Spatial IT Project GEOM90043

Project Report

Adapting traditional survey methods to acquire precise ground truth for localization methods using LIDAR scan

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Abstract

In this paper, we focus on creating an accurate ground truth dataset corresponding to the key frames captured from a moving LIDAR sensor, using a robotic total station. All the steps for data collection is recorded as a demo for further similar experiments. This dataset can be used for localization methods or other related positioning experiments. An example using one of the latest SLAM methods Lego-LOAM is included , and the statistics of the empirical error are recorded. The theoretical error is calculated from error's propagation law, and its statistics are also attached.

Keywords: total station, SLAM, ground truth, LIDAR, error's propagation, empirical error, theoretical error

1. Introduction

Early in this century, people developed their demand of localizing objects and reconstructing them into 3D world with applications like digital twin or simplest parking lot occupation identifier (Bachtiar, M. M., Besari, A. R. A., & Lestari, A. P. ,2020). With the rapid development of machine learning & computer vision & pattern recognition, they became the hotspot of researching, as well as getting new branches using not only images but videos (Lu, G., Zhang, X., Ouyang, W., Xu, D., Chen, L., & Gao, Z. ,2020). It is reasonable to state that currently there exists countless applications like traffic flow control using those technologies.

However, due to a few severe problems associated with the nature of computer vision methods, the research direction nowadays is gradually switching to others. The problems include the precision problems in matching resulted from sampling, which means when fulling up the pixels of images, the real world is down sampled and as the trajectory analysis requires matching between images, this can severely reduces the match rate, or the difficulty of depth reconstruction, which is caused by the lacking of depth information for images and the fact that those depth-recovering algorithms can further sacrifice precision. The most dangerous one among them can be the instability of CNN blackboxes. Currently although built networks have stable performance, the generation of networks can be out of control, thus it is hard to make further improvements based on them according to additional requirements.

As a result, LIDAR based methods are now replacing the position of CV based ones, with its natural advantages in depth detection and higher precision. Although LIDAR sensors are of higher prices compared to standard cameras, but in most of experimental scenarios they do worth it. Typical applications of LIDAR based methods include intelligent vehicles and autonomous driving(Zhao, J., Li, Y., Zhu, B., Deng, W., & Sun, B. , 2021), feature/pattern extraction (Gargoum, S.,

& El-Basyouny, K. , 2017) or basic mapping and rendering (Anqing Y., Xiaoyan H., Xiaoping W., & Dan T. ,2013). The data collected from LIDAR sensors can also be used as an input for CNN, but in some circumstances like detection, it is not necessary, and thus reduces the total cost and instability of the whole structure.

However, although LIDAR based methods may not use machine learning, they still ask for huge amount of raw data as ground truth in experiments. For example, the typical positioning or localization like key frame based SLAM (Simultaneous Localization And Mapping) from LIDAR data has to estimate the orientation of the sensor at each key frame according to its adjacent frames, which will produce sight error. This error might be acceptable with only a few frames, but for reconstructing a contiguous trajectory from a moving LIDAR sensor array, the errors between each pairs of key frames will accumulate, and developing compensation methods accordingly becomes necessary. In order to evaluate those methods and make possible improvements, various ground truth datasets are required for examination.

To acquire ground truth datasets, it is possible to download public ones like KITTI (A. Geiger, P. Lenz, and R. Urtasun ,2012) which were designed for SLAM related works, but the fact that they are usually in various data formats or lack of background knowledge can make the comparison towards localized trajectory too frustrating. In addition,it has be observed that current existing methods start growing over-fitted to those datasets and behaving less accurate on other testing ones, which can be dangerous for developing new methods like Lego-LOAM (Shan, T., & Englot, B. ,2018). Due to these challenges, nowadays researchers like Shan and Englot prefer to collect their own brand new datasets as this can be the most efficient way and also boosts the understanding to the raw data.

2. Aim of the project

This project is originally designed to collect an accurate set of ground truth dataset of points among the trajectory, corresponding to key frames of the captured data from a moving LIDAR sensor, which can be used in LIDAR based localization and navigation experiments or possible further applications.

The project itself assumes a combination of indoor and outdoor environments which makes GPS based coordinate systems not the best choice since there is high probability that the structures will severely block the GPS signal. In this case, to obtain high precision ground truth especially for indoor circumstances, it is reasonable to adapt the similar method from traditional survey, using total stations for ground truth points. Based on the assumption that indoor feature surfaces like walls and corridors will not change frequently unless the whole structure is rebuilt, the data points collected this way can stay reliable for a considerable long period.

3. Setting up the equipment

The equipment included in this project is a Sokkia iX robotic total station as well as its additional components such as the PC-PR5 remote control, a 360 degree -7mm robotic prism SitePro Builder Series ATP360 and a velodyne HDL-32 LIDAR scanner carried by Husky, an autonomous robot vehicle with remote control built by the MUR team of the University of Melbourne.

figure1, left: Sokkia iX robotic total station; mid:PC-PR5 remote control & ATP360 prism; right: velodyne HDL-32 LIDAR scanner

As the ground truth to be collected by the total station system which by origin designed for static targets, is actually serving the LIDAR scanning system which is usually carried by a constantly moving vehicle in reality, the reflection prism should not be mounted onto the prism poles but somewhere on the bot. For the transition between total station static collecting and LIDAR scanner dynamic collecting, a simple stop-and-go method is adapted, which means the bot will stay at designed locations for a few seconds for the total station to track the prism and record the point coordinate data.

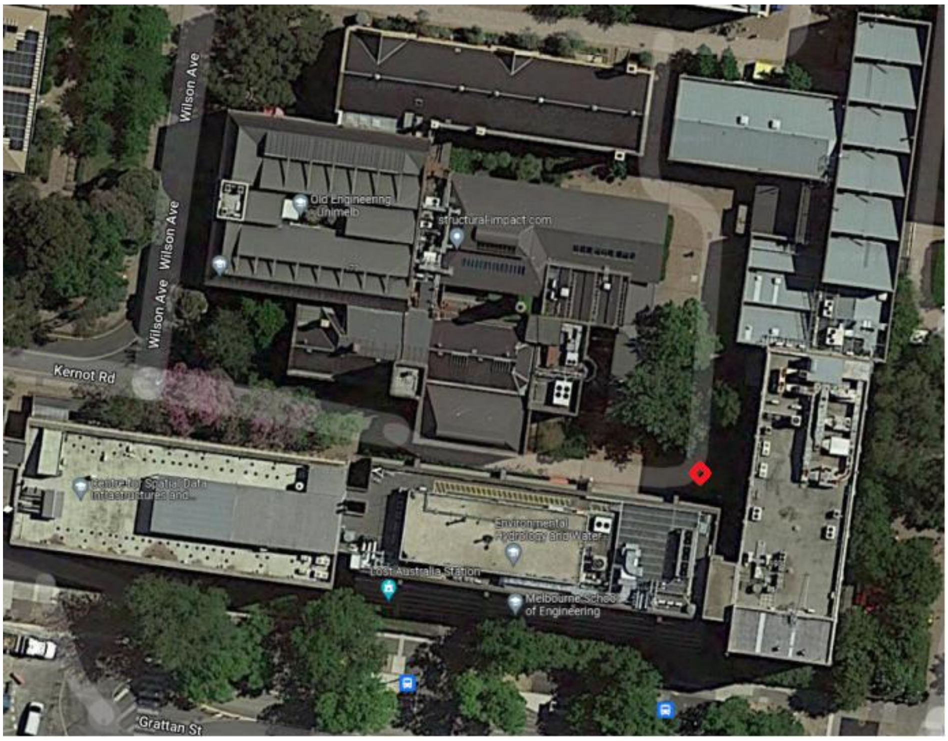

figure2, data collection location at Grattan St 193

The location for data collection is set to the U-shaped corridor near the Engineering building of the University of Melbourne on Grattan St, which has a low pedestrian volume and various types of surfaces including vegetation, glassy entrances and solid walls. The start point of the trajectory is marked with red diamond above, and the surrounding looks like the photo below.

figure3, surrounding view of trajectory start point

figure4, Husky with all necessary equipment attached

The experiment bot is shown above. The LIDAR scanner (the sliver cylinder-like device) is placed at the highest location in order to scan also part of the ground surface without being blocked by the bottom base of Husky. As the scanner itself can only reach -30 degree at maximum, the 360 degree prism is mounted at the back base of the bot to avoid blocking the scan ray, and also minimize the chance of occlusion. Although for traditional surveys it is necessary to keep the prism pole vertical to the ground, in this project it is not necessary as the ground surface around the collecting location is almost flat.

figure5, joint section of the prism, made with cable ties and a modified tripod

Please note that the joint section between the prism and the base of Husky was not robustly stable as it was not allowed to drill or use magnet on the Husky base for safety concern.However it is acceptable to connect with cable ties as the designed movement speed of Husky is limited to 1m/s, which will not be intense enough to move the prism.

The collecting process consists of several steps:

a. mount the prism and the remote control of total station to the tripod on Husky. Check the Bluetooth connection towards total station and the handheld control pad. Make sure the prism is stable. Measure and record the relative distance from prism to scanner&ground. The most important sets of data are recorded here as an example:
station height = 1.42m
prism height = 0.52m
scanner height = 1.11m
scanner distance to prism (Horizontal) = 0.39 m

b. set up the total station to be leveled. Pre-locate the device onto the nailed point as the back sight point for the job. Set up the parameters for fieldwork including prism constant, tracking method (auto-tracking)and communication method as Slave which will enable and send all data to the control pad.

   Since relocating of scan data only asks for a relative coordinate system, using for example particle filter (Chi, F., Xiao, Y., & Gao, C. 2021), it can be unnecessary to record the true North direction and actually the size of those line segments. However, the total station does provide them in an efficient way, therefore please save both the coordinate file (in meters) which has true North information and the raw data file (in angles).

   Although this serves only relative trajectory measuring, it is still necessary to set up a stable backsight for the total station. The default direction of the total station here, was from a nailed block as (0,0,station height) to the corner of the nearest building, with 0 vertical angle.

c. create a topo survey and set the method to coordinate measurement, set up the remote control for Husky, active the LIDAR scanner and set its rotation frequency to 10 per second.

d. drive the Husky using planned route. For every a few meters distance, stop the Husky, wait the tracking from total station becomes stable, then record a point. The planner route has a closed loop for further re-localization as this helps increase the precision(Dai, K., Cheng, L., Yang, R., & Yan, G. ,2021).

e. transmit the scanned data to personal device and remove the temporary data from Husky storage. Transmit the total station data from control pad, seize all the connections, and then pack up the device safely.

4. Results

4.1 Recorded data & formats

The scanner has a 10Hz regular self rotation, and will collect depth data per ray which can be reconstructed into a point cloud representing the walls.

The raw data collected by the total station will have horizontal angle (degree-minute-second), vertical angle, and distance like shown below.

```
BS,1000,0.50,0.0000000000,-18.2851500000,2.80,WELL
BS,1000,0.50,0.0000000000,-18.2851500000,2.80,WELL
SS,1001,0.50,359.5953000000,-18.2853000000,2.80,CL
SS,1002,0.50,359.5953500000,-18.2853500000,2.80,CL
SS,1003,0.50,359.5950500000,-18.2855000000,2.80,CL
SS,1004,0.50,2.0122000000,-18.0720000000,2.85,CL
SS,1005,0.50,13.5855500000,-15.5549000000,3.22,CL
SS,1006,0.50,24.4555000000,-13.0919500000,3.85,CL
SS,1007,0.50,30.3751500000,-10.4525000000,4.66,CL
SS,1008,0.50,36.2940500000,-9.2658000000,5.34,CL
```

figure6, the raw data text file from the total station

Here for example, a standard survey(SS) type point with ID = 1005 has its measurements as 0.5m prism height(represents the height of the prism above the basement of HUSKY), 13° 58’ 55.5” in horizontal angle, -15° 55’ 49” in vertical angle and 3.22 meters in distance towards the total station, recorded in centre line(CL) method specially for trajectory measurements.

In addition since the coordinate measurement is on, there will also be a file writing in Lon/Lat/height (calculated with GPS) with centimeter level precision.

```
1002,-2.30,1.32,0.01,CL
1003,-2.30,1.32,0.01,CL
1004,-2.30,1.43,0.01,CL
1005,-2.23,2.15,0.02,CL
1006,-2.16,3.06,0.02,CL
1007,-2.25,3.98,0.03,CL
1008,-2.11,4.83,0.02,CL
1009,-2.15,6.06,0.03,CL
1010,-1.46,6.91,0.02,CL
1011,-1.04,8.02,0.00,CL
```

figure7, the GPS based coordinate measurement data text file from the total station

It is enough for plotting works, but the precision will be calculated manually in another section below.

Note, if it is necessary to reconstruct the trajectory from angles, for example for points that cannot use GPS to get its coordinates, the missing rotation which was included in the auto-calculation of total station has to be added. As the point coordinates file has a standard North direction acquired from GPS even with only 2 points, it is possible to adjust all other points with that rotation. That is probably the most efficient way to acquire precise North in an indoor environment: by carrying prior knowledge from outdoor segments.

The LIDAR data captured by velodyne are stored in .pcap data frames like shown below.

Block Number	Point ID	adjustedtime	azimuth	distance m	intensity	laser id	timestamp	vertical angle
1	12745	4111522759	6932	5.946	10	30	511522759	-10.670
1	12776	4111522805	6947	5.960	10	30	511522805	-10.670
1	12806	4111522851	6965	5.964	8	30	511522851	-10.670
1	12837	4111522897	6983	5.966	7	30	511522897	-10.670

figure8, the captured data file in Excel from the velodyne scanner

Although it is possible to rebuild the point cloud with these data frames, this is not directly human-readable for there are too many frames. Instead, there exists an official tool application called veloview to visualize this point cloud. Here the total station is highlighted with the red rectangle, and the operator (me) is marked in pink near the right bottom corner.

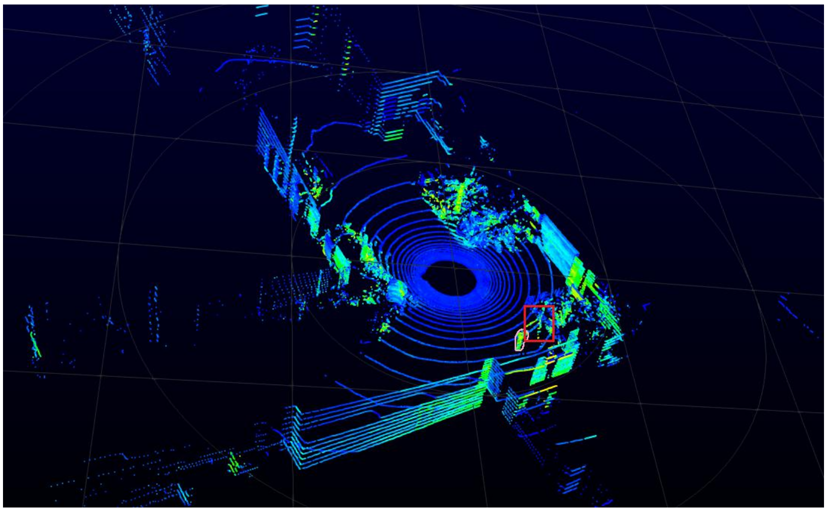

figure9, the captured data file replayed in veloview4.1.3

In veloview, the data frame shows as a video and will play itself at a fixed fps, which is 10Hz as set in the velodyne LIDAR scanner.

With the stop-and-go method, it can be observed that the HUSKY did stop at points for several seconds, and the readings of the total station were recorded during those periods. Only one frame from those will be used as the corresponding point in calculation, although the frames near it will also be used in orientation calculation.

4.2 Coordinates & trajectory

Using simple calculations, the angle formatted data can be transformed into XYZ, which is more suitable for ground truth array.

D is the depth(length) data, VA is vertical angle, HA is horizontal angle. stationHeight is measured from the measuring tape and it is 1.43 m.

$X = D * \cos VA * \sin HA$ .... (1.1)

$Y = D * \cos VA * \cos HA$ ....(1.2)

$Z = D * \sin HA + \text{stationHeight}$ ....(1.3)

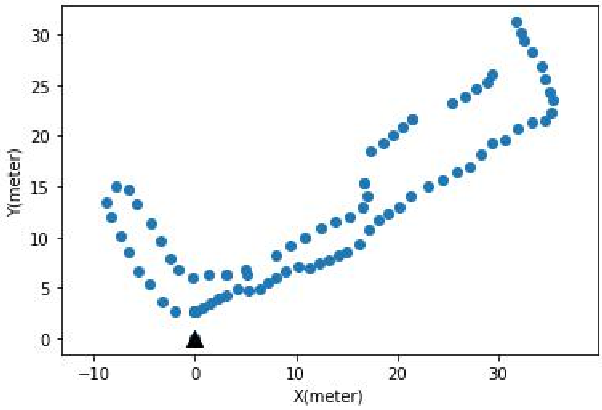

figure10, plot the calculated ground truth points

The black triangle is the location where the total station was set up.

Because in the back sight setting, the 0 degree direction was using the direction from total station towards the start of trajectory, here X and Y don't represent east or north. But with the reference from that GPS set, it is still possible to make the rotation and overlap it onto the map, shown as below in figure 11.

figure11, rotated ground truth points according to Lat/Lon GPS based set, mapped onto the real world map

4.3 Comparison with the SLAM data

The results from one of the lastest SLAM methods, Lego-LOAM, calculated from the LIDAR scan:

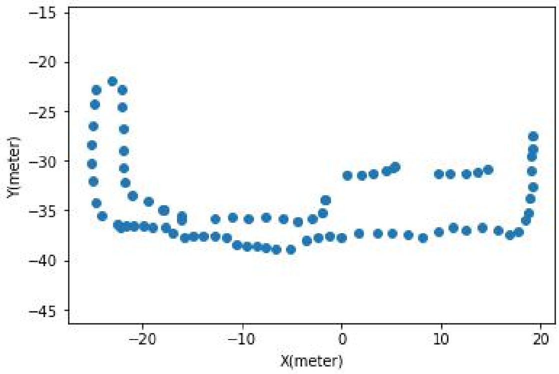

figure12, plot of Lego-LOAM results from the LIDAR data

The total station location is not marked here as Lego-LOAM cannot recognize the total station as a special object. Note that the directions of axis can be different since the reconstruction always uses the initial orientation of the collector bot as their own X axis direction as shown above. To make a comparison between the ground truth and the result, a relative rotation is enough to do the transformation in between.

For example, pick two pairs of corresponding point sets like shown below, then calculate the transition and rotation between these two vectors, and the result can be used for the whole point set. In practical, the rotation is calculated with 50% of the points with dot products, and the average result is 29.76 degree. For the transition, as actually the length differences between point pairs are all about 0.1% to 0.2%, which can be assumed to be the acceptable error of reconstruction, it is reasonable to use a 1:1 scale in between and shift only according to a few points.

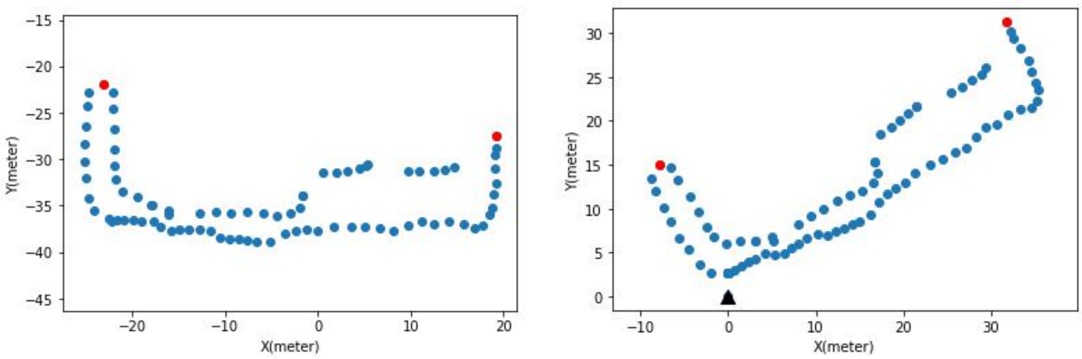

figure13, left: example of picking special points from SLAM result; right: picking corresponding points in the ground truth

This is the rotated trajectory, now in yellow, mapping onto the ground truth blue points. The trajectory does not really go exactly across the centres of points, but that is acceptable.

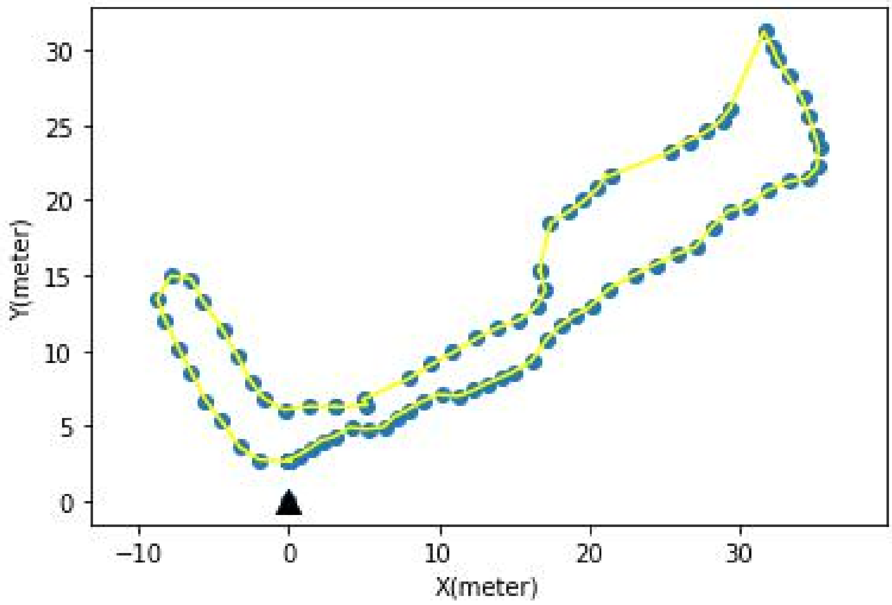

figure14,SLAM result trajectory after transformation overlapped onto the ground truth

The empirical error which is the difference between ground truth and the Lego-LOAM is plotted with blue arrows below in figure 15, and the statistics of empirical error are shown in table1.

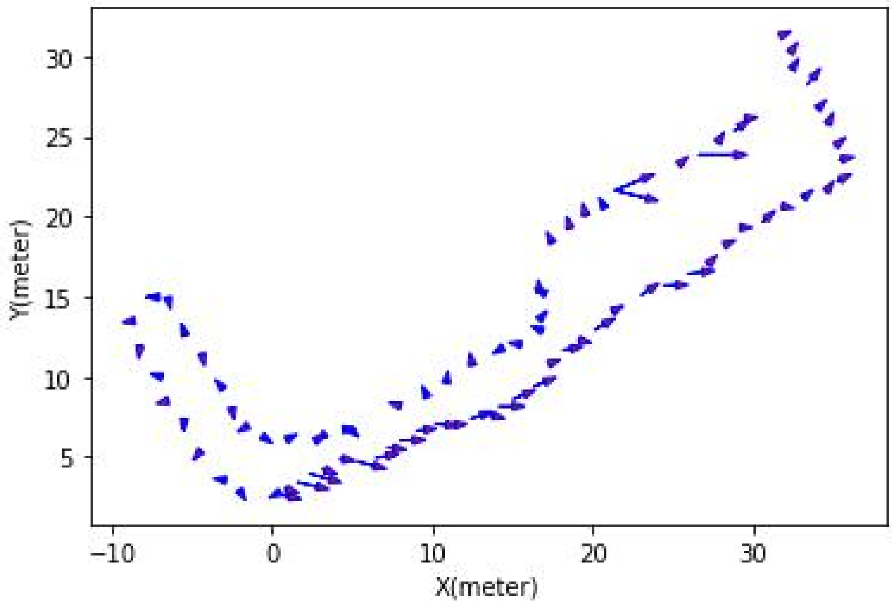

figure15, empirical error arrows with 1:10 scale

statistics(meter)	min	max	mean	median	std	RMSE
diffX	-0.0746	0.3051	0.0601	0.0538	0.0812	0.0356
diffY	-0.0862	0.1043	0.0144	0.0138	0.0430	0.0185
diffZ	-0.0084	0.0952	0.0107	0.0079	0.0173	0.0019
$\sqrt{(\mathrm{diffX})^2 + (\mathrm{diffY})^2 + (\mathrm{diffZ})^2}$	0.0000	0.3088	0.0948	0.0815	0.0608	0.0402

table1, empirical error statistics

4.4 Error & precision

As a ground truth dataset, it is necessary to analysis and calculate its own precision. The major part of precision issues come from the precision of total station reads, and there is possibly a systematic error for calibration issues because the centre of scanner is not the same as the prism.

From the Sokkia user manual (2021), the precision of sokkia IX total station is: distance=1mm, vertical angle=1sec, horizontal angle=1sec. Note that the angles must be calculated in radius,

$$1\ \text{second} = 2\pi / 360.0 / 3600 \quad \cdots\cdots (2)$$

The total station height and the prism height, as measured with standard measuring tapes, share a 0.5 cm precision.

Using the error's propagation law as below (Glen, 2021), it is possible to estimate the variance for the measurements.

If $$Q = \frac{a, b, \ldots c}{x, y, \ldots z}$$

then $$\boxed{\frac{\delta Q}{|Q|} = \sqrt{\left(\frac{\delta a}{a}\right)^2 + \left(\frac{\delta b}{b}\right)^2 + \ldots + \left(\frac{\delta c}{c}\right)^2 + \left(\frac{\delta x}{x}\right)^2 + \left(\frac{\delta y}{y}\right)^2 + \ldots + \left(\frac{\delta z}{z}\right)^2}.}$$

figure16, section of error's propagation law examples

Again, D is the depth(length) data, VA is vertical angle, HA is horizontal angle.δis the error associated with each measurement, and here δD = 1mm, $\delta VA = \delta HA$ = 1second = $2\pi / 360.0 / 3600$.
From equations 1.1, 1.2 and 1.3, the error is:

$$\delta X = \sqrt{(\delta D * \cos VA * \sin HA)^2 + (D * \sin VA * \sin HA * \delta VA)^2 + (D * \cos VA * \cos HA * \delta HA)^2} \quad \cdots\cdots (3.1)$$

$$\delta Y = \sqrt{(\delta D * \cos VA * \cos HA)^2 + (D * \sin VA * \cos HA * \delta VA)^2 + (D * \cos VA * \sin HA * \delta HA)^2} \quad \cdots\cdots (3.2)$$

$$\delta Z = \sqrt{(\delta \text{stationHeight})^2 + (\delta D * \sin VA)^2 + (D * \cos VA * \delta VA)^2} \quad \cdots\cdots (3.3)$$

By plotting the precision area of each point into eclipses with a x1000 scale for it to be visible enough, the theoretical error result is shown below in red. The median size of those eclipses is 0.8mm x 0.6mm as marked specially in the figure, as a suitable standard of ground truth precision.

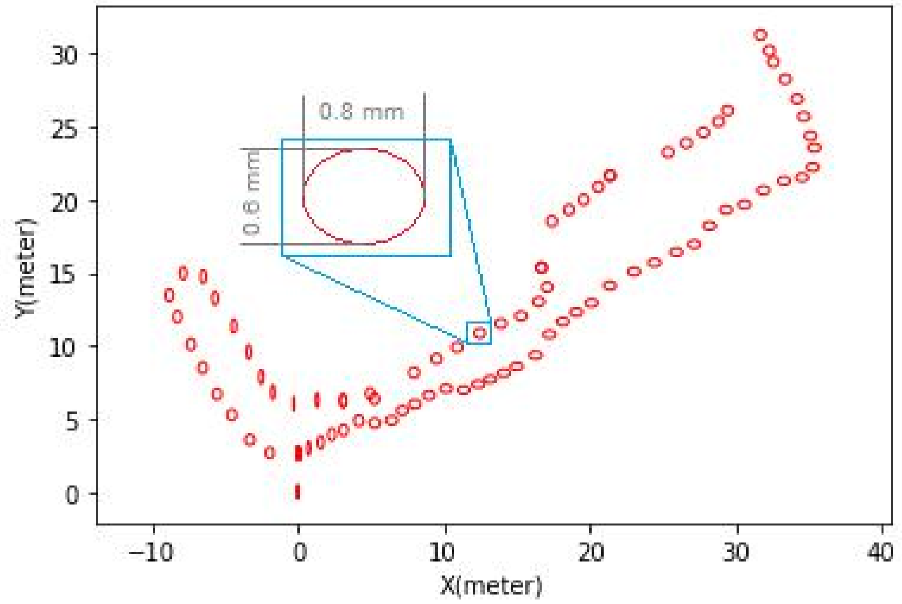

figure17, theoretical error eclipses with 1:1000 scale

The size and the shape tend to grow only with the distance and the direction towards the total station, and do not really change according to the orientation of HUSKY itself, therefore the systematic error estimated before does not really exist or matter too much.

The statistics of theoretical error (from error propagation) are shown below in table2.

statistics(millimeter)	min	max	mean	median	std	RMSE
δX	0.0129	0.8680	0.6183	0.7395	0.2708	0.0543
δY	0.5014	0.9891	0.7208	0.6884	0.1508	0.9455
δZ	5.0	5.0103	5.0030	5.0018	0.0026	5.0103
$\sqrt{(\delta X)^2 + (\delta Y)^2 + (\delta Z)^2}$	5.0990	5.1081	5.1016	5.1002	0.0028	5.0991

table2, theoretical error statistics

5. Conclusion

5.1 Accuracy analysis

The ground truth dataset covers an approximate size of 1000 square meters and the trajectory total length is about 125 meters. For Lego-LOAM, it achieved an average error of 0.09meter for its position estimation, which is less accurate compared to the performance when it uses KITTI dataset, but still acceptable as the trajectory reconstructed matches the ground truth points quite well. Some relatively large error are resulted from larger gaps between ground truth points, and being lack of reference only for a few seconds can accumulate error towards 0.3 meter level, just as mentioned as one of the challenges in introduction part.

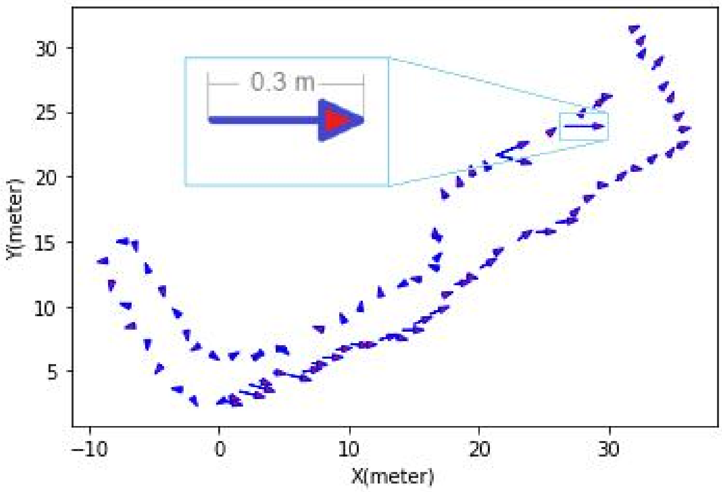

figure18,max value of empirical error due to error accumulation

The ground truth itself has an average theoretical error of 5millimeters, which is mostly due to the huge uncertainty of Z axis measurements using measuring tapes. For X and Y axis it reaches less than 1 mm precision. Compared to the traditional way of using GPS fro ground truth, its has a 10-times better accuracy. It has the ability to support those latest location methods.

5.2 Further improvements

To calculate the orientation of HUSKY and improve the precision of the ground truth, the scanner data has to be used. However, that dataset is actually pending to be re-localized with the ground truth and should not be used ahead. In order to solve this, it is probably nice to use an IMU as an independent source of direction data, although it will also introduce a new source of error as well, which may not be acceptable.

Another possible way to prove this can be performing another set of test survey, by only rotating the HUSKY bot at one location, and see if the readings and the variance eclipses change.

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