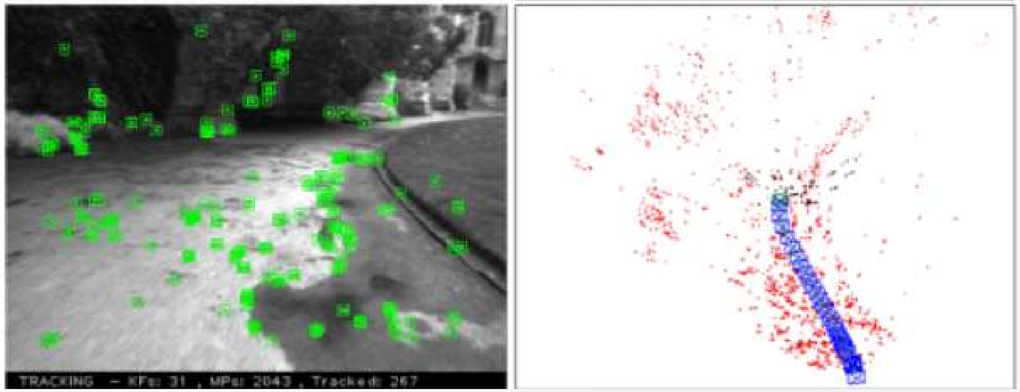
2. Methodology

ORB-SLAM2 (Monocular Camera Only)

- ✓ ORB (Oriented FAST and Rotated BRIEF) feature-based real-time SLAM system
- ✓ ORB-SLAM2: Compatible with monocular, stereo, and RGBD camera



Overview of ORB-SLAM system

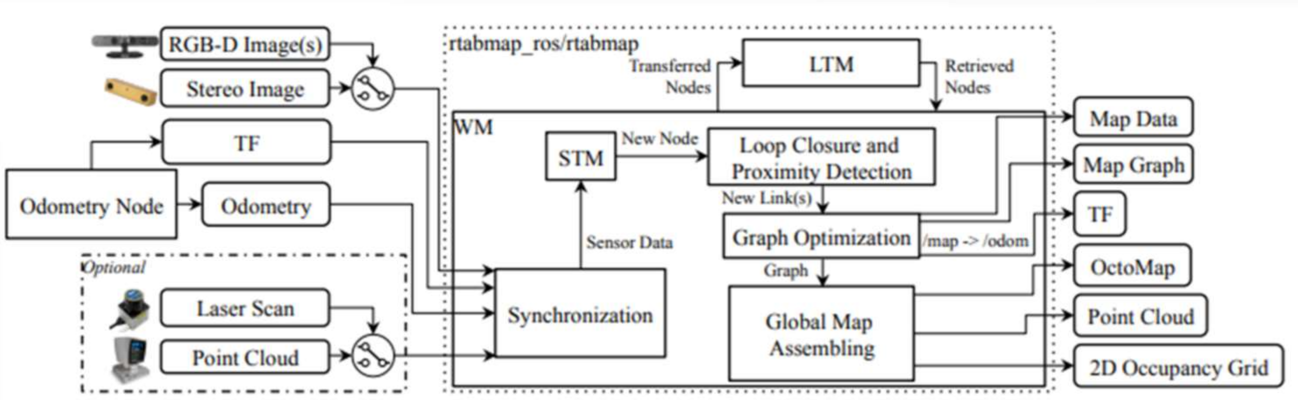


Example of ORB-SLAM Initialization

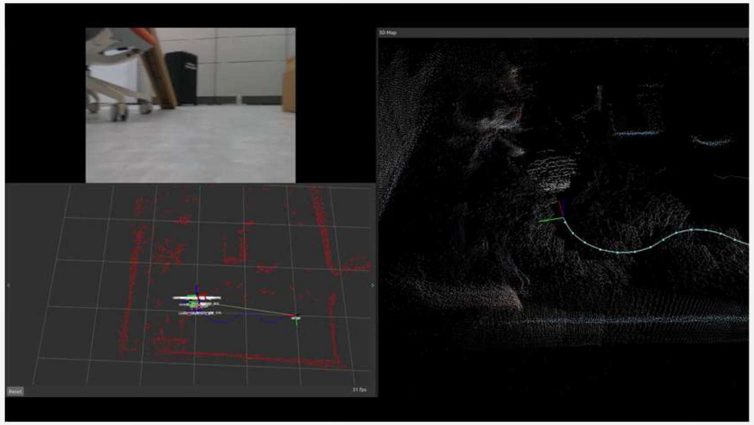
2. Methodology

RTAB Map

- ✓ 'Real-Time Appearance-Based Mapping' with various sensor inputs
- ✓ GFTT feature detection for RGBD images, loop closure using the bag-of-words approach
- ✓ 4 combinations used: RGBD only, Wheel+IMU+RGBD, LiDAR+RGBD, Wheel+IMU+LiDAR+RGBD



Block diagram of *rtabmap* ROS node



***rtabmap* in our dataset**

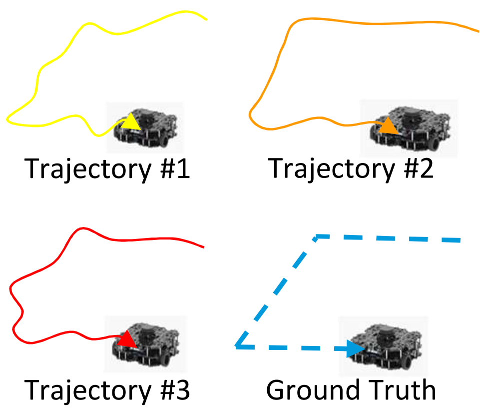
Labbé, M, Michaud, F., *J Field Robotics.* **35** (2019) 416-446

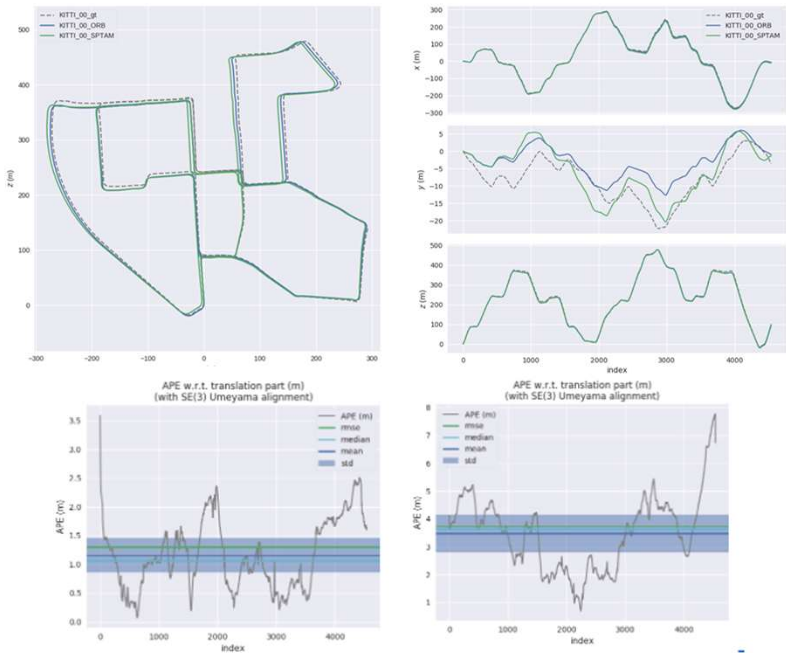
2. Methodology

Evaluation Method

EVO

a python-based toolkit to visualize and compare trajectory results
Sensor fusion methods will be evaluated in different environments



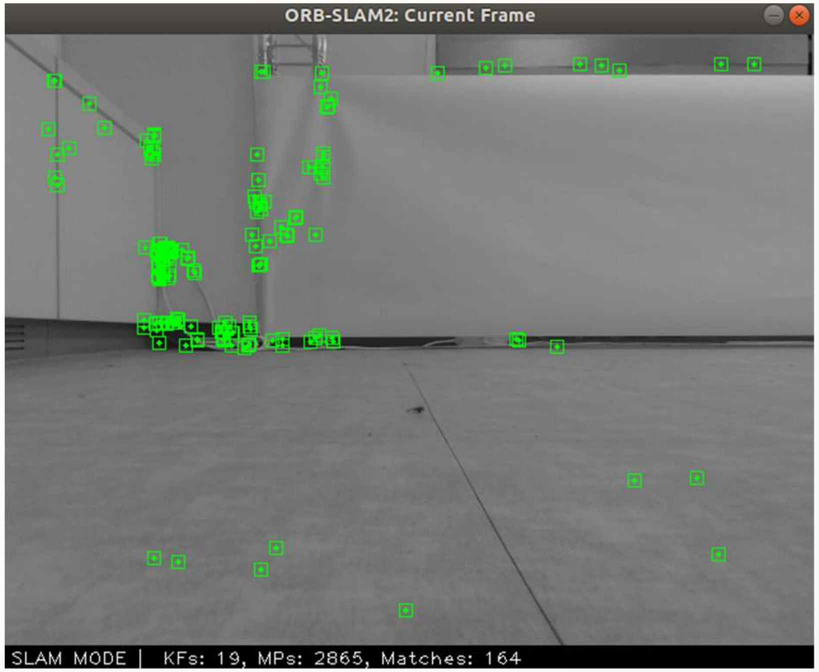


https://github.com/MichaelGrupp/evo

3. Results

Track Loss in Monocular Only(ORB-SLAM2)

✓ When the robot rotates at the corner, the algorithm does not recognize the feature.

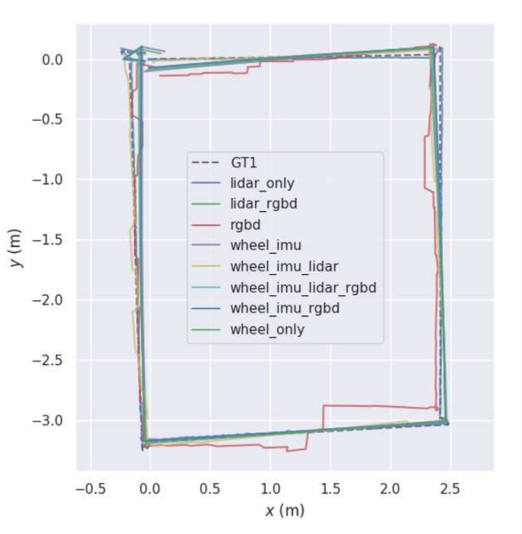


Detect proper features

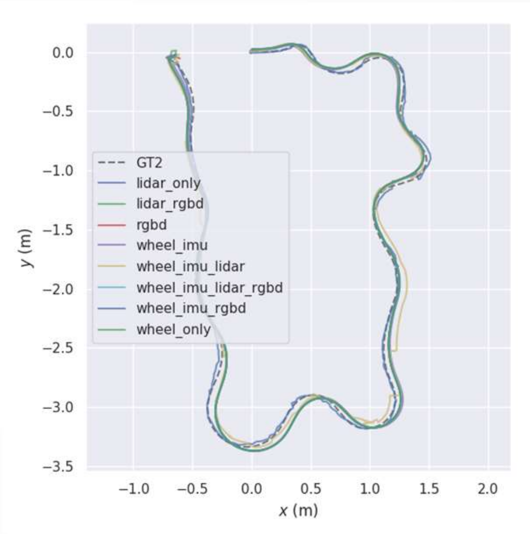
Motion Blur with Rotation

3. Results

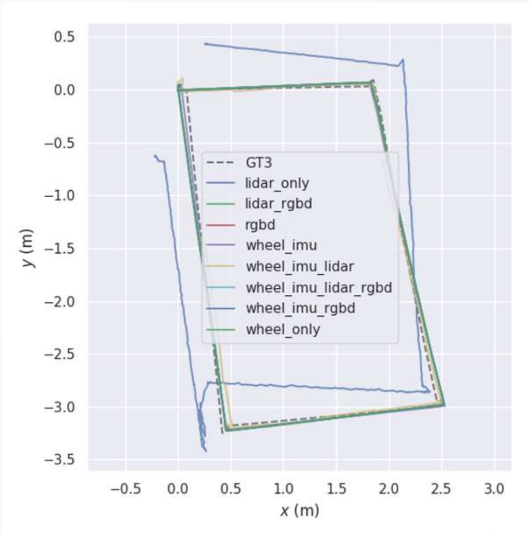
Ground Truth and Estimated Trajectory Results – <u>**Office**</u> scenarios (S1 ~ S4)



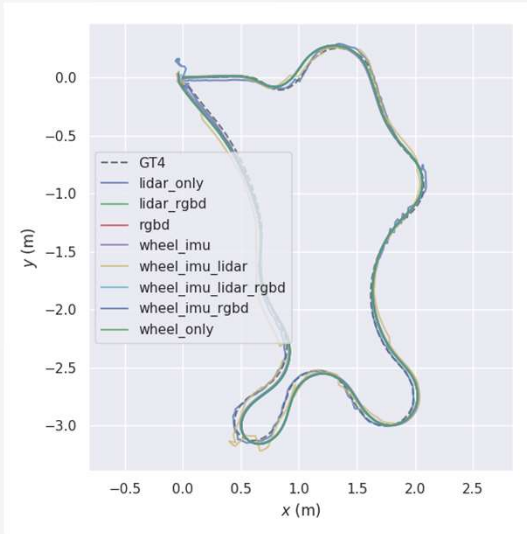
S1



S2



S3

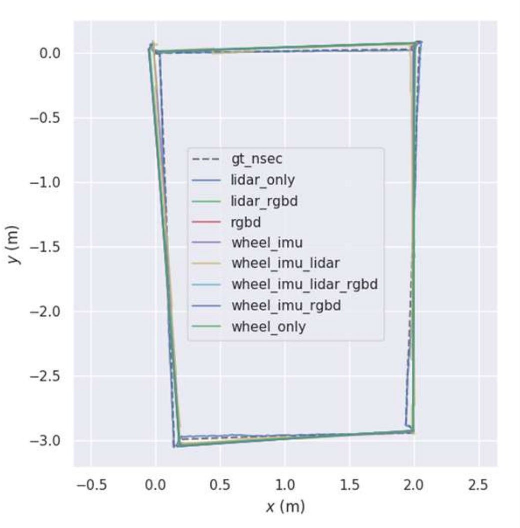


S4

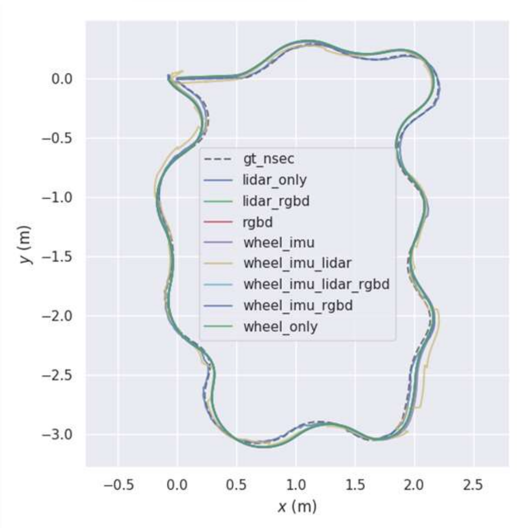
<u>**Office**</u> (Not many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**

3. Results

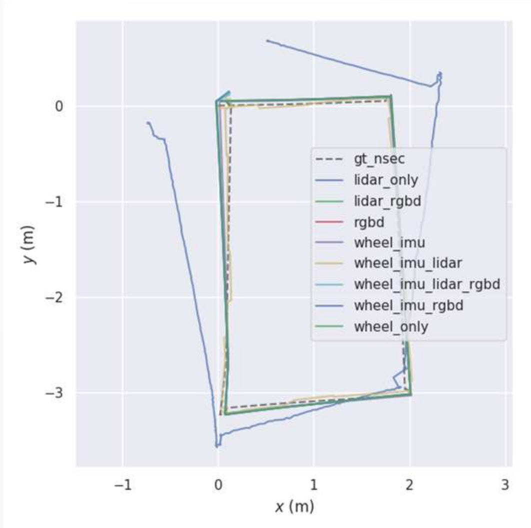
Ground Truth and Estimated Trajectory Results – **Living Room** scenarios (S5 ~ S8)



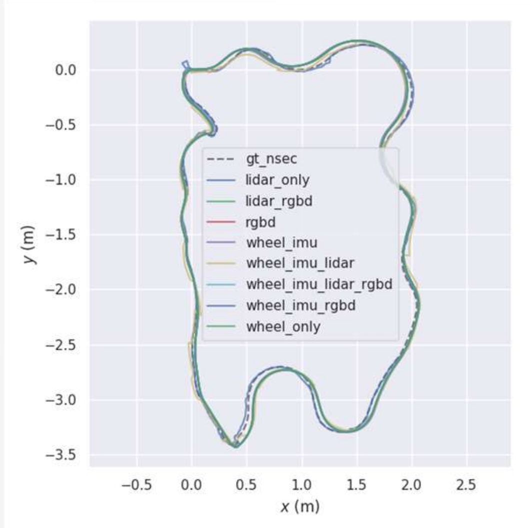
S5



S6

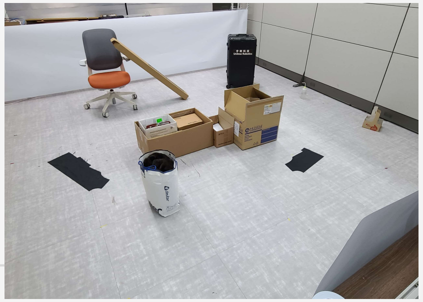


S7



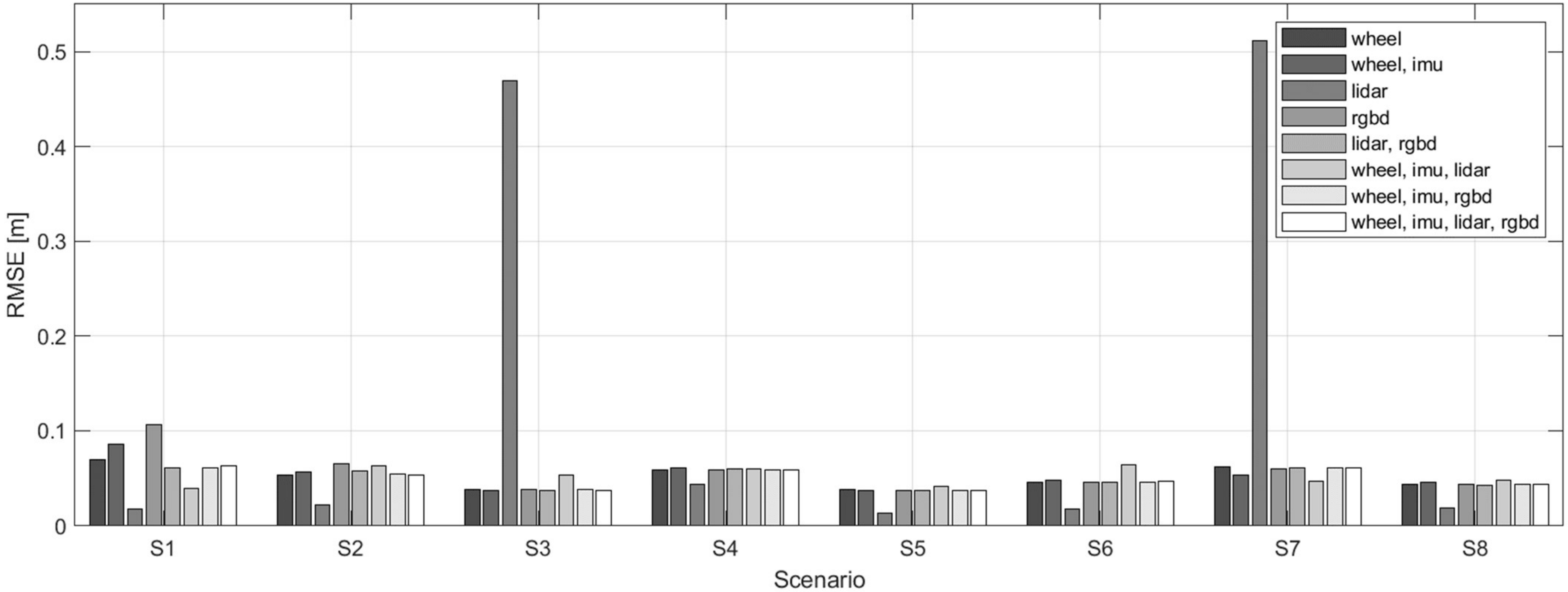
S8

Living Room (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**
S5	**S6**	**S7**	**S8**



3. Results

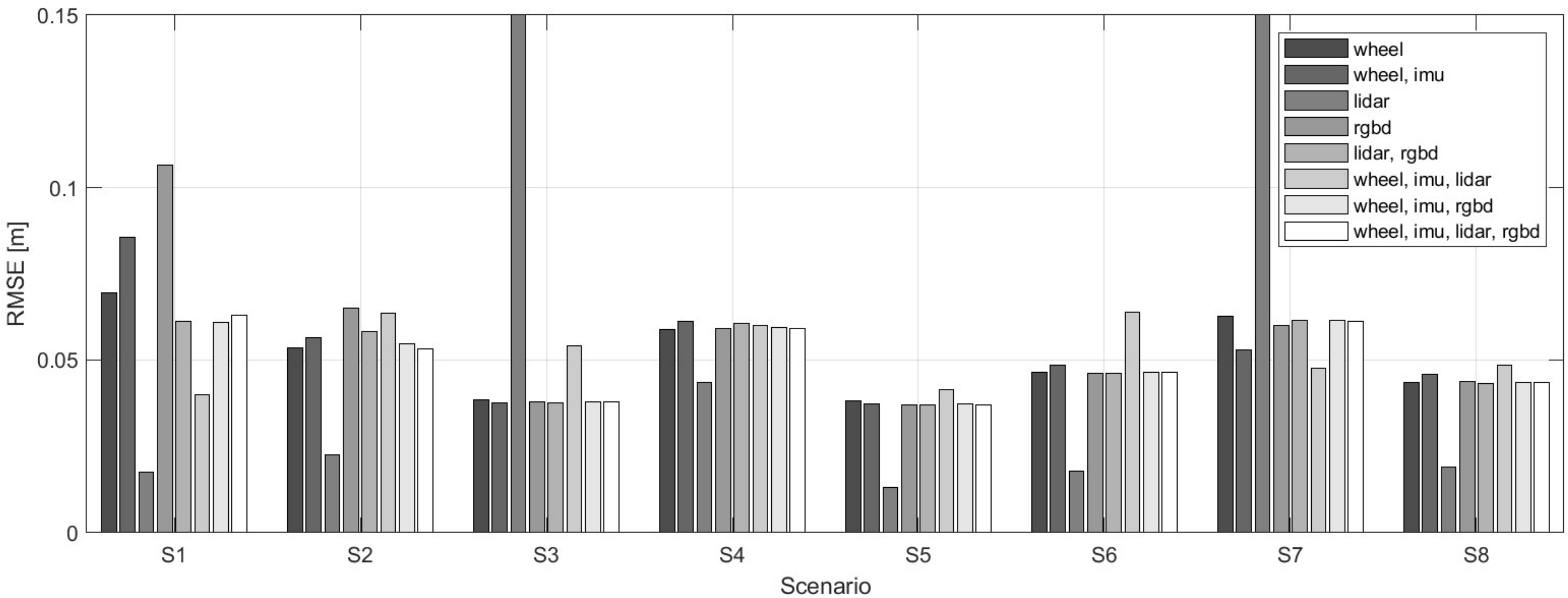
RMSE results of Absolute Pose Error(APE)



Office (not many feature)				**Living Room** (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)		**No Human** (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**

3. Results

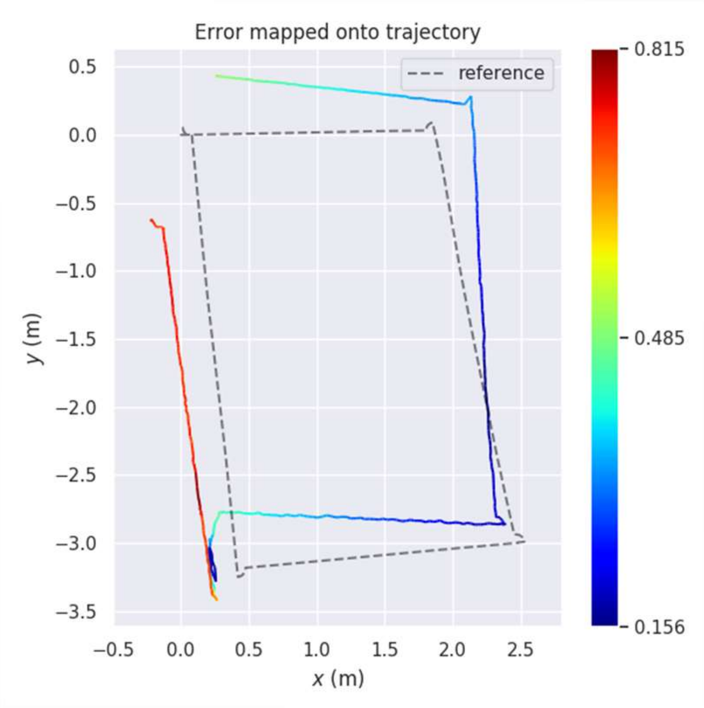
RMSE results of Absolute Pose Error(APE)

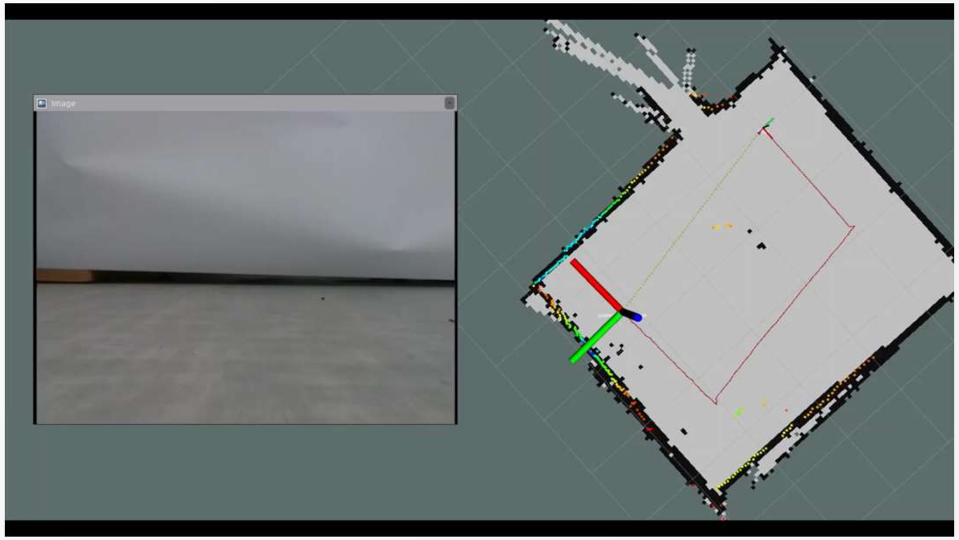


Office (not many feature)				**Living Room** (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)		**No Human** (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**

3. Results

Analysis of LiDAR only SLAM

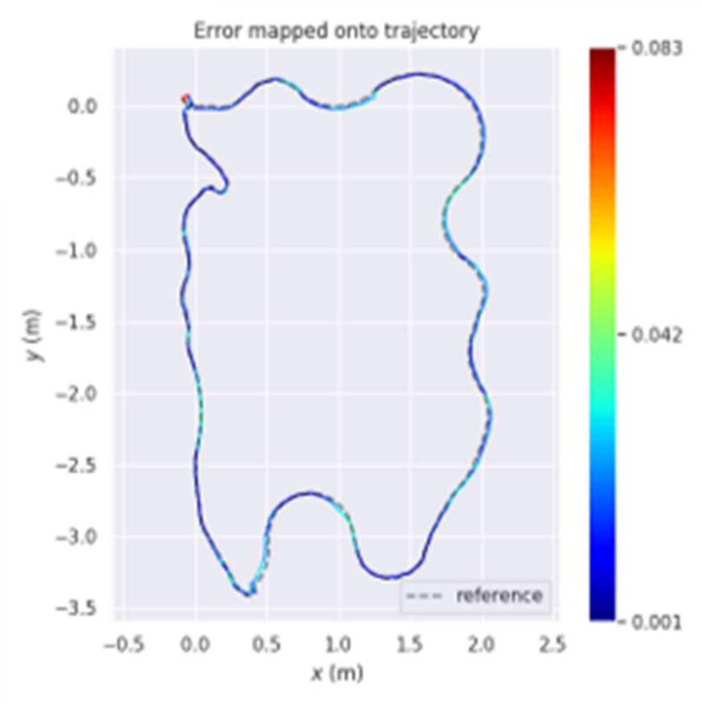


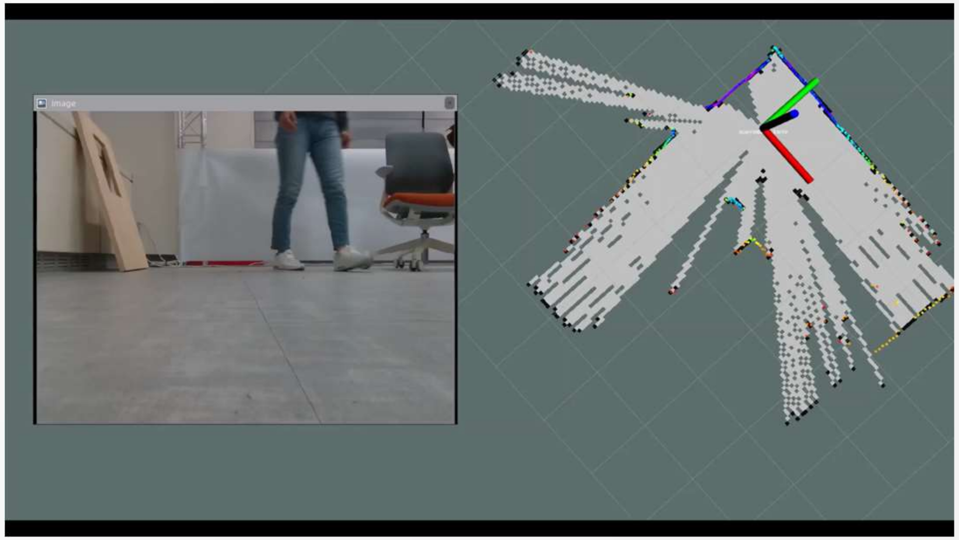


Scene 3 (Straight + Office + Human)

3. Results

Analysis of LiDAR only SLAM



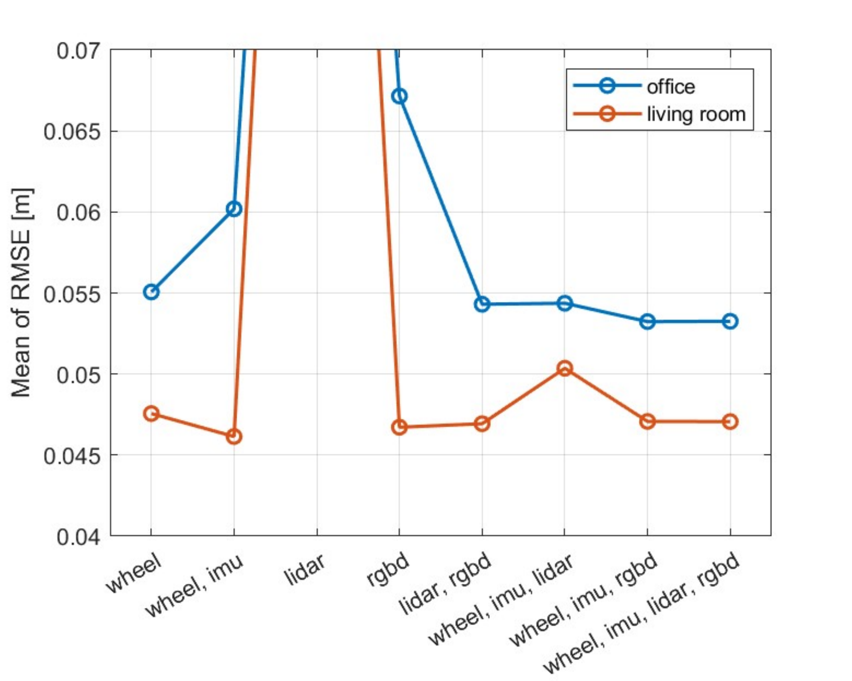


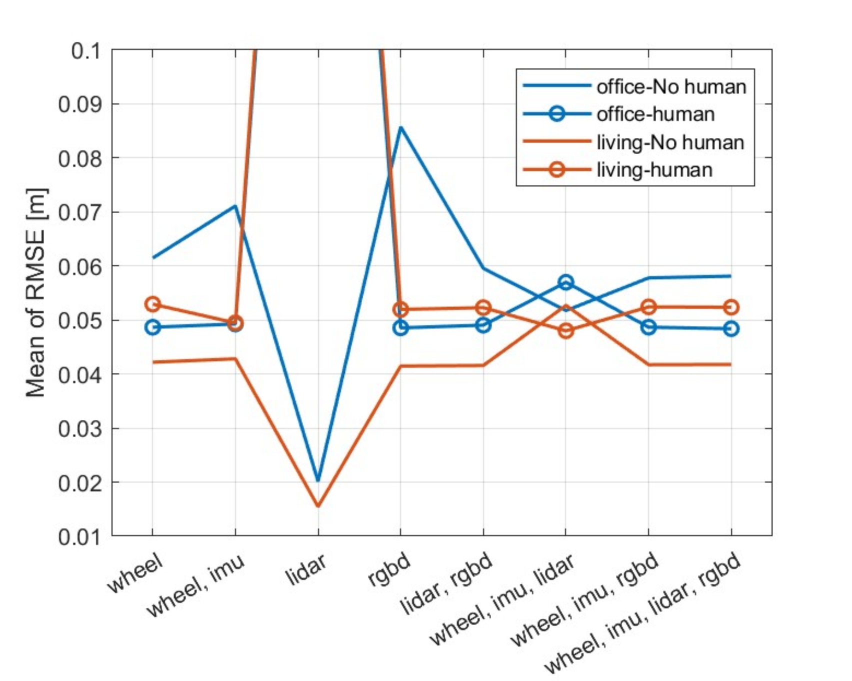
Scene 4 (Zig-Zag + Office + Human)

3. Results

Effects of environment and human variables.

Office (not many feature)				**Living Room** (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)		**No Human** (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**

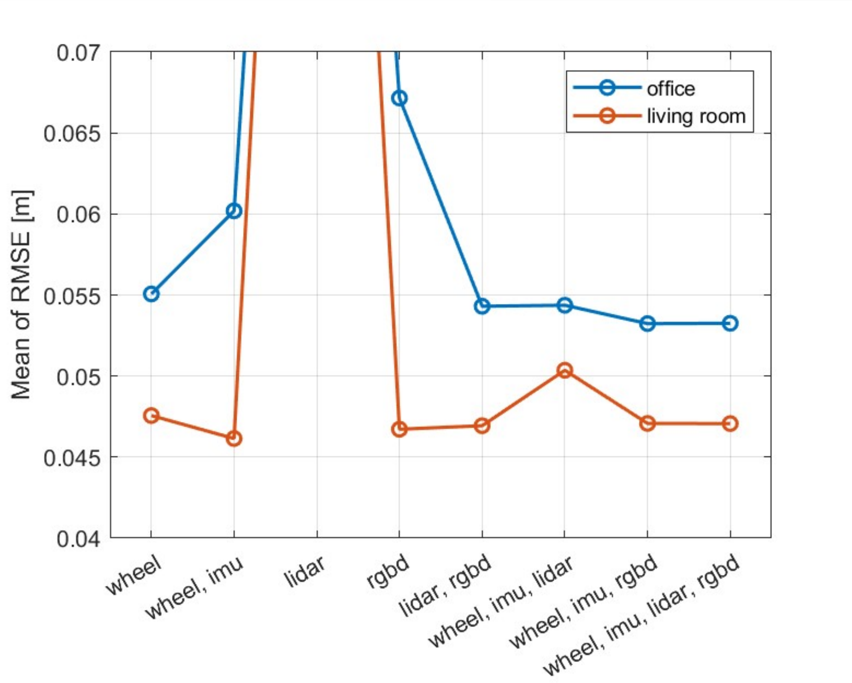


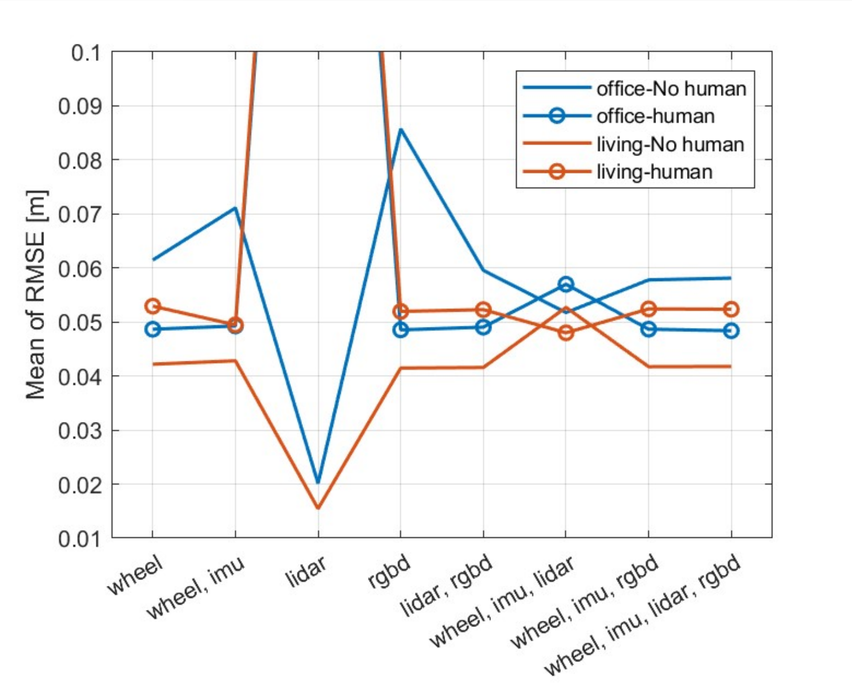


3. Results

Effects of environment and human variables.

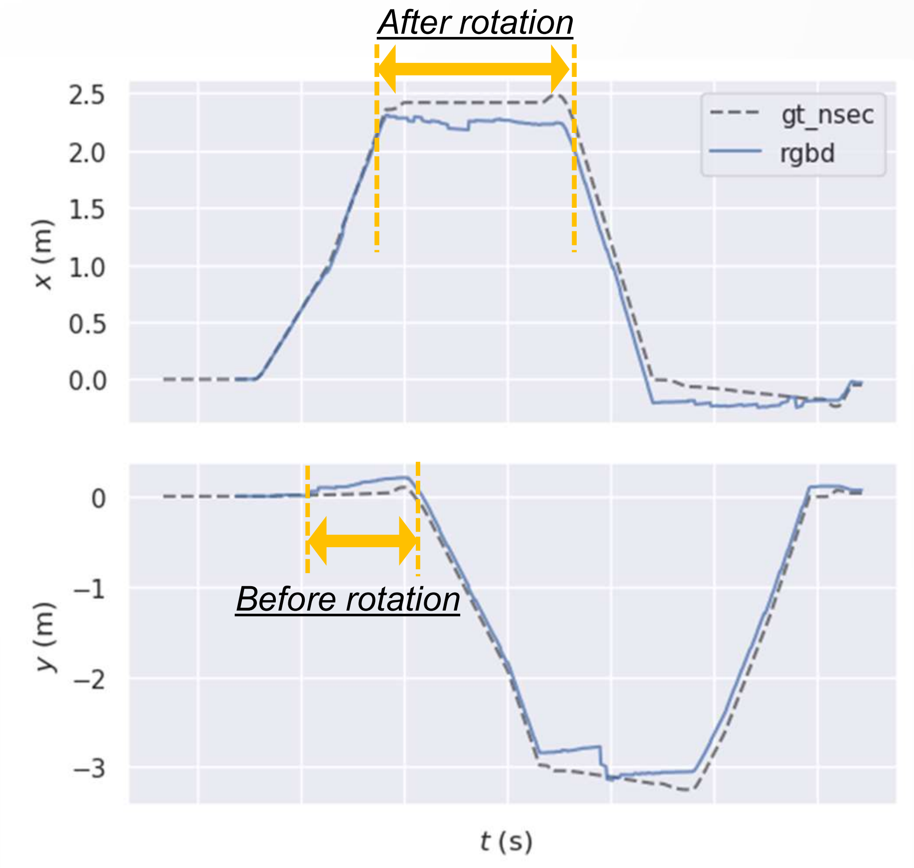
Office (not many feature)				**Living Room** (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)		**No Human** (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**





3. Results

Analysis of RGB-D only SLAM

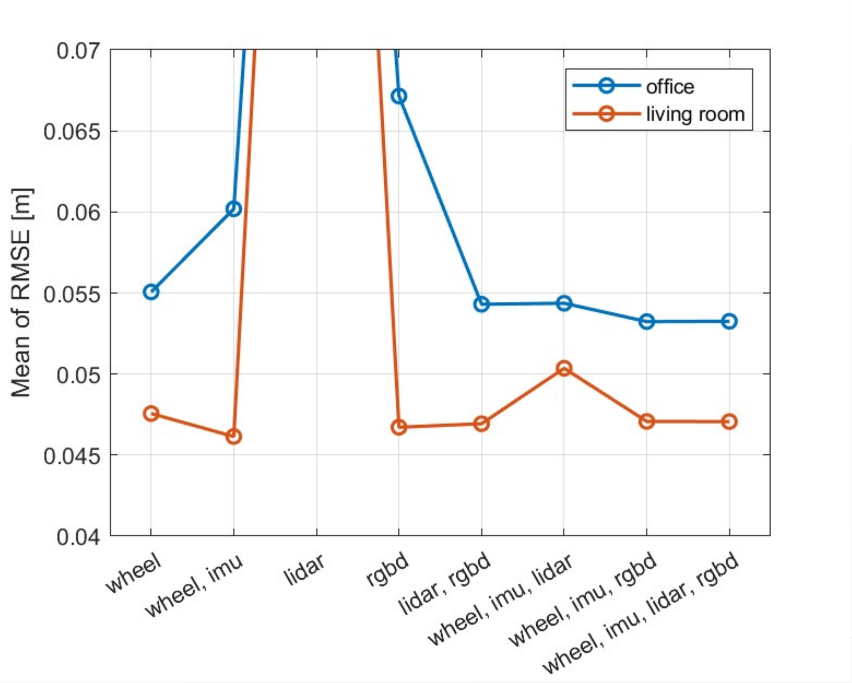


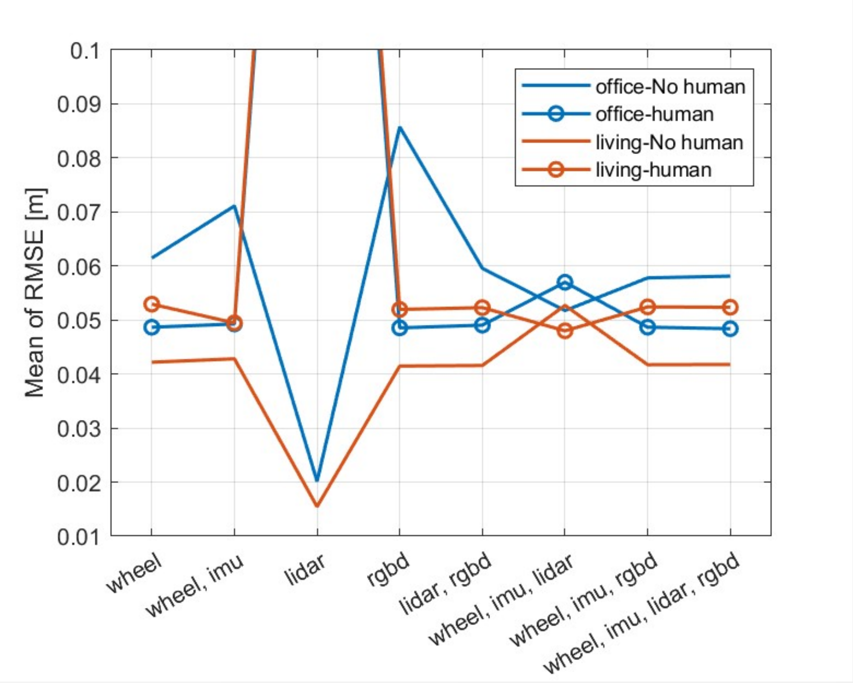
Lack of wall depth information leads to big error of vertical direction

3. Results

Effects of environment and human variables.

Office (not many feature)				**Living Room** (many feature)			
No Human (Static Object)		**With Human** (Dynamic Object)		**No Human** (Static Object)		**With Human** (Dynamic Object)	
Straight	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**	**Straight**	**Zig-zag**
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**





4. Conclusion

Select the Best Combination of Sensors with respect to environments

$ 196.10

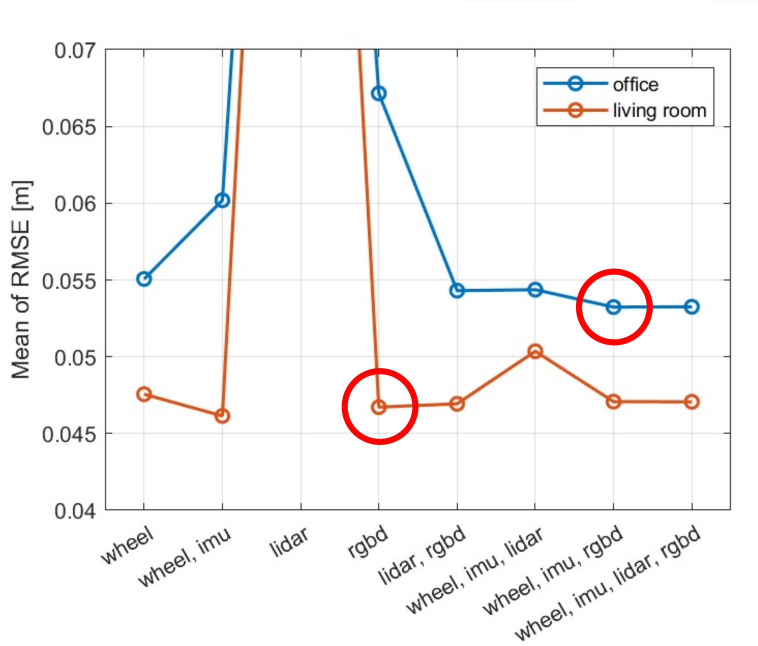
2D LiDAR sensor

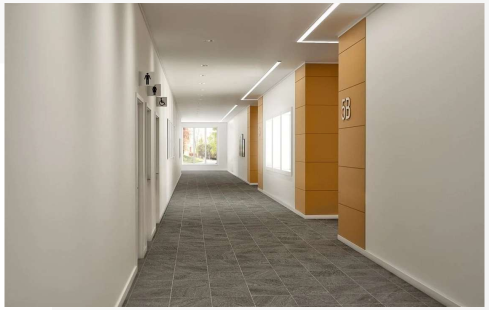
LDS-01

$ 279.99

RGB-D camera

RealSense D415





Not many features

→ **Wheel + IMU + RGB-D Only**

Many features

→ **RGB-D Only**

Thank You!