Msc in Artificial Intelligence and Robotics

Thesis Presentation

Sparse LiDAR Odometry using intensity channel: a comparison

A real-time front-end SLAM system for odometry estimation of a vehicle

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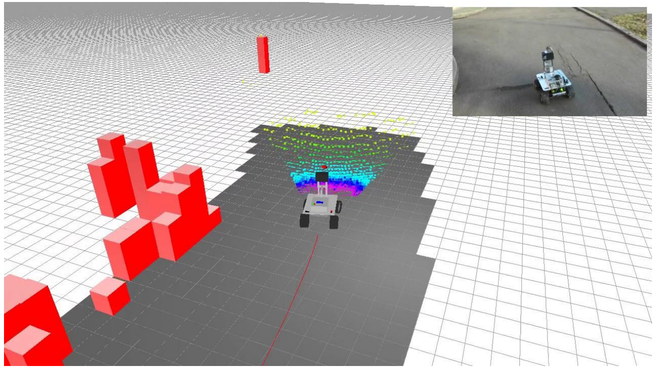
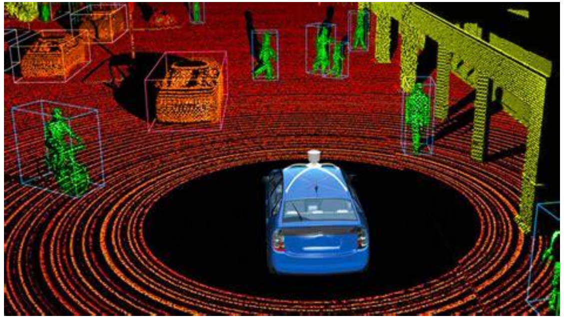
Motivations



Robot navigation system

exploration, smart farming, surveillance, military, autonomous driving …

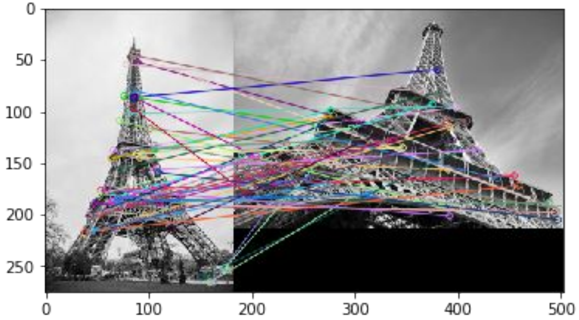


Modern sensors

laser scanners provide a dense representation of the environment

Variety of techniques

feature detection and matching, transform estimation



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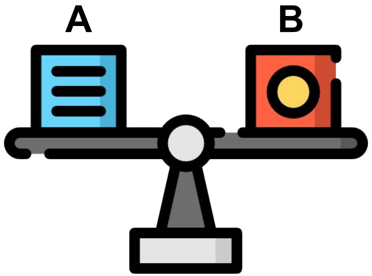
Project Goal

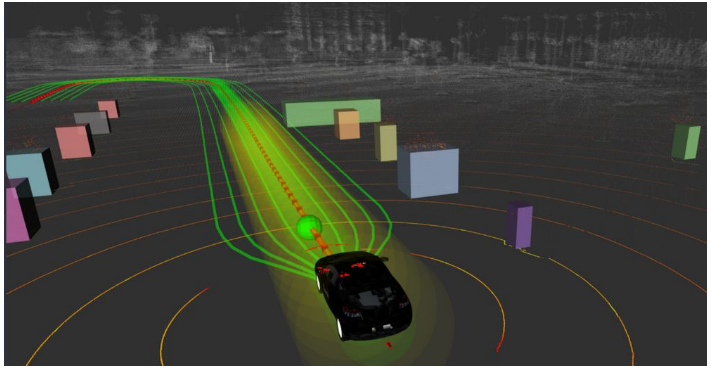
Methods comparison

highlighting differences between solutions available nowadays



Odometry estimation pipeline

building an entire tracking system which estimates the car trajectory along the path



Real-time performance

entire process within the sensor frequency

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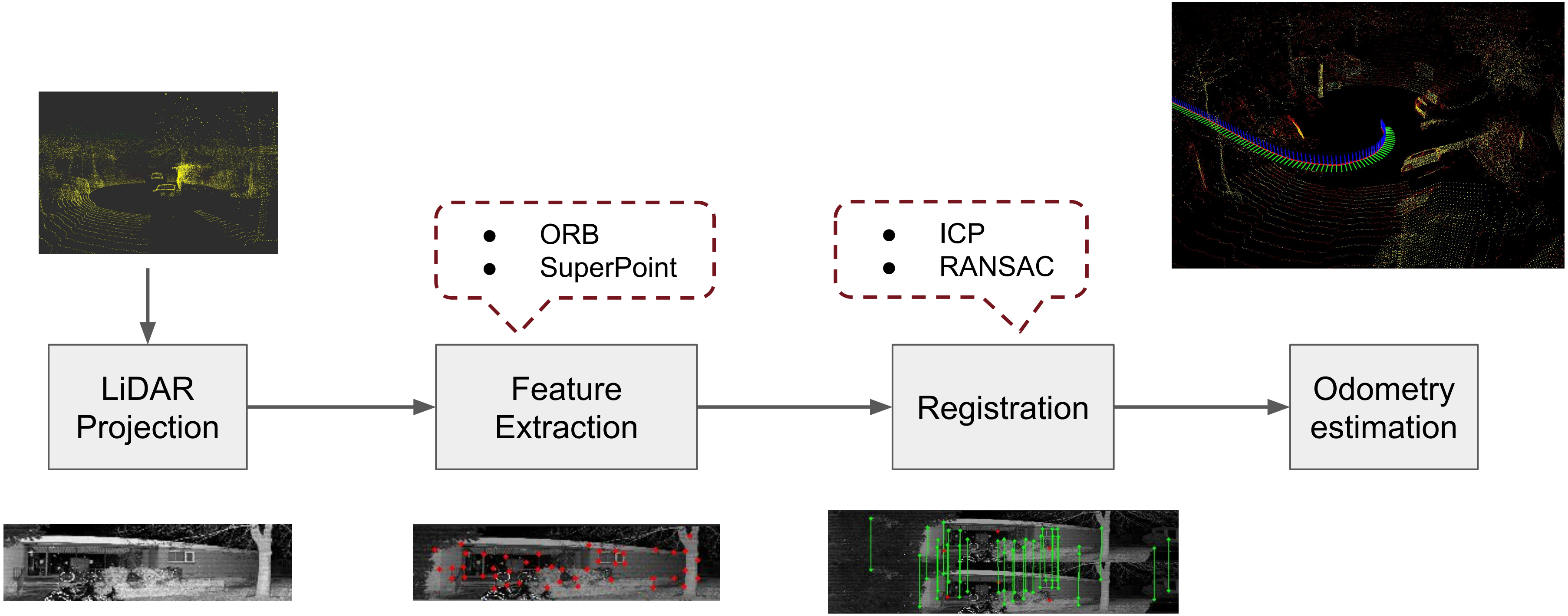
Pipeline



ORB
SuperPoint
ICP
RANSAC
LiDAR Projection
Feature Extraction
Registration
Odometry estimation

LiDAR Projection

Projection | Extraction | Association | Registration | Odometry

IPB Car dataset

acquired in urban environment, with LiDAR and GNSS sensors

Projection function

from 3D Euclidean space to 2D image

$$r = \sqrt{x^2 + y^2 + z^2} \in \mathbb{R}$$

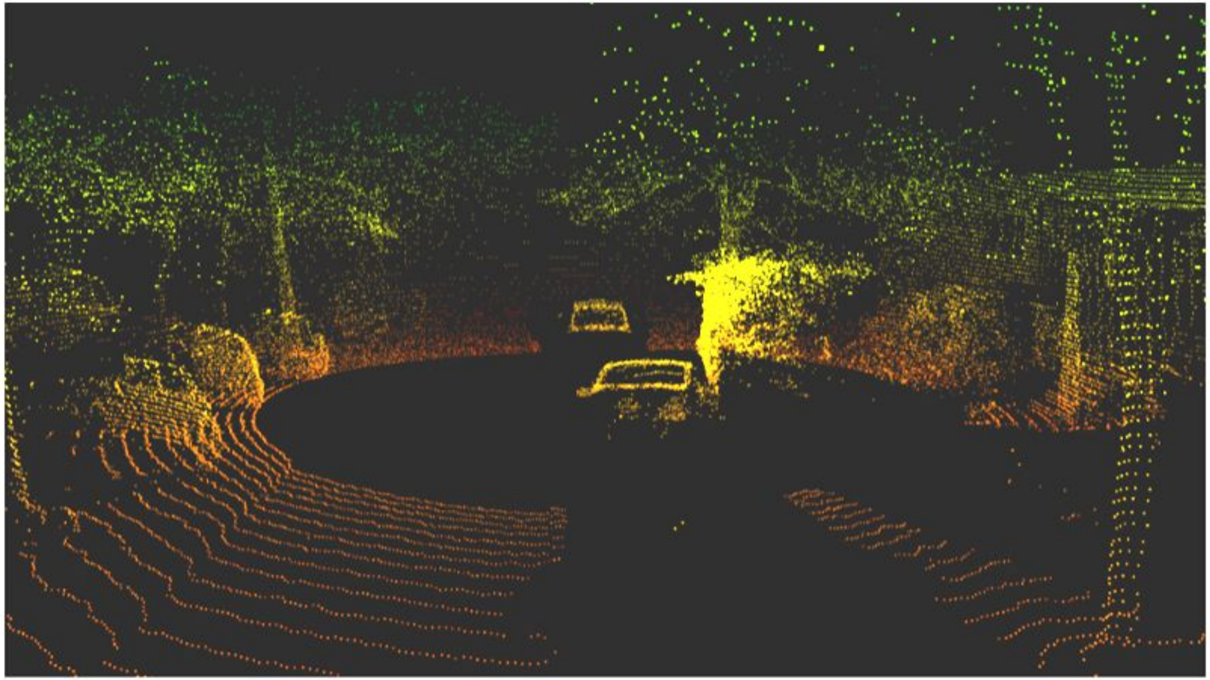
$$\theta = atan2(y, x) \in [-\pi/2, \pi/2]$$

$$\varphi = asin(z/r) \in [-\pi, \pi]$$

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} \frac{W}{2}(1 + \frac{\theta}{\pi}) \\ H \frac{f_{up} - \varphi}{f_{up} - f_{down}} \end{pmatrix}$$

Conversion issues

- multiple points may fall in the same pixel
- empty pixel



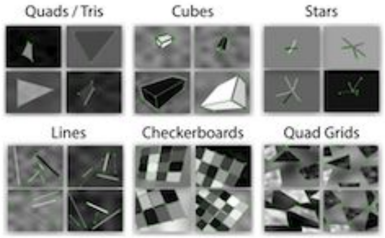
(a)

(b)

(c)

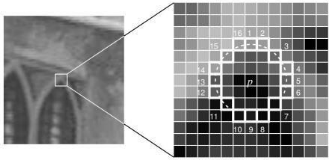
Feature Extraction

Projection | Extraction | Association | Registration | Odometry

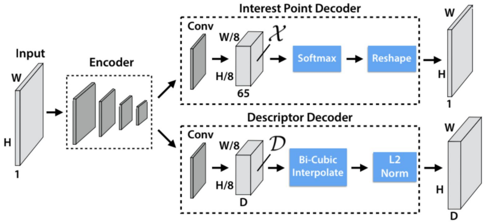


Traditional vs Deep Learning

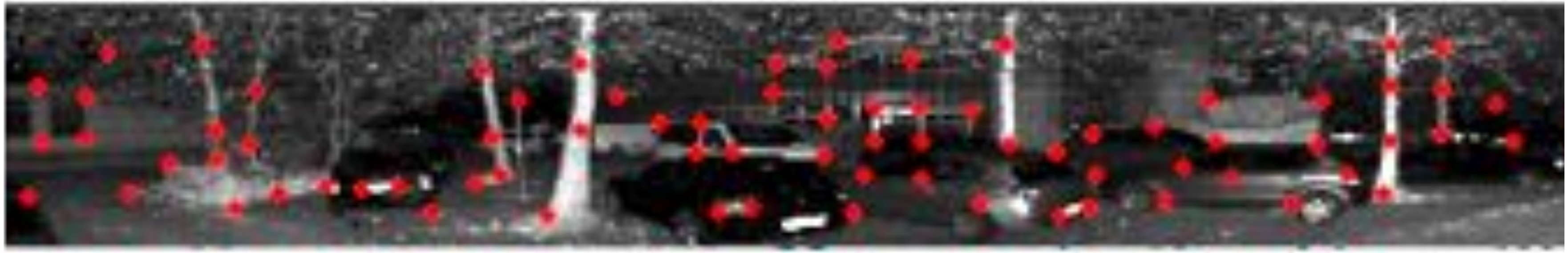
- Oriented FAST and Rotated BRIEF (ORB)
- SuperPoint

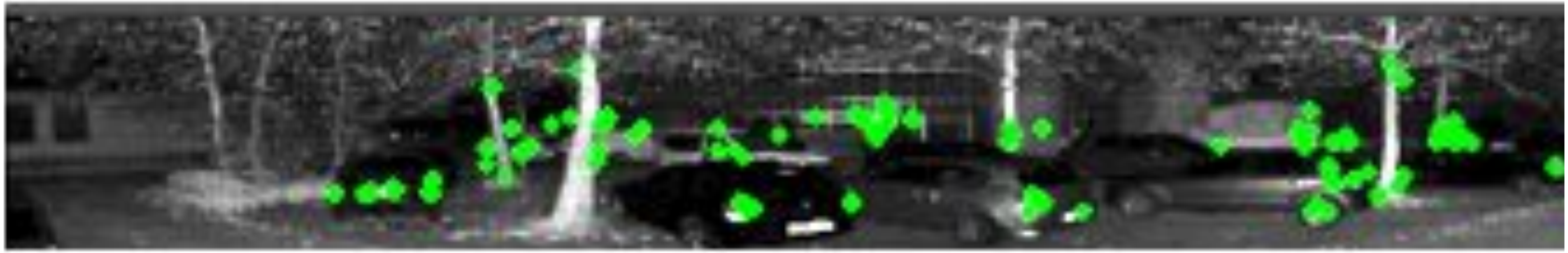


VS



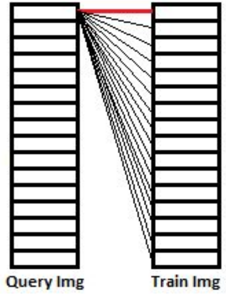
	Traditional	Deep Learning
Detection	Multiscale and oriented FAST detection of surrounding pixels	MagicPoint + Homographic Adaptation
Description	Gaussian kernel smoothing and binary test on image patch **128 bit vector**	semi-dense model + bi-cubic interpolation + L2 norm **256 float vector**





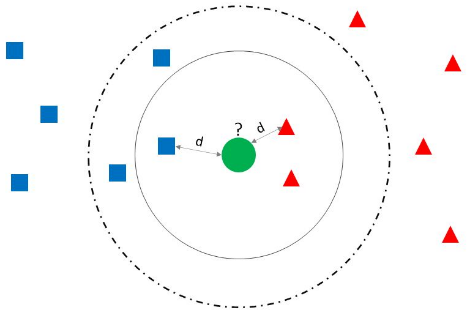
Data Association

Projection Extraction Association Registration Odometry



Brute-force approach

matching each descriptor with all the others



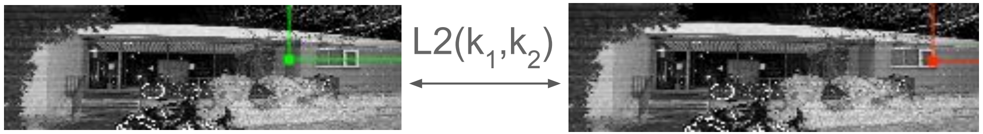
K-nearest neighbor (k=2)

choice is made by a ratio test

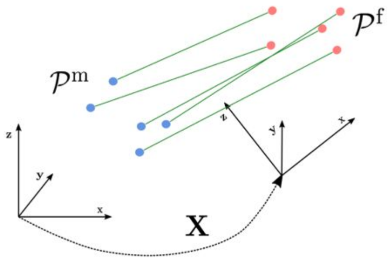
$$L(m_{k=1}, m_{k=2}) = \begin{cases} \text{keep} & \text{if } m_{k=1}.distance < m_{k=2}.distance * \text{ threshold)} \\ \text{discard} & \text{otherwise} \end{cases}$$

Euclidean norm check

looking for geometrical consistency



Transform Registration - Method



Projection — Extraction — Association — Registration — Odometry

Incremental approach

Iterative Closest Point (ICP)

- State $\quad \mathbf{X} = [\mathbf{R} \mid \mathbf{t}]$
- Perturbation $\quad \Delta\mathbf{x} = (\Delta x \; \Delta y \; \Delta z \; \Delta\alpha_x \; \Delta\alpha_y \; \Delta\alpha_z)$
- Operator $\quad \mathbf{X} \boxplus \Delta\mathbf{x} = v2t(\Delta\mathbf{x})\mathbf{X}$

- Measurement function $\quad \mathbf{h}_k^{icp}(\mathbf{X}) = \mathbf{R}^T(p_{j(k)}^m - \mathbf{t})$
- Error function $\quad \mathbf{e}_k^{icp}(\mathbf{X}) = \mathbf{h}_k^{icp}(\mathbf{X}) - p_{j(k)}^f$
- Jacobian $\quad \mathbf{J}_k^{icp}(\mathbf{X}) = \left(\mathbf{I} \; - [p_{j(k)}^m]_\times\right)$

Direct approach

Closed-form solution to Least-Square (SVD)

Algorithm 2 Closed-form Solution of Least-Squares Optimization

Require: point correspondences $\{\langle x_0, y_0\rangle, ..., \langle x_K, y_K\rangle\}$

Ensure: closed-form solution of $\mathbf{R}$ and $\mathbf{t}$

$\boldsymbol{\mu}_x \leftarrow \frac{1}{k}\sum_{i=1}^k \mathbf{x}_i, \quad \boldsymbol{\mu}_y \leftarrow \frac{1}{k}\sum_{i=1}^k \mathbf{y}_i$

$\boldsymbol{\sigma}_x \leftarrow \frac{1}{k}\sum_{i=1}^k ||\mathbf{x}_i - \boldsymbol{\mu}_x||^2, \quad \boldsymbol{\sigma}_y \leftarrow \frac{1}{k}\sum_{i=1}^k ||\mathbf{y}_i - \boldsymbol{\mu}_y||^2$

$\boldsymbol{\Sigma} \leftarrow \frac{1}{k}\sum_{i=1}^k (\mathbf{y}_i - \boldsymbol{\mu}_y)(\mathbf{x}_i - \boldsymbol{\mu}_x)^T$

$\mathbf{UDV}^T \leftarrow SVD(\boldsymbol{\Sigma})$

if $det(\mathbf{U})det(\mathbf{V}) = 1$ **then**

  $\mathbf{S} = \mathbf{I}_{3\times 3}$

else

  $\mathbf{S} = diag(1, 1 - 1)$

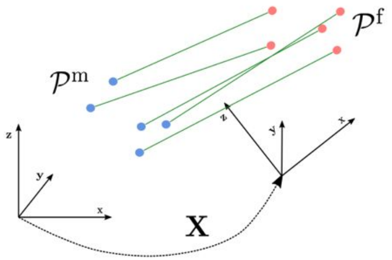
end if

$\mathbf{R} \leftarrow \mathbf{USV}^T$

$\mathbf{t} \leftarrow \boldsymbol{\mu}_y - \mathbf{R}\boldsymbol{\mu}_x$

return $\mathbf{R}, \mathbf{t}$

Transform Registration - Outlier Rejection



Projection — Extraction — Association — Registration — Odometry

Incremental approach

Robust estimator

- L1 Omega norm of the error function
- New error term
- Reducing contributions of higher errors

$$\underset{X}{argmin} \sum_{k=1}^{m} \rho(u_k(x))$$

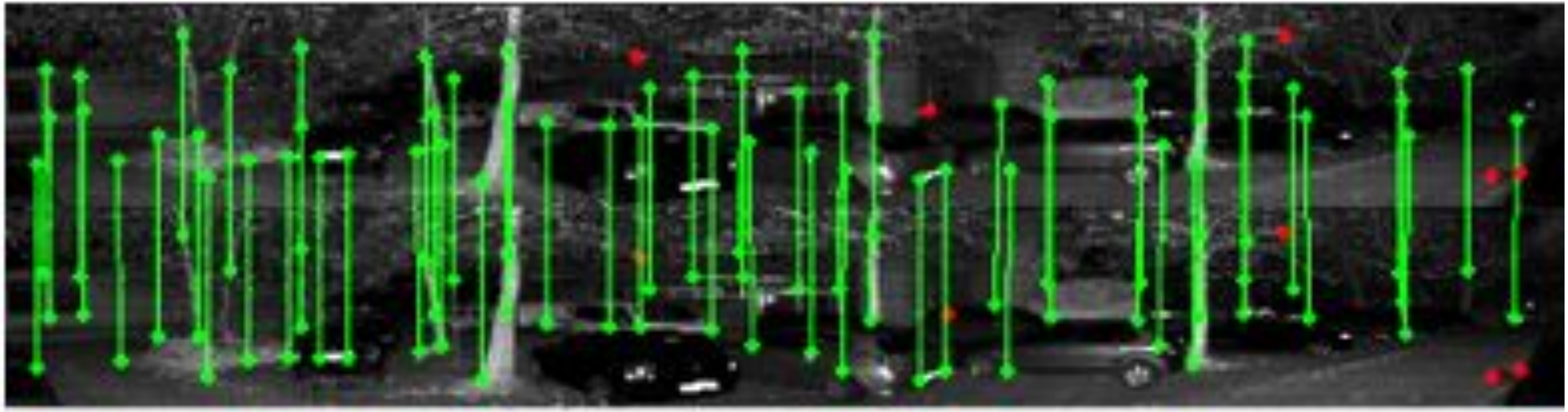
$$\begin{aligned}
&\mathbf{e}_k \leftarrow \mathbf{h}_k(\check{\mathbf{x}}) \boxminus \mathbf{z}_k \\
&\mathbf{J}_k \leftarrow \frac{\partial \mathbf{e}(\check{\mathbf{x}} \boxplus \Delta\mathbf{x})}{\partial \Delta\mathbf{x}}\Big|_{\Delta x=0} \\
&u_k \leftarrow \sqrt{\mathbf{e}_k(\mathbf{x})^T \Omega_k \mathbf{e}_k(\mathbf{x})} \\
&\gamma_k \leftarrow \frac{1}{u_k}\frac{\partial \rho_k(u)}{\partial u}\Big|_{u=u_k} \\
&\Omega_k = \gamma_k \Omega_k \\
&\mathbf{H} \leftarrow \mathbf{H} + \mathbf{J}_k \Omega_k \mathbf{J}_k \\
&\mathbf{b} \leftarrow \mathbf{b} + \mathbf{J}_k \Omega_k \mathbf{e}_k
\end{aligned}$$

Direct approach

Random Sample Consensus (RANSAC)

1. Randomly select a minimum amount of data
2. Compute a model (closed-form)
3. Evaluate the model (Euclidean distance)
4. Repeat the procedure k times

iterations: $$k = \frac{log(1-p)}{log(1-w^n)}$$



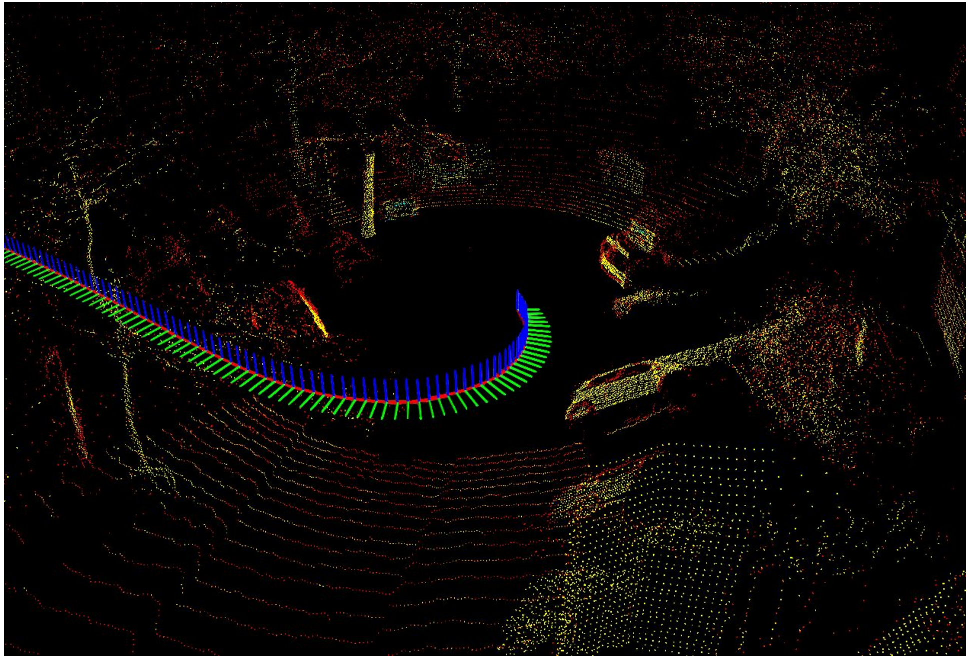
Odometry Estimation

Projection — Extraction — Association — Registration — Odometry

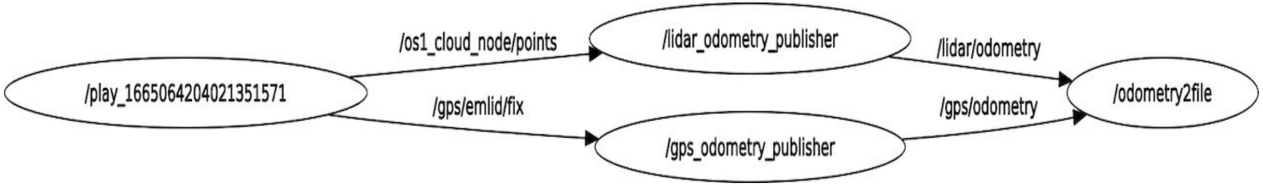
Accumulation of transforms

frame by frame matrix multiplication

$$\mathbf{T}_k^0 = \mathbf{I}_{4\times4}\ \mathbf{T}_1^0\ \mathbf{T}_2^1\ \ldots\ \mathbf{T}_k^{k-1}$$

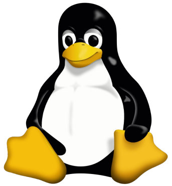


Experiments



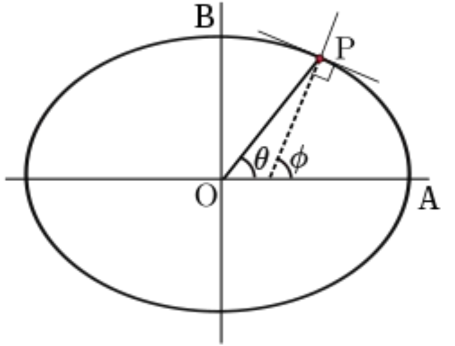
Hardware

- Ubuntu 20.04, C++
- 8-core Intel core i9 without graphic card
- LiDAR OS1-64 vertical, 1024 horizontal, 10Hz, 65536 points per frame



GNSS estimation

conversion from geodetic to geocentric coordinates



$$x = R_{Heart}(\mathbf{P}) \cdot cos(long) \cdot cos(\mathbf{gLat}(lat))$$
$$y = R_{Heart}(\mathbf{P}) \cdot sin(long) \cdot cos(\mathbf{gLat}(lat))$$
$$z = R_{Heart}(\mathbf{P}) \cdot sin(\mathbf{gLat}(lat))$$

Robot Operating System

ROS middleware for playing dataset and run pipeline

Evaluation

Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k} ||\hat{\mathbf{t}}_k - \mathbf{t}_k^{GNSS}||^2}$$

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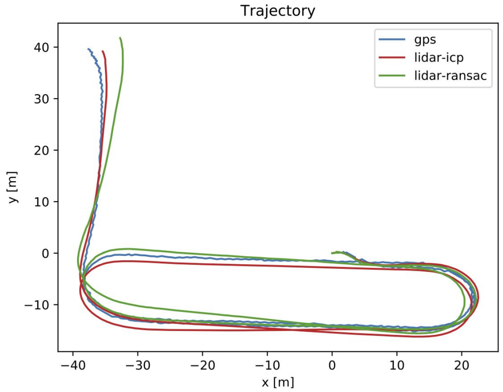
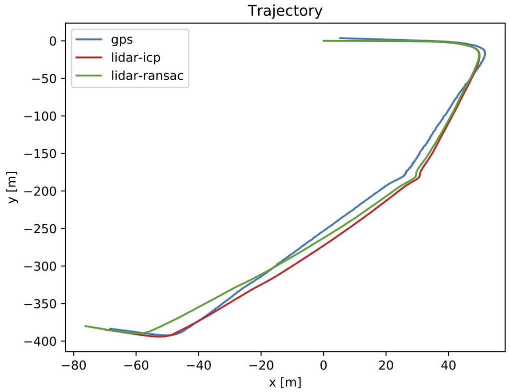
Parameters Tuning

Feature Extraction			Tracking		
SuperPoint	nFeatures	300	BF Matcher	knnThreshold	0.7
	threshold	0.1		normType	L2/H
	nmsBlockSize	6		normThreshold	30
FAST	threshold	30	**Registration**		
ORB	nFeatures	300	IRLS	iterations	1
	scaleFactor	1.1		kernelThreshold	5e-5
	nLevels	8		damping	0.5
	edgeThreshold	15	RANSAC	iterations	30
	patchSize	15		inliersThreshold	20cm

Results


Trajectory
gps
lidar-icp
lidar-ransac
x [m]
y [m]


Trajectory
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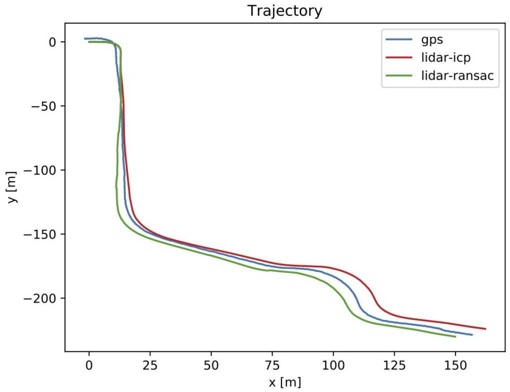
Trajectory
gps
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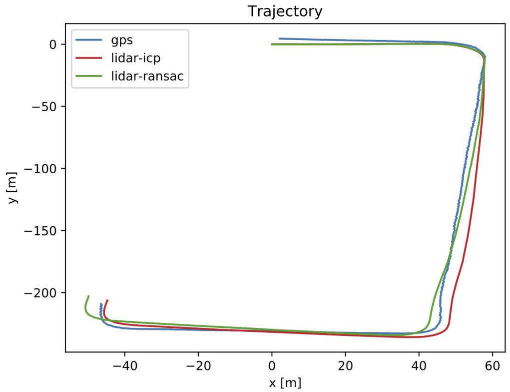
lidar-ransac
x [m]
y [m]


Trajectory
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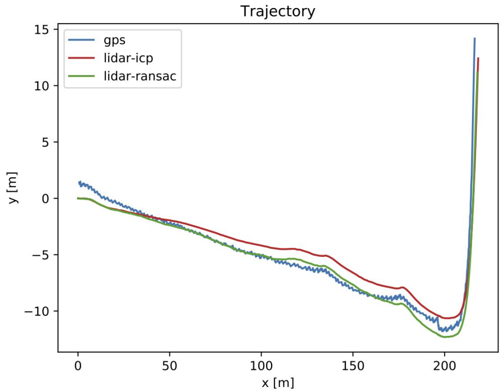
x [m]
y [m]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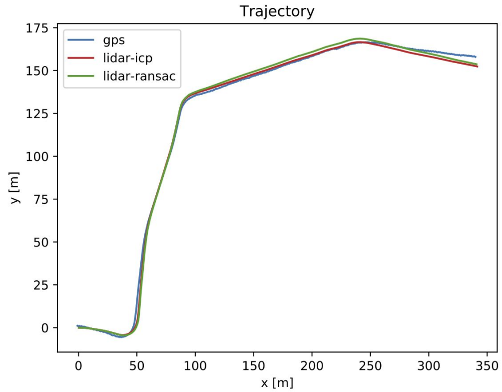

Trajectory
gps
lidar-icp
lidar-ransac
x [m]
y [m]

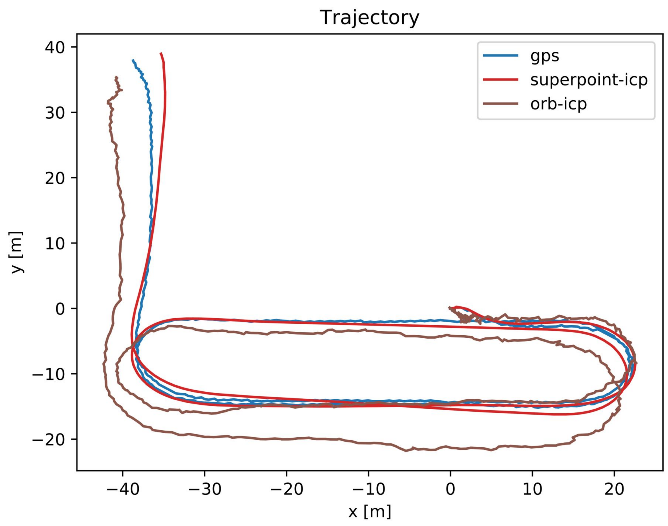
Comparison

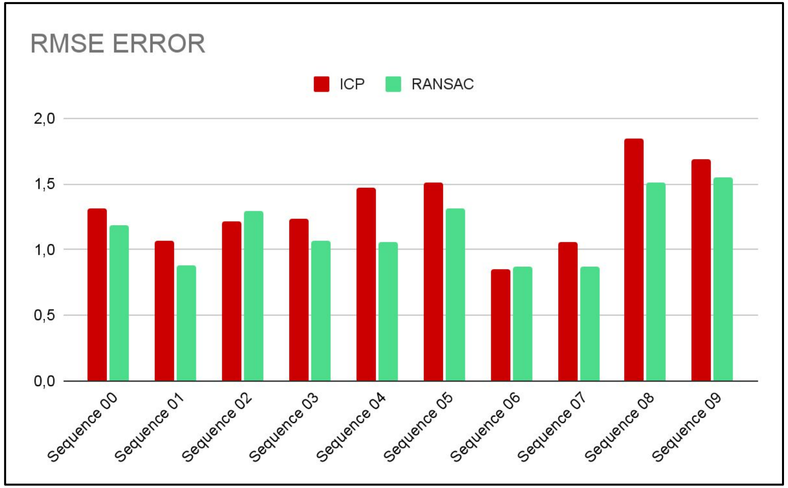
SuperPoint > ORB
(with ICP)

- SuperPoint detections sparse and repeatable
- ORB detections poorly distributed
- ORB 110HZ >> SuperPoint 20Hz

RANSAC > ICP
(with SuperPoint)

- RANSAC more accurate
- ICP 70 kHz >> RANSAC 20kHz
- ICP no longer valid in global optimization
- RANSAC suitable for loop closure





Conclusions

- ➢ **Feature extraction**

  Machine learning is overcoming traditional approaches

- ➢ **Transform estimation**

  probabilistic framework more accurate than least-square optimization and more suitable for other task in SLAM frameworks

- ➢ **Hardware requirements**

  machine learning technique feasible also without graphic card

Future Work

- Use of LiDAR depth information in conjunction with intensity
- Registration in non-successive frame
- Loop closure detection and bundle adjustment

Thanks