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Project 102

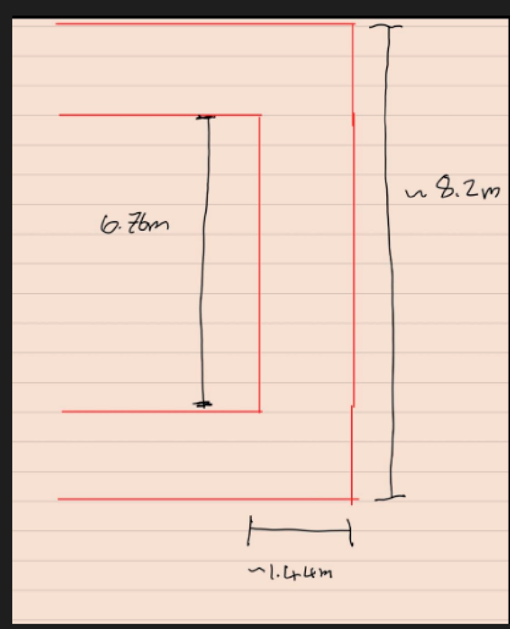
Millimeter-wave based Simultaneous Localization and Mapping (SLAM) for indoor robots

Project background

Where there is a need to save victims and people within house fires, it is vital that first responders such as firefighters are present on the scene to prevent any casualties within their team where possible. SLAM (Simultaneous Localisation and Mapping) is the computational process of constructing or updating a map of an unknown environment while localising the operator and using sensors to detect distance, material types, velocity, and many other parameters. Some real-world examples in which SLAM is utilised are within self-driving cars, unmanned aerial vehicles, and autonomous robot vacuums used for households. Our project aims to fill the gap in knowledge of using millimeter-wave (mmWave) for indoor localization by testing the sensor in a variety of scenarios and across two different algorithms: Iterative Closest Point (ICP) and Point Cloud SLAM (PC).

Set Up & Measurements

- Empty and short corridor width
- Ability to do different motions for tracking
- Square corridor for easy measuring
- The sensor was 740 cm above ground
- Collected data for straight line, L-shape and U-shape motion
- Collected 3 sets of data for each motion



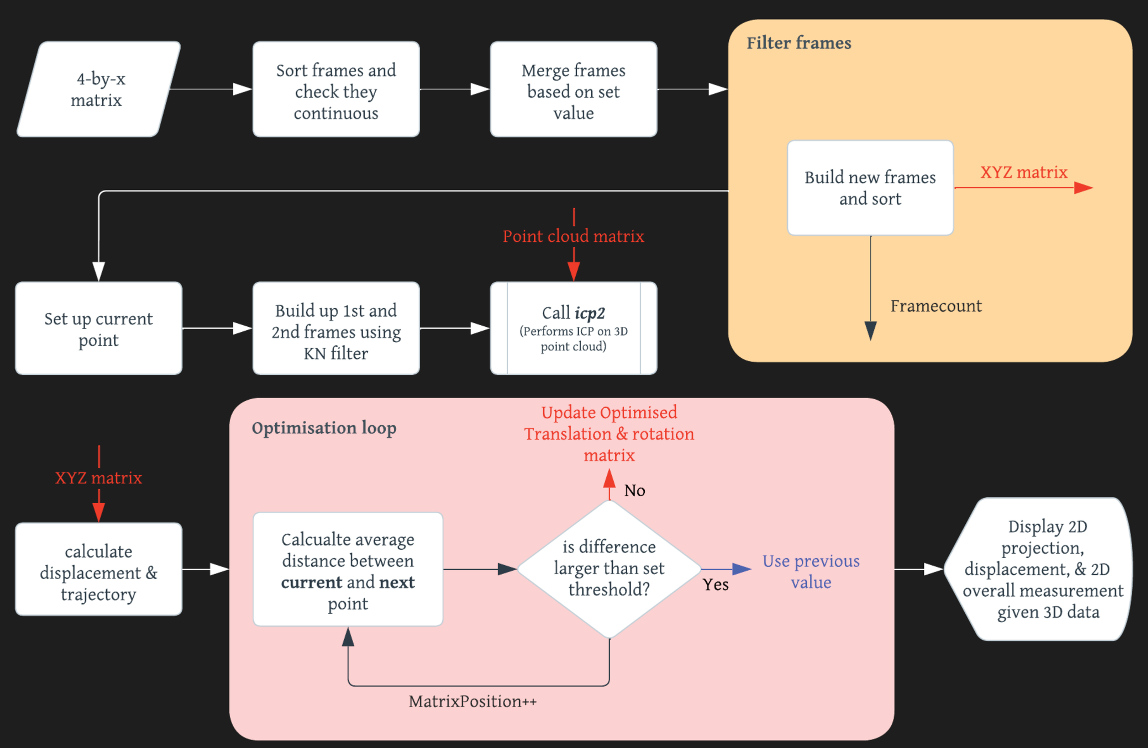
Sensor Config

Effective range: 8.19m
Range resolution: 0.04m
Azimuth angle: 15 + Elevation
Frame rate: 15
Doppler peak grouping: Disable
Walking speed: Slow

Research Objective: Evaluate whether millimeter-wave sensors can be used successfully for indoor SLAM to assist in emergency response situations. In this project we compared the performance of two algorithms for mmWave sensor data in various indoor environments and motions. Our key focus was accuracy of localization and path trajectory.

ICP Algorithm

Iterative closest point (ICP) is an algorithm employed to minimize the difference between two clouds of points. We have used this algorithm to reconstruct a 2D path with localization. This algorithm has proven to work in most straight forward scenarios such as a straight line path, L-shape, and in some cases, a U-shape path. However, the result varies greatly depending on the amount of frames merged.



PC Algorithm

This Point Cloud (PC) algorithm orginally performs SLAM using 3D Lidar Point Clouds. Parameters have been tuned for mmWave. The algorithm works by estimating a relative pose (rotation and translation) by comparing the previous and current scans. A scan is only registered if it exceeds the distanceMoved threshold, adding to the estimated trajectory. It performs successfully with Lidar and reasonably well with mmWave However, mmWave results vary significantly, depending on set parameter values and number of frames merged.

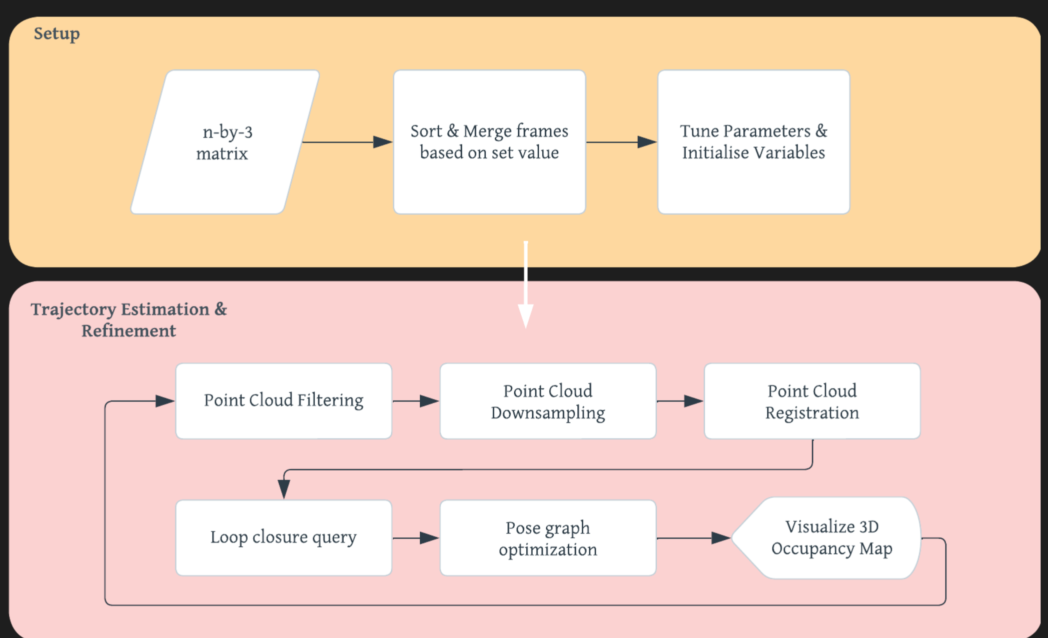
Point cloud filtering:
Omits outlier points, including ground & ceiling.

Point cloud downsampling:
N/A mmWave sensor data is sparse.

Point cloud registration:
Estimates relative pose and adds to trajectory.

Loop closure query:
Estimates whether location has already been visited.

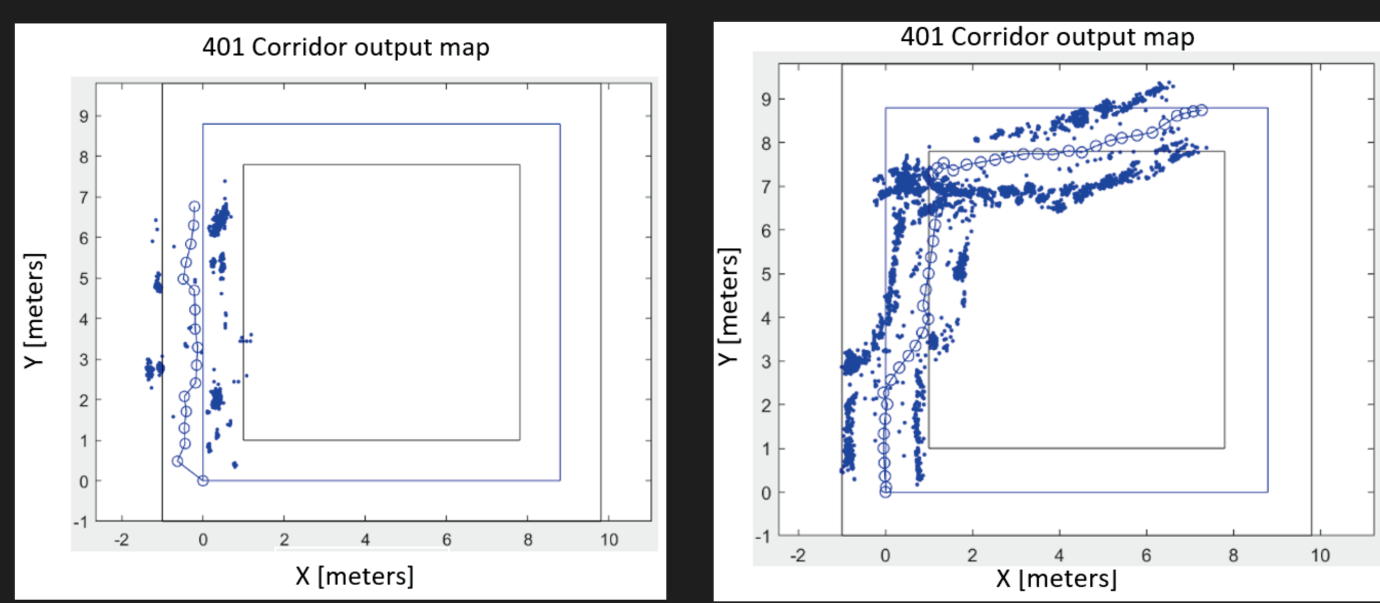
Pose graph optimization:
Reduces trajectory drift.



Results & Comparisons

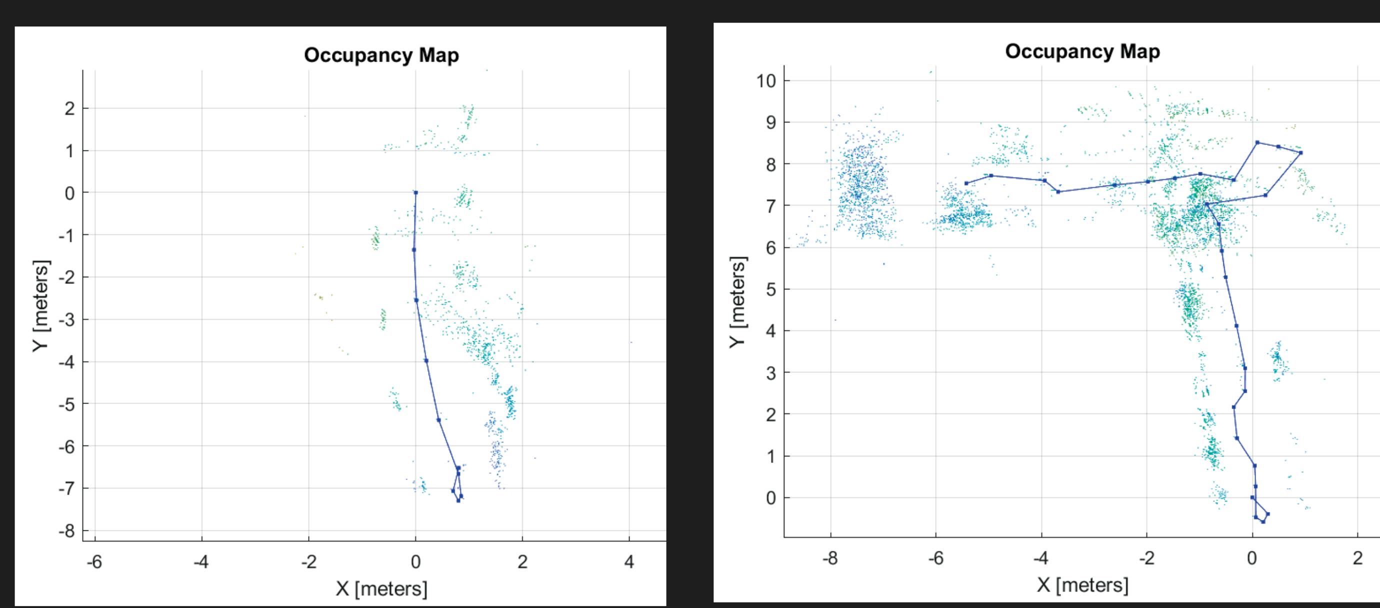
ICP

Solid dots = surrounding points
Hollow dots = Localization trajectory



PC

*PC Output appears inverted on axis but matches sensor motions



Objective Function (Projected vs Real)	ICP	PC	Real	ICP Accuracy	PC Accuracy
Straight line total distance	6.76	7.28	6.76	100%	92.9%
Straight line turns	0	0	0	100%	100%
Straight line deviation	0.6	0.8	0		
L shape total distance	14.85	13.88	14.24	95.62%	97.5%
L shape turns	1	1	1	100%	100%
L shape deviation	1.4	0.86	0		

Conclusions & Future works

From our research, both ICP and PC algorithms are performing adequately, but the accuracy of indoor tracking is limited by the sparse amount of data points collected by the mmWave sensor. There was poor consistency in accuracy across the **same** straight line and L-shape movements collected 3 times with the same set up. Additionally, we were unable to produce any accurate results for U-shape and loop motions.

Our conclusions show that mmWave sensors can be used for localization in controlled indoor environments as a proof of concept. However, the sparsity of mmWava data results in significant inconsistencies and drift. Future works in this area include:

- Tuning algorithms to increase consistency of results and minimize drift.
- Explore performance in controlled and uncontrolled environments as well as U-shapes and loops.
- Combining mmWave with other sensors, such as Lidar, and explore how this influences consistency of results.