Developing an affordable alternative for autonomous vehicle localization using high-definition radar images

Capstone Project

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David Scanlan (IEOR)
Bowen Wang (ME)

In partnership with:
Zendar

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Agenda

1. Project Introduction and Overview (David)

2. Preprocessing (Bowen)

3. Mapping and Localization (Pierre-Louis)

4. Results and Conclusion (Johan)

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Project Introduction and Overview

David Scanlan

Capstone Project Motivation

- 94% of accidents on the road today are due to human error

- Autonomous Vehicle (AVs) provide a solution that is safer, more efficient, and easier to use

- Current solution to precise AV localization is cost prohibitive

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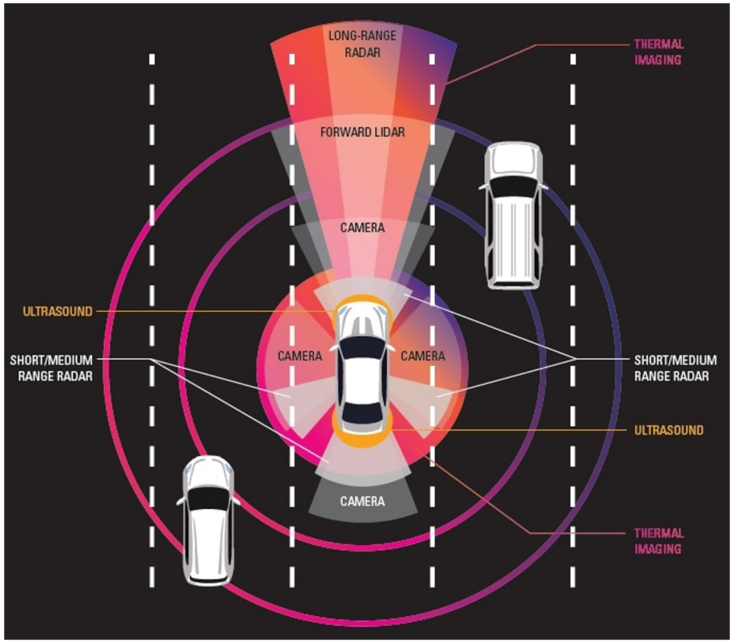
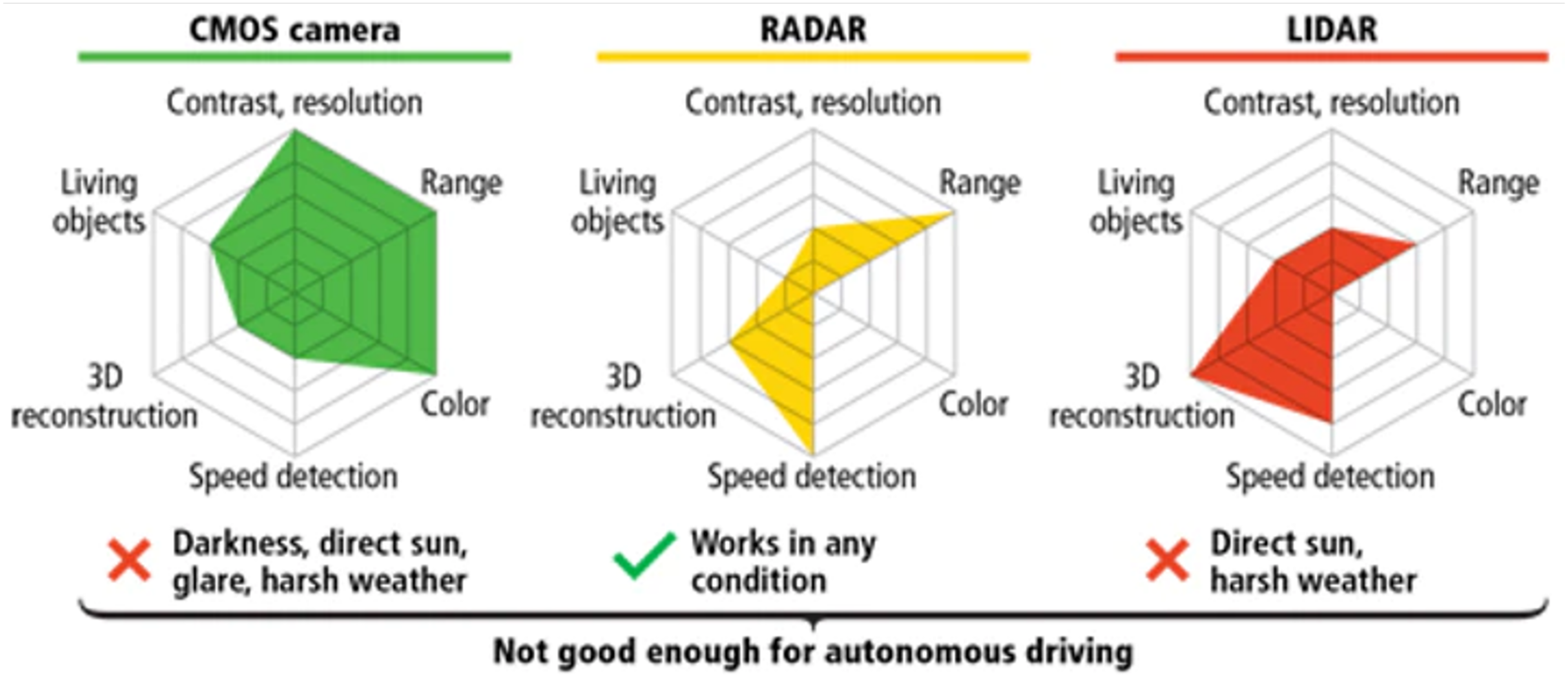
Traditional Sensor Suite for AVs

- Camera
  - Object detection (Traffic Camera etc.)
  - High resolution but sensitive to lighting
- LiDAR
  - Build 3D maps of environment
  - Cost Prohibitive
- Radar
  - Hazard detection and range finding
  - Immune to adverse weather condition



Comparison of AV Sensors



Our solution is to utilize radar sensors for both mapping and localization

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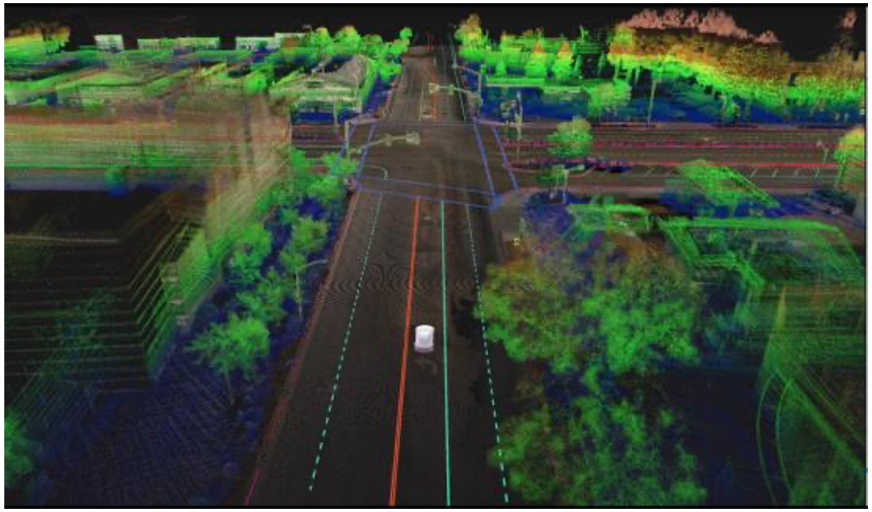
Mapping and Localization

- Mapping
  - Creating a 2D top down map of the environment from radar images

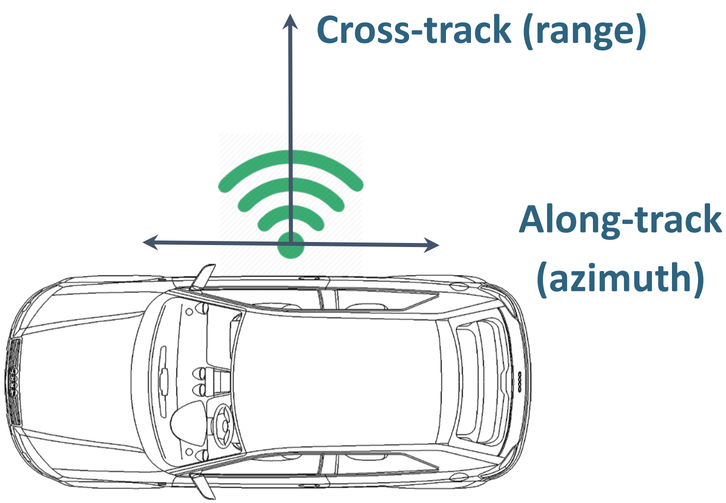
- Localization
  - Calculating location of vehicle using basic GPS position, map, and new radar image input



Background on Zendar

Company found in 2017 with the vision to develop innovative radar sensors for AVs

- **Real-time**
- **0.1 degree azimuth resolution**
- **360 degrees field of view**



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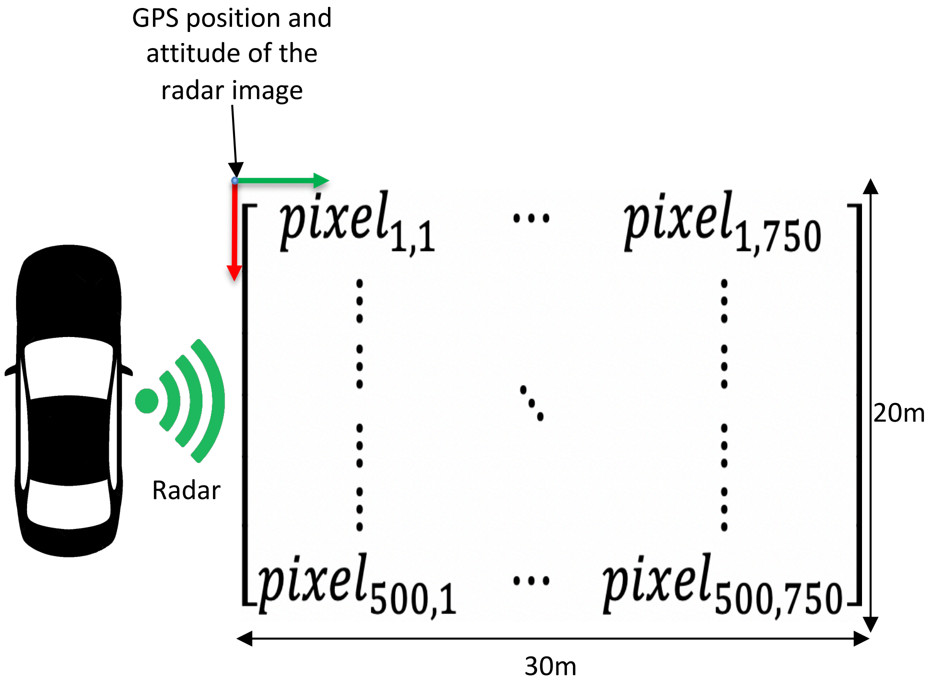
Raw Data received from Zendar

- **Raw data from Zendar contained the following elements:**
  - Raw Radar Data
  - Coarse GPS Position
  - High Accuracy GPS Position
  - Attitude



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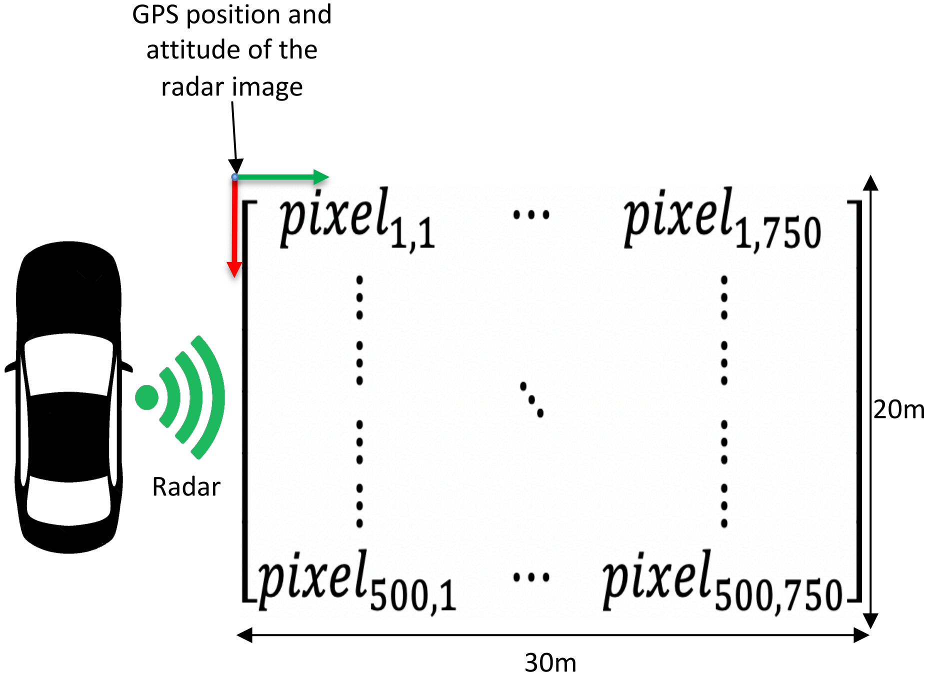
Radar Images Preprocessing

Bowen Wang

Raw Data from Zendar and Data Integration

- **Format:** HDF5
- **Radar data matrix:**
  - Pixel value *(complex number)*
  - ECEF *(Earth-Centered, Earth-Fixed)* GPS position *(including VN200 GPS and SBG GPS)*
  - Attitude *(a quaternion transferring vector from ECEF plane to the image plane)*
  - Timestamp *(every 0.1 second)*
- **Tracklog**:
  - Car's position, attitude and timestamp



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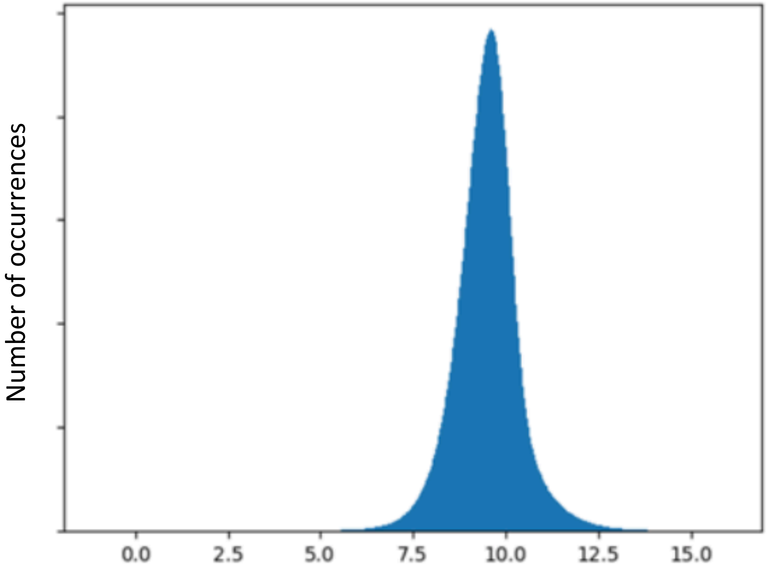
Preprocessing algorithm

- Logarithm of Magnitude
- Globally Shifted Normalization
- Otsu Thresholding
- Density-based Clustering

Logarithm of magnitude

- **Goal**: Visualize the data properly
- **Action**: calculate the log value of each pixel
- **Problem**: foreground is not clear

Video demo



Logarithm of pixel values distribution

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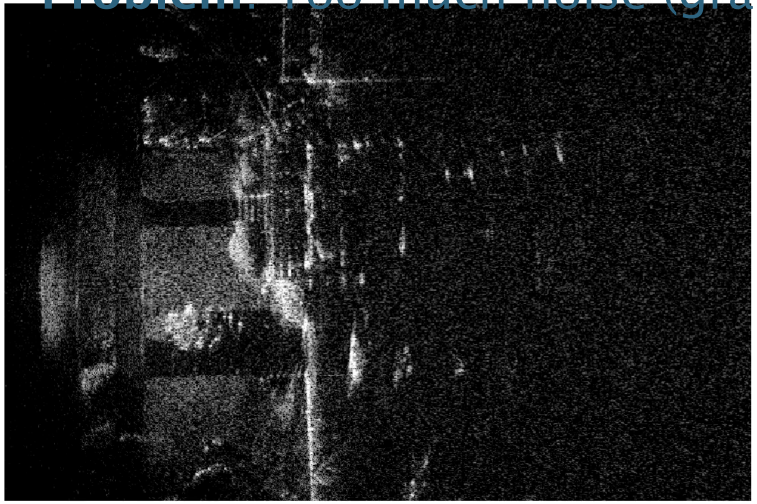
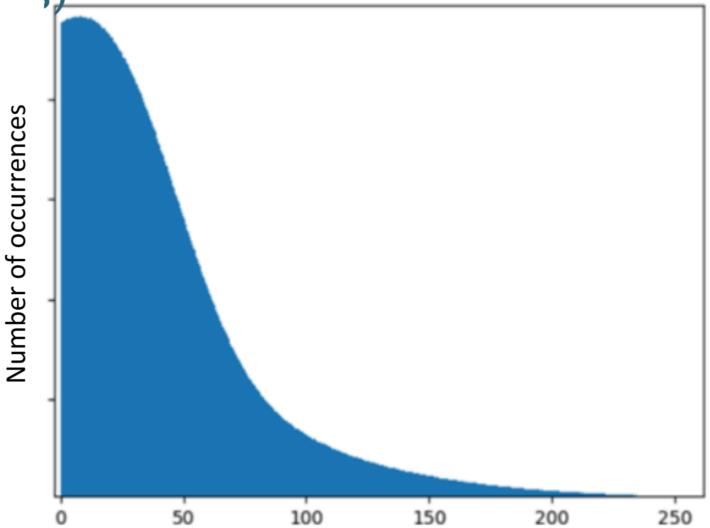
Globally Shifted Normalization

- **Goal**: extract the most informative pixels of the image
- **Action**: Globally shifted normalization
- **Problem**: Too much noise (gray poi s)



Video Demo



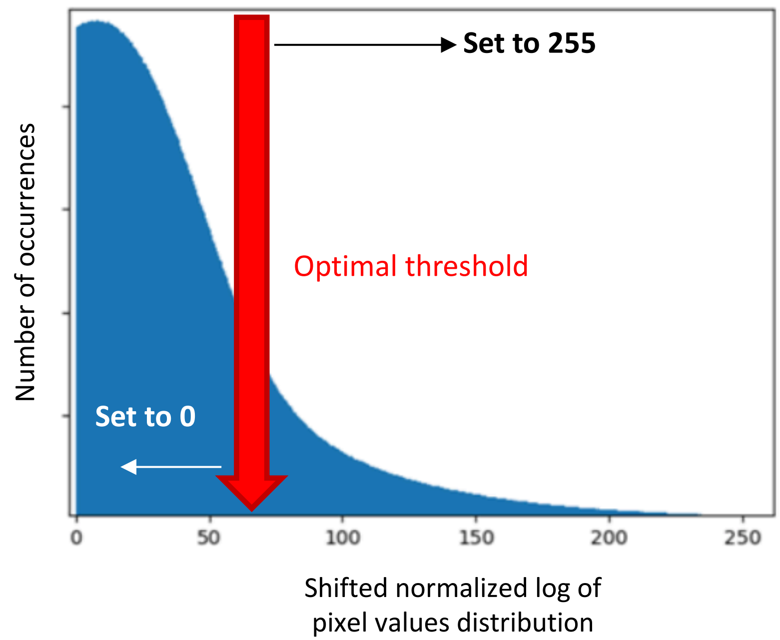
Shifted normalized log of pixel values distribution

Otsu Thresholding

- **Goal**: extract the pattern of the objects for later clustering
- **Action**: Find the pixel value threshold automatically.
- **Problem**: binary image will lose n

$$\max\ \sigma_\omega^2(t) = \overbrace{\omega_0(t)\sigma_0^2(t)}^{\text{Background}} + \overbrace{\omega_1(t)\sigma_1^2(t)}^{\text{Foreground}}$$

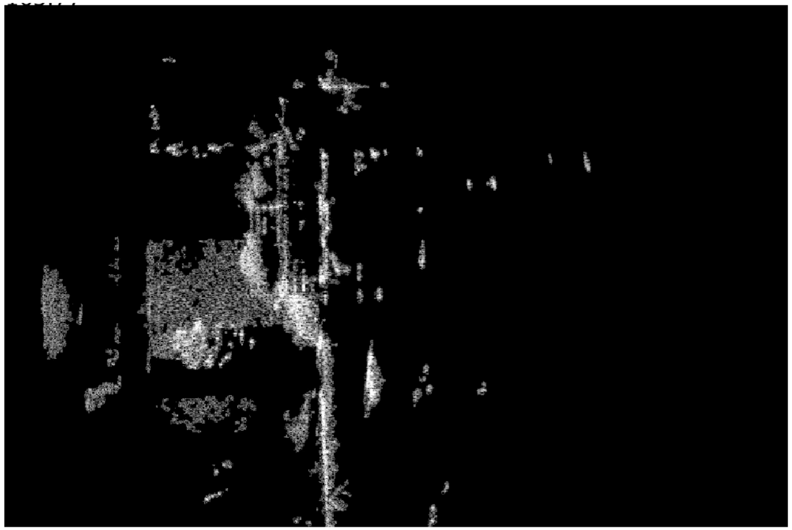
Video Demo



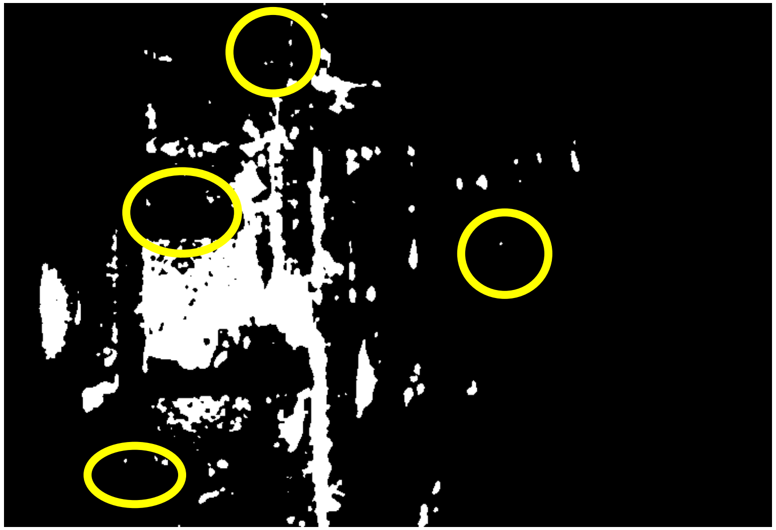
Density-based Clustering

- **Goal**: remove some small pixel spots to increase the performance of image-based analytic method.

- **Action**: Utilize DBSCAN algorithm



Video Demo



Binary Image before DBSCAN

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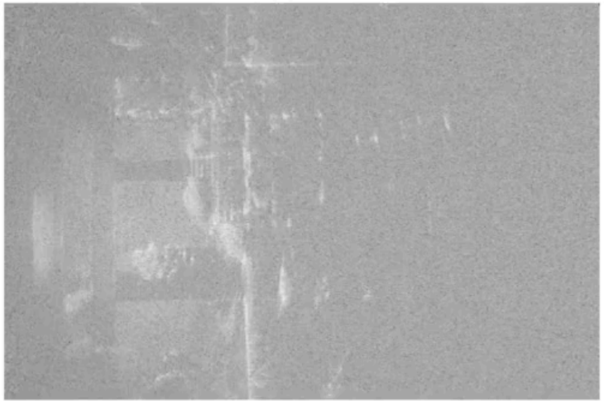
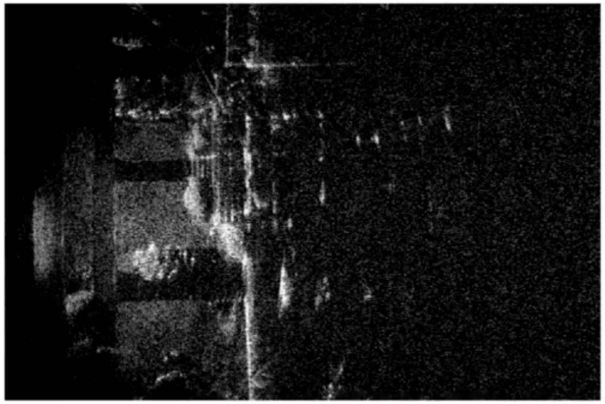
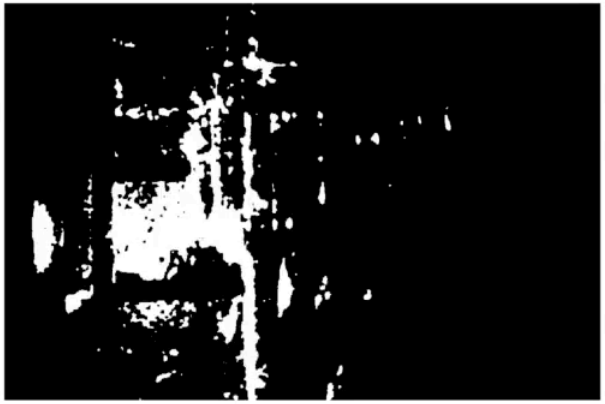


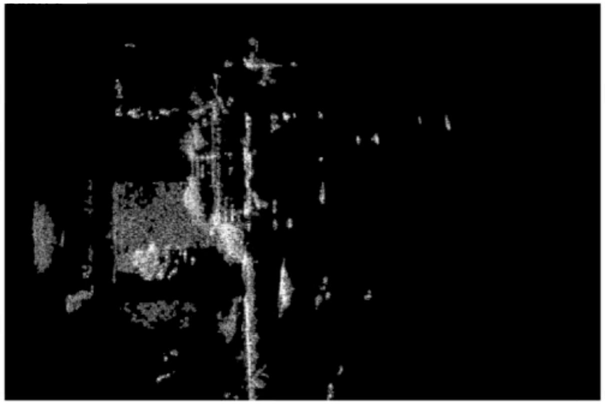
Step1:
Logarithm of the magnitude



Step2:
Global shifted normalization



Step3:
Otsu thresholding



Step4:
Density-based clustering

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Mapping and Localization Algorithms

Pierre-Louis Blossier

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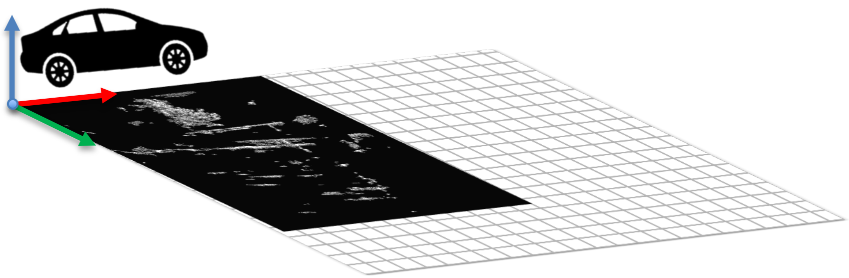
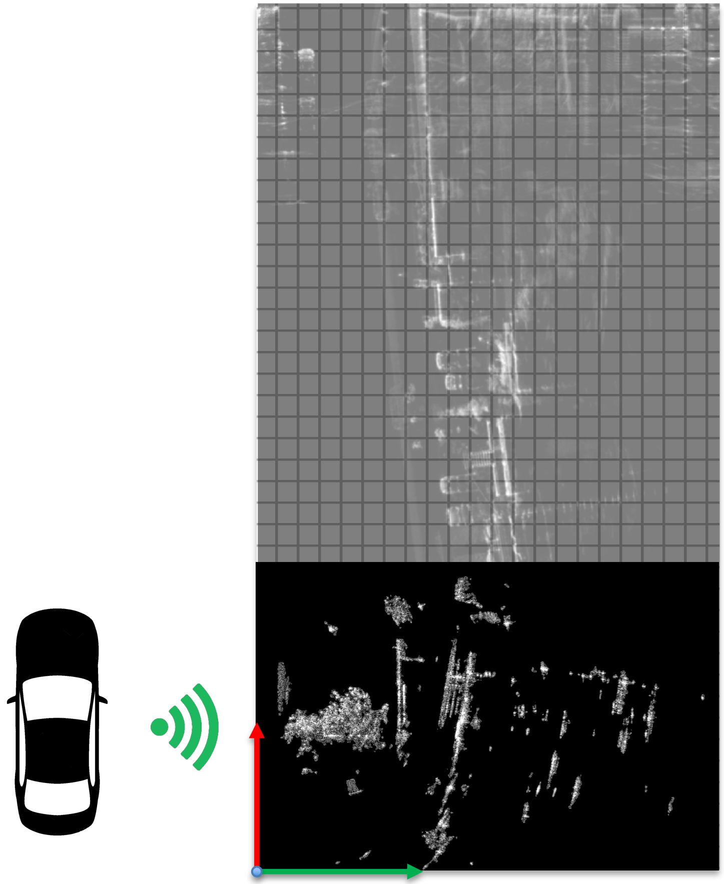
2D Map Representation

Assumption:

All the radar images are in the same plane





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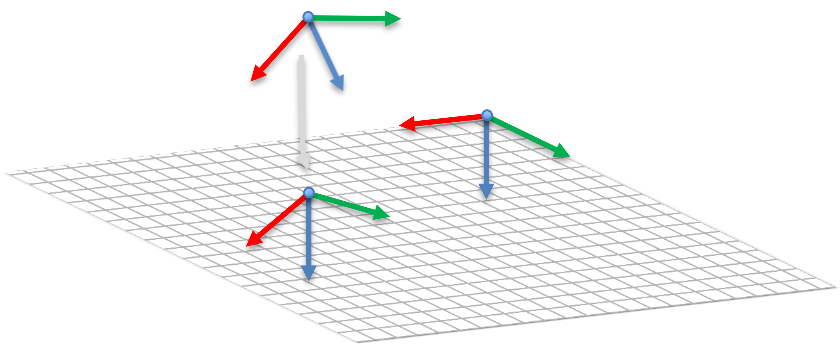
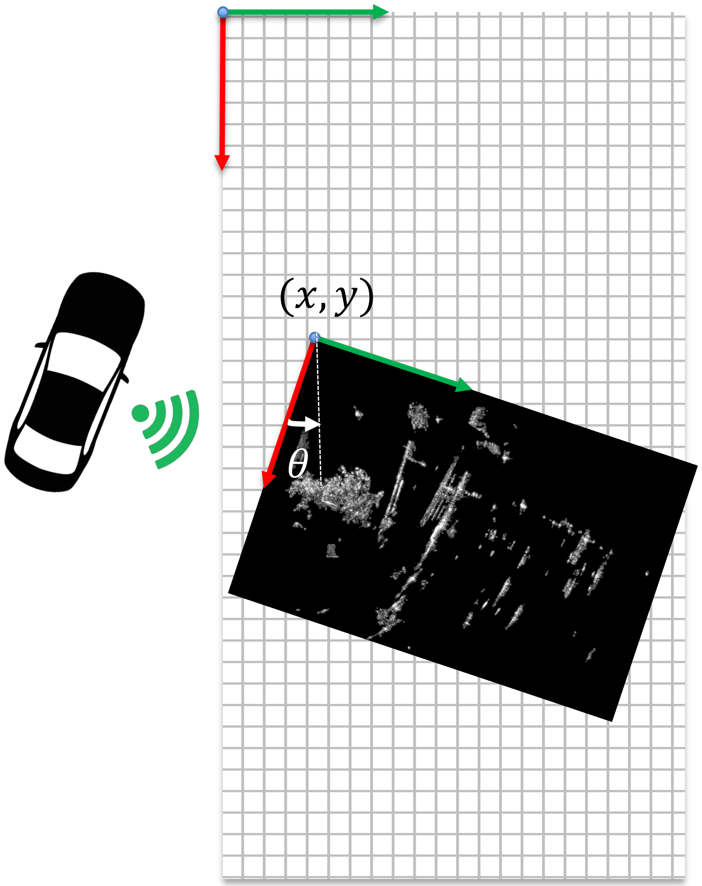
2D Map Representation

Assumption:

All the radar images are in the same plane

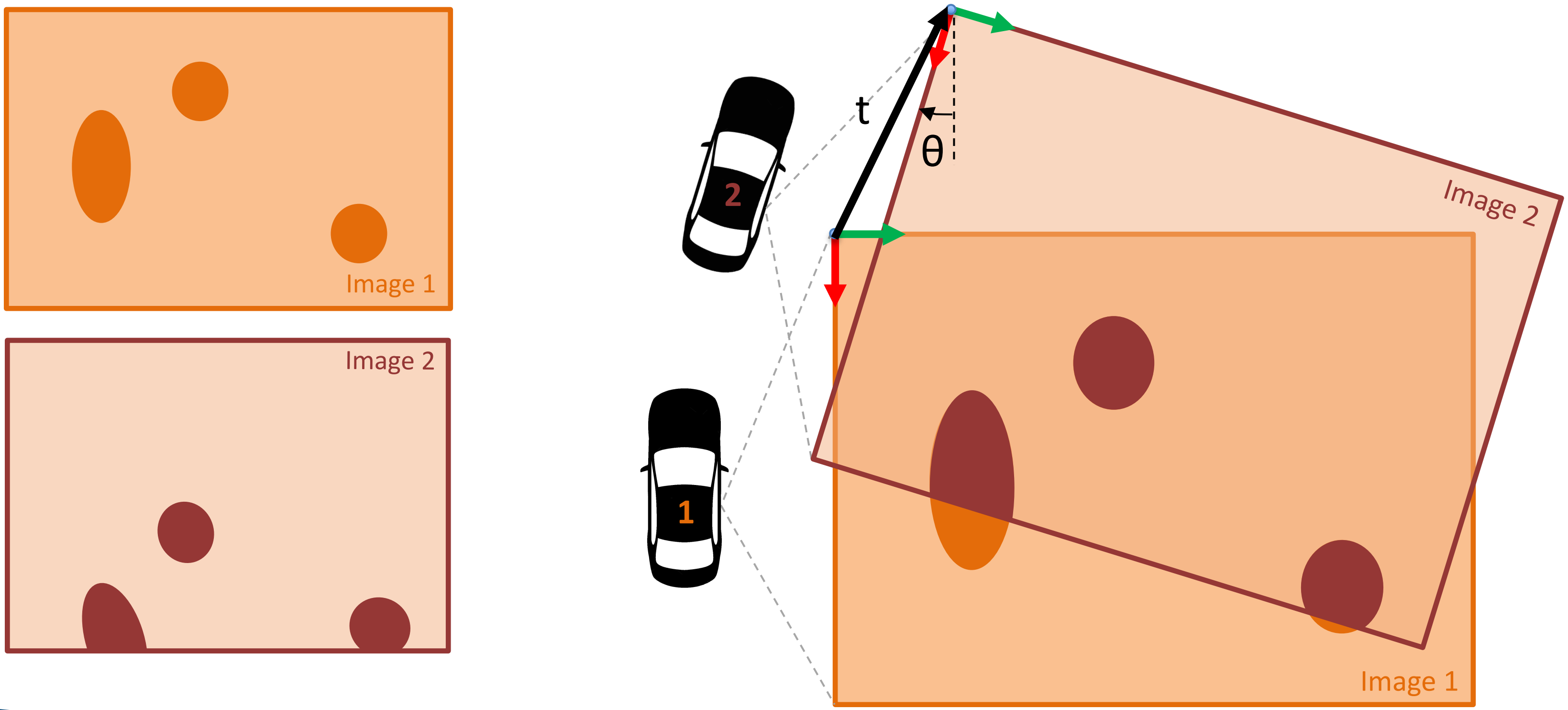
Three Degrees of Freedom: x, y, θ





Direct Image Alignment

- It is possible to have additional position and orientation information of each image thanks to direct image alignment



Enhanced Correlation Coefficient (ECC)

Find Euclidean transformation between two images based on a robust correlation coefficient

- Euclidean transformation:

$$\Psi(p) = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{14} & p_{15} & p_{16} \end{pmatrix} = \begin{pmatrix} \cos\delta\theta & \sin\delta\theta & \delta x \\ -\sin\delta\theta & \cos\delta\theta & \delta y \end{pmatrix}$$

- Optimization problem:

$$\min_p E_{Ecc}(p) = \min_p \left\| \frac{\bar{\iota}_r}{\|\bar{\iota}_r\|} - \frac{\bar{\iota}_w(p)}{\|\bar{\iota}_w(p)\|} \right\|^2 \Leftrightarrow \max_p \frac{\bar{\iota}_r{}^t \bar{\iota}_w(p)}{\|\bar{\iota}_r\| \|\bar{\iota}_w(p)\|}$$

$\bar{\iota}_r$ vector representation of the reference image

$\bar{\iota}_w(p)$ vector representation of the warped image

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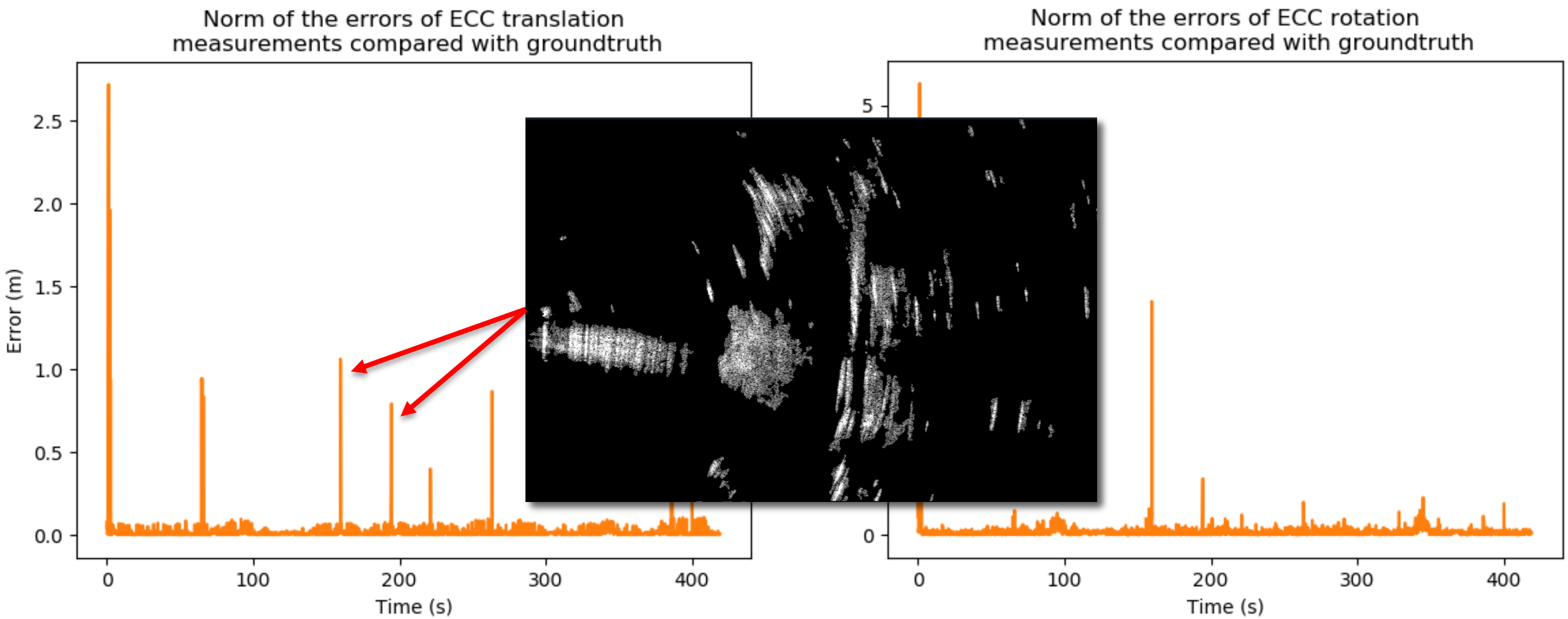
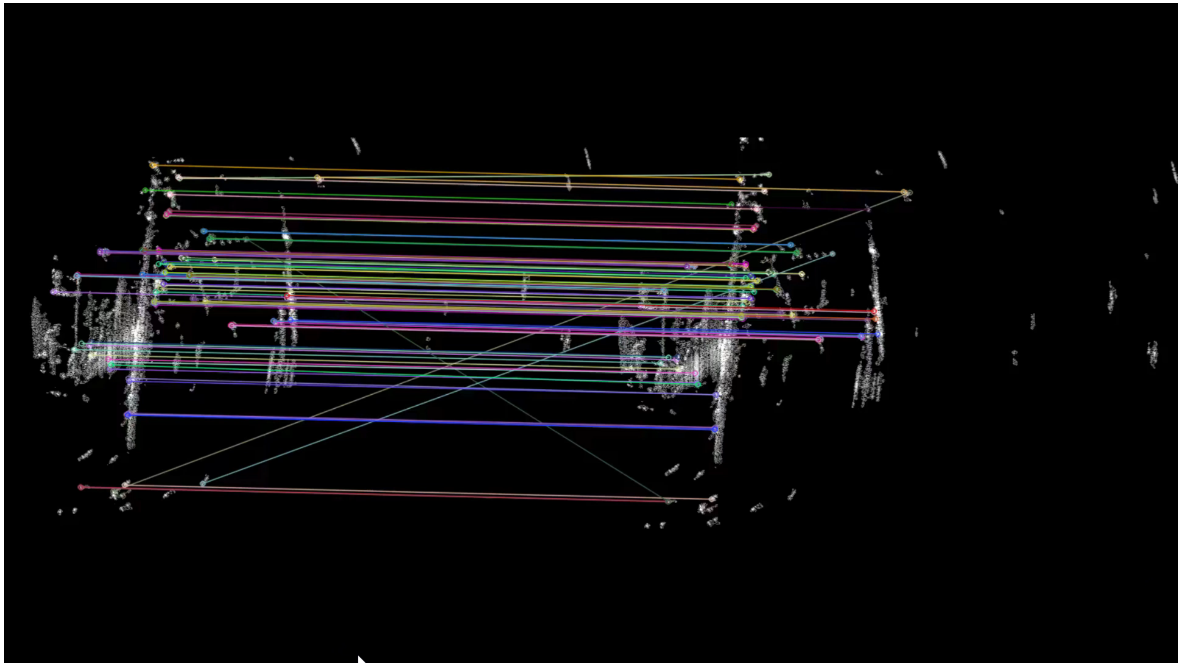
ECC Performance



- Translation average error: $1.37cm$ (standard deviation: $7.24cm$)
- Rotation average error: $0.03°$ (standard deviation: $0.10°$)

Comparison with other methods

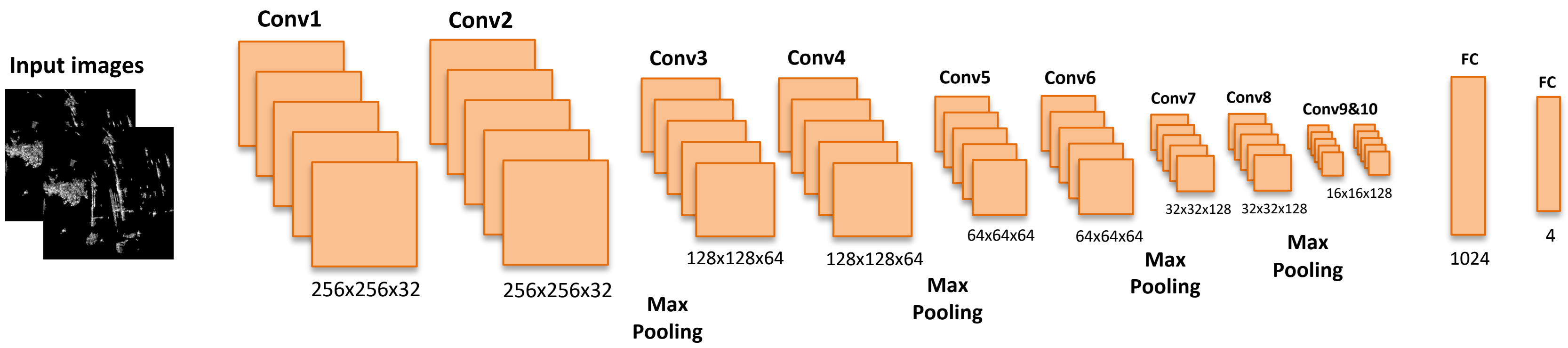
- ORB: feature matching



- Translation average error: $19.5cm$ (standard deviation: $3.19m$)
- Rotation average error: $0.34°$ (standard deviation: $22.1°$)

Comparison with other methods

- Deep Convolutional network (VGGnet like structure)



- Never reached the performance of an optimization on the ECC
- Could be an interesting area of research

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Refining 2D pose estimation with a Kalman Filter

Two measurements to refine position estimation:

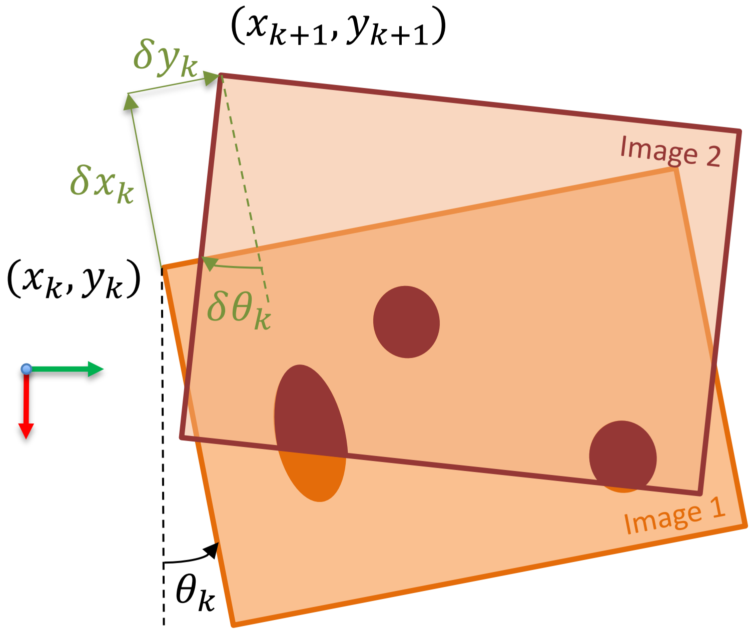
- GPS position (projected on map plane): x^{GPS}, y^{GPS}, θ^{GPS}
- Direct Image Alignment translation and rotation: δx, δy, $\partial\theta$

Prediction step:

$$\begin{pmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \\ \theta_k \end{pmatrix} + \begin{pmatrix} \cos\theta_k & -\sin\theta_k & 0 \\ \sin\theta_k & \cos\theta_k & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \delta x_k \\ \delta y_k \\ \delta\theta_k \end{pmatrix}$$

Measurement model:

$$y_k = \begin{pmatrix} x_k^{GPS} \\ y_k^{GPS} \\ \theta_k^{GPS} \end{pmatrix}$$



Kalman Filter Implementation

- Uncertain model of our system:

$$\begin{cases} \begin{pmatrix} x_{k+1} \\ y_{k+1} \\ \theta_{k+1} \end{pmatrix} = \begin{pmatrix} x_k \\ y_k \\ \theta_k \end{pmatrix} + \begin{pmatrix} \cos\theta_k & -\sin\theta_k & 0 \\ \sin\theta_k & \cos\theta_k & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \partial x_k - b_k^x + w_k^x \\ \partial y_k - b_k^y + w_k^y \\ \partial y_k - b_k^\theta + w_k^\theta \end{pmatrix} \\ y_k = \begin{pmatrix} x_k^{GPS} + v_k^x \\ y_k^{GPS} + v_k^y \\ \theta_k^{GPS} + v_k^\theta \end{pmatrix} \end{cases}$$

$$w_k = \begin{pmatrix} w_k^x \\ w_k^y \\ w_k^\theta \end{pmatrix} \sim N(0, Q) \qquad v_k = \begin{pmatrix} v_k^x \\ v_k^y \\ v_k^\theta \end{pmatrix} \sim N(0, R) \qquad X_k = \begin{pmatrix} x_k \\ y_k \\ \theta_k \\ b_k^x \\ b_k^y \\ b_k^\theta \end{pmatrix}$$

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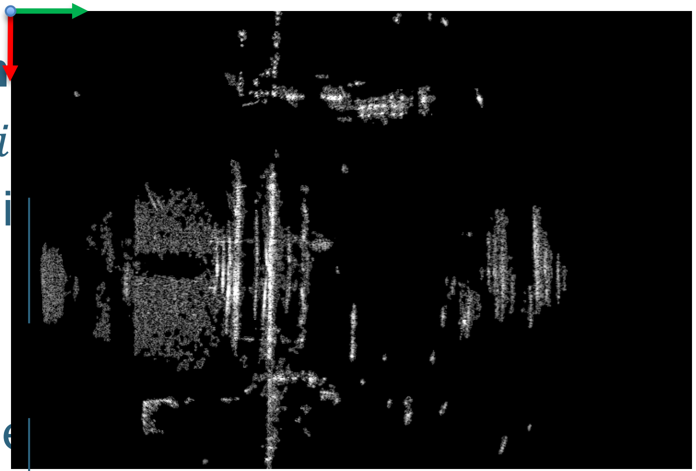
Mapping Process

- The map is a pair value/covariance: (x_{ij}, P_{ij}) where i, j are the index of the pixel position
- New input radar image: pixels (y_{ij}, R)

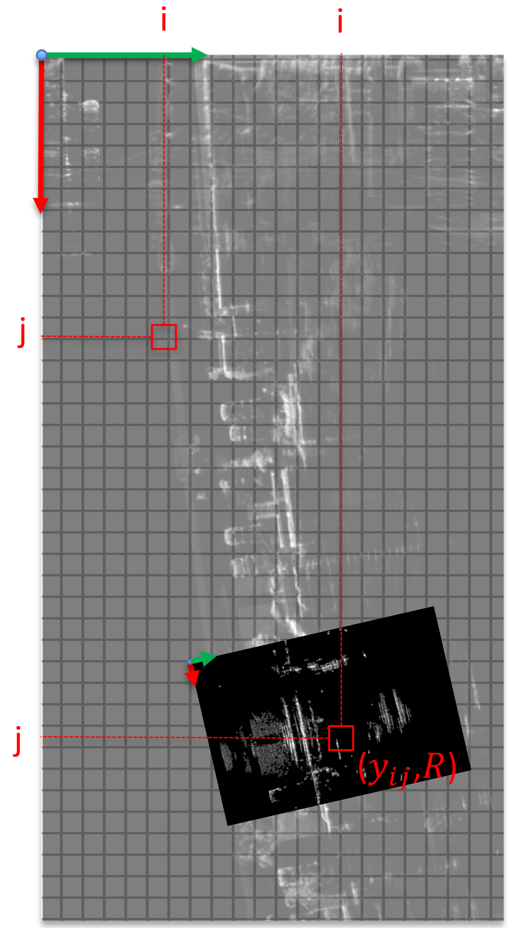


Algorith

For i

$$x_{ij} = (P_{ij}\ y_{ij} + R x_{ij})/(x_{ij} + R)$$

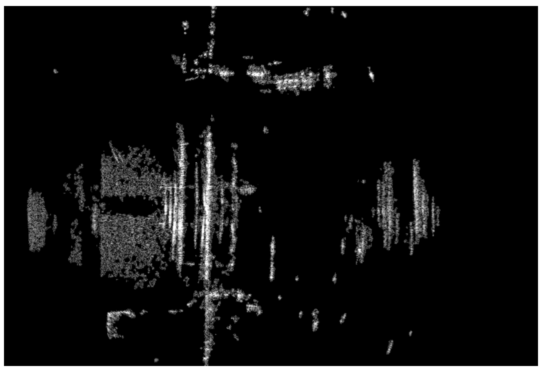
$$P_{ij} = (P_{ij}\mathrm{R})/(P_{ij} + R)$$



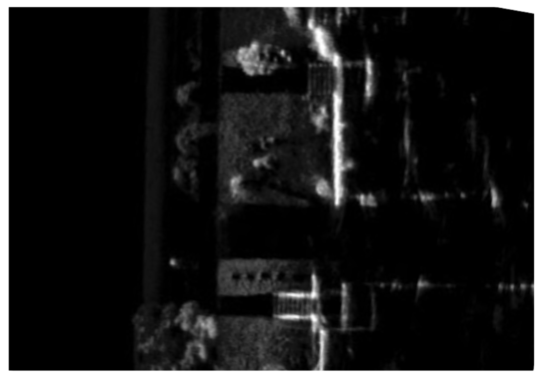
Mapping results

Localization Process

- The car can localize itself only with the prebuilt map and its radar images
- Only a starting position needs to be given

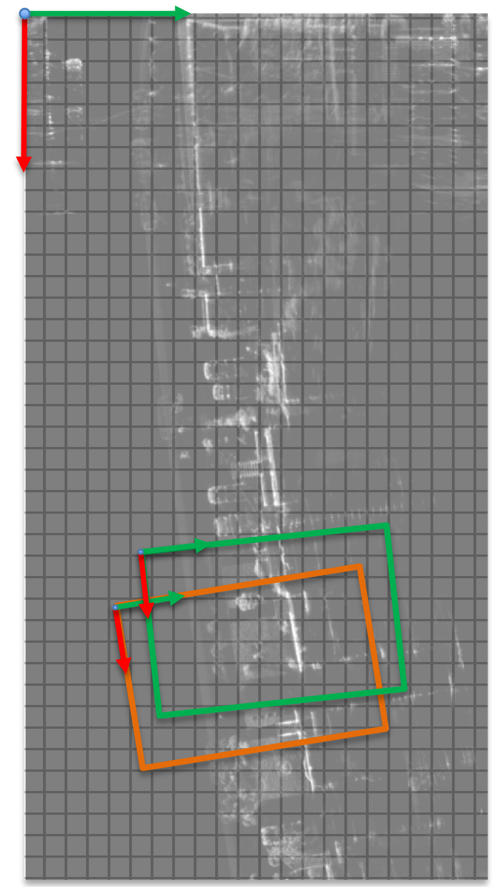


New radar image



Map extraction

Image alignment



Results and Conclusion

Johan Gerfaux

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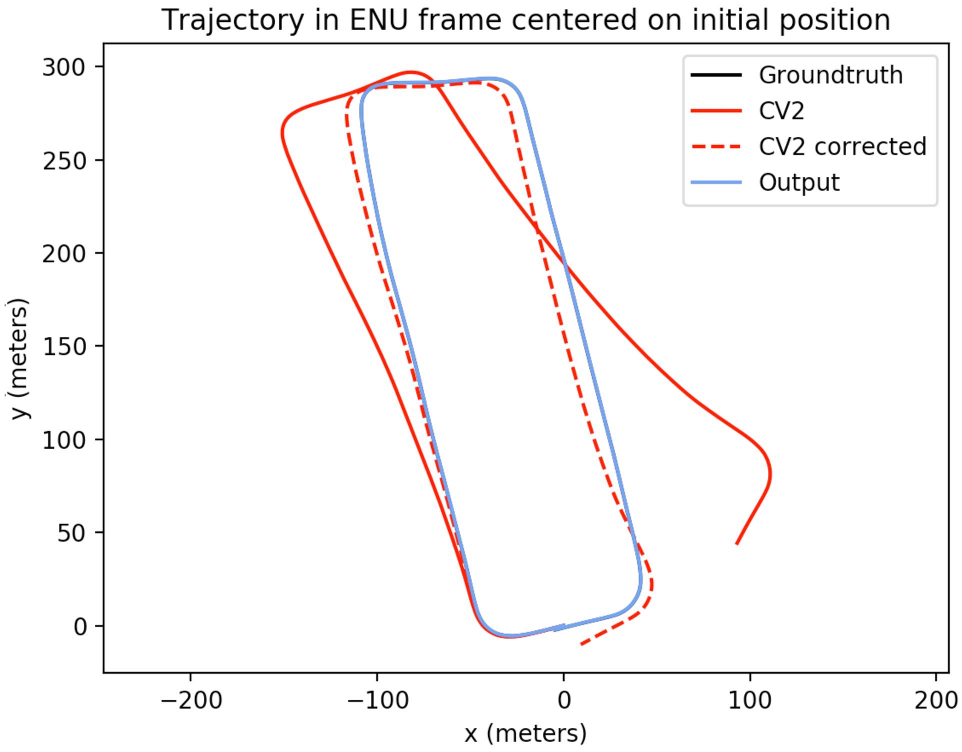
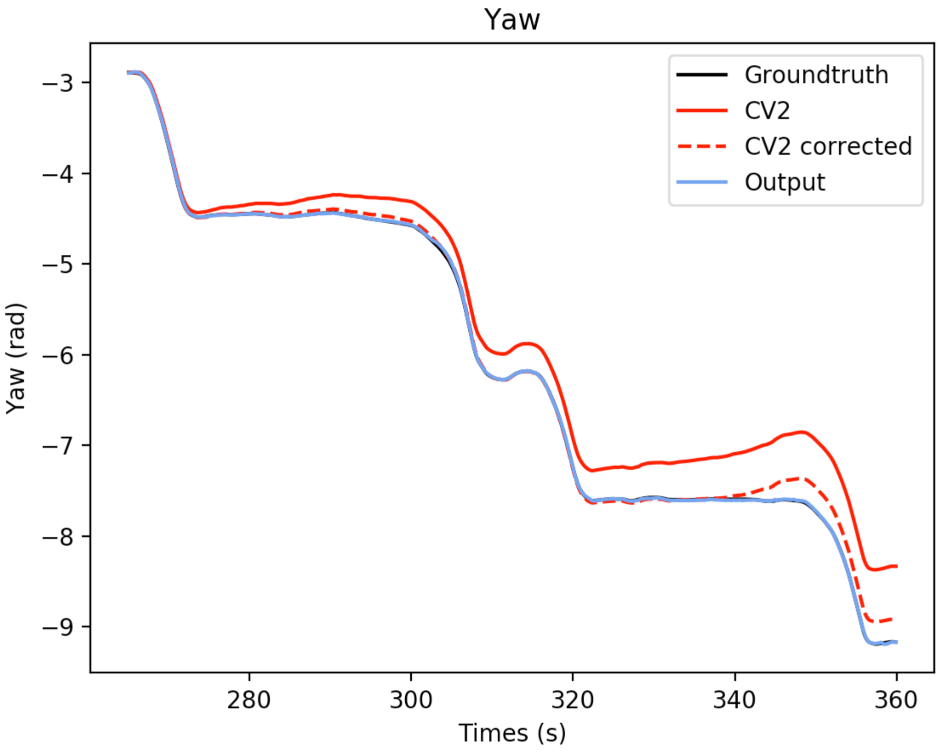
Performance Evaluation of the Localization Algorithm





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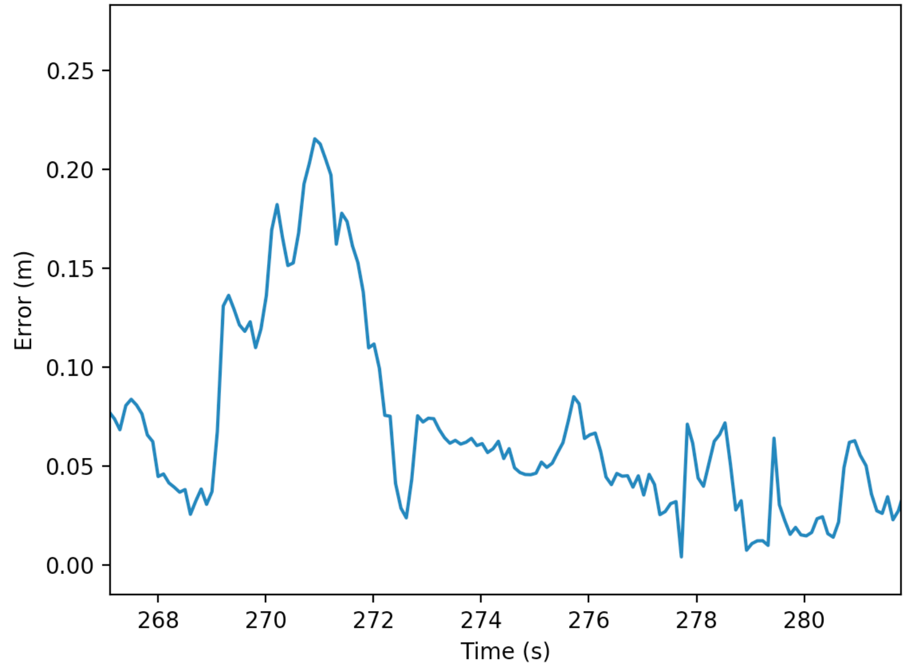
Performance Evaluation of the Localization Algorithm

Average error in position
8.2 cm

Average error in orientation
0.24 deg

Error in position of the localization algorithm in the map frame



Performance Evaluation of the Localization Algorithm

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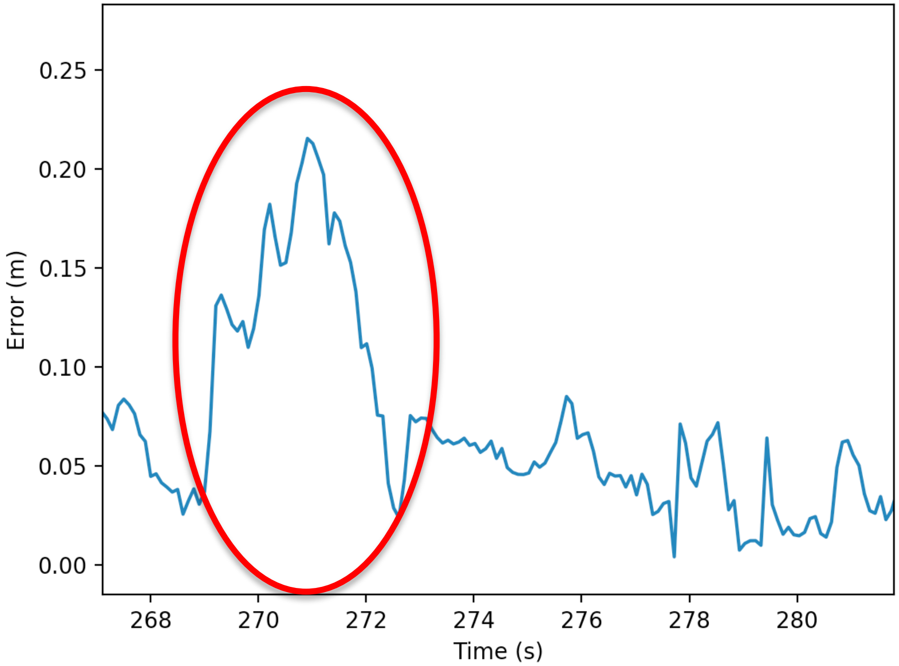

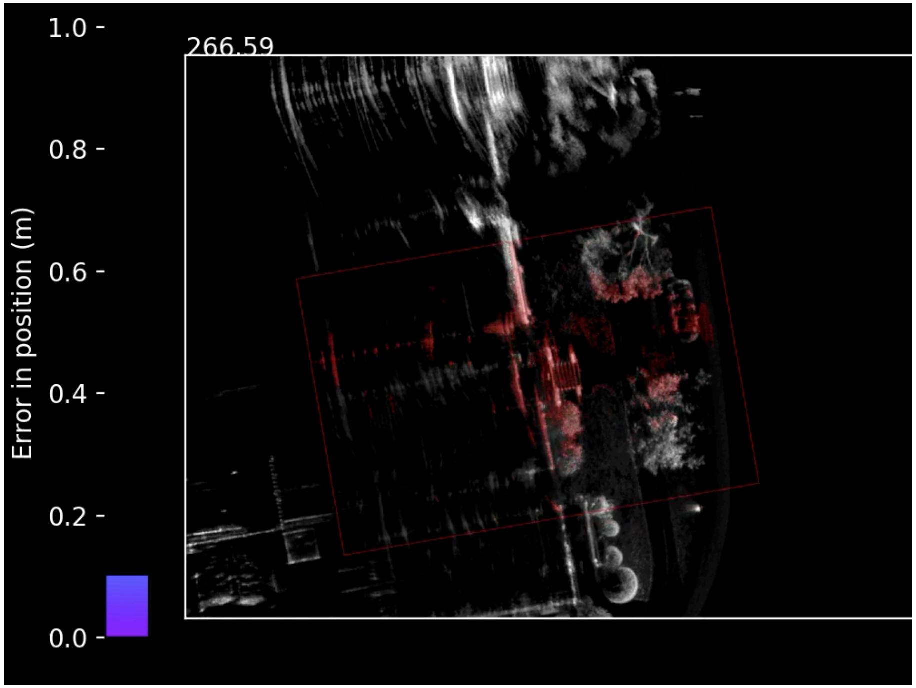

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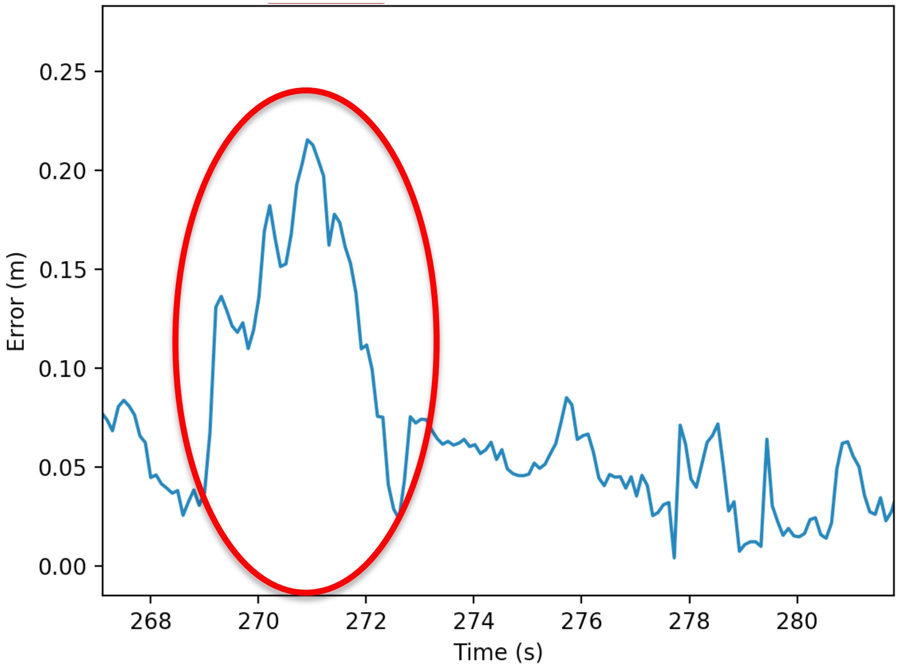
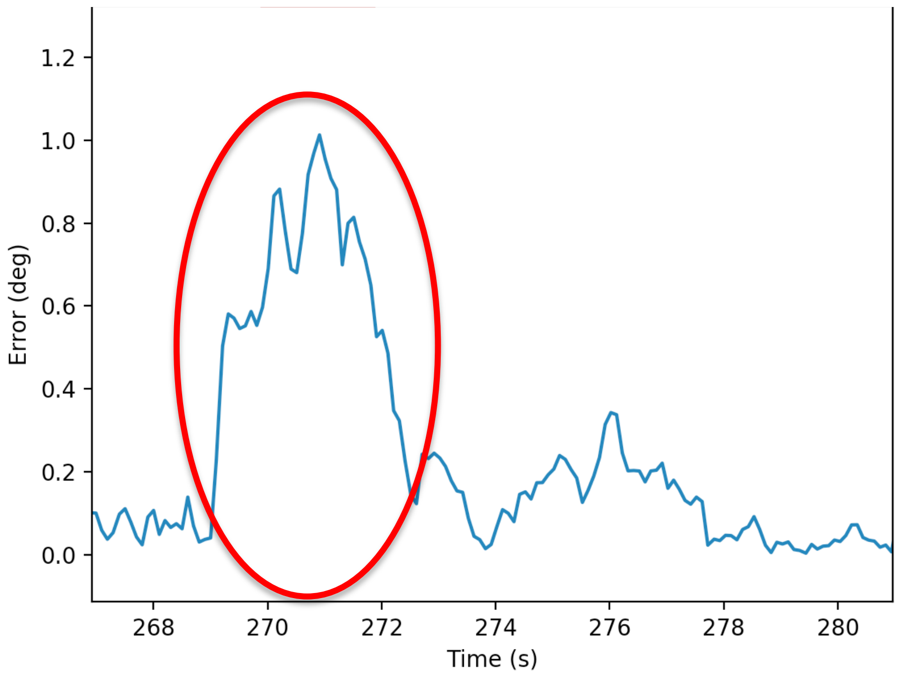
Performance Evaluation of the Localization Algorithm

Error in position of the localization algorithm in the map frame



Error in attitude of the localization algorithm in the map frame



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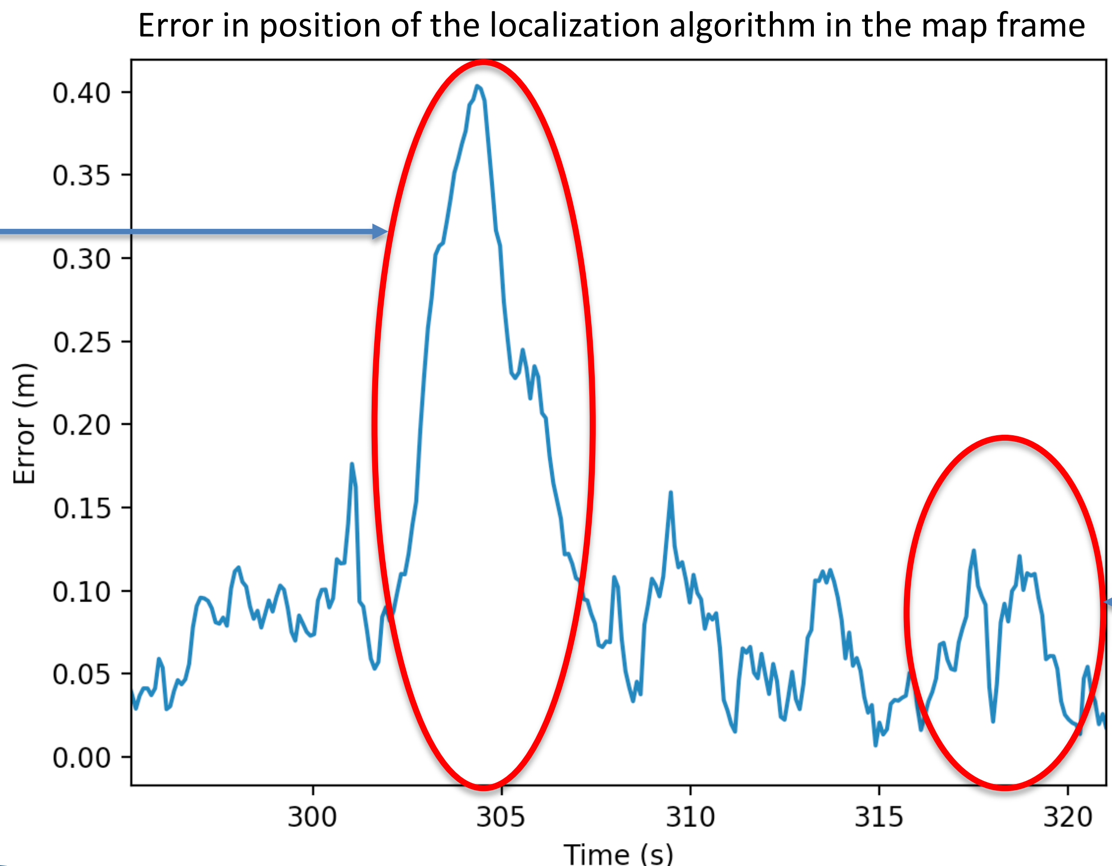
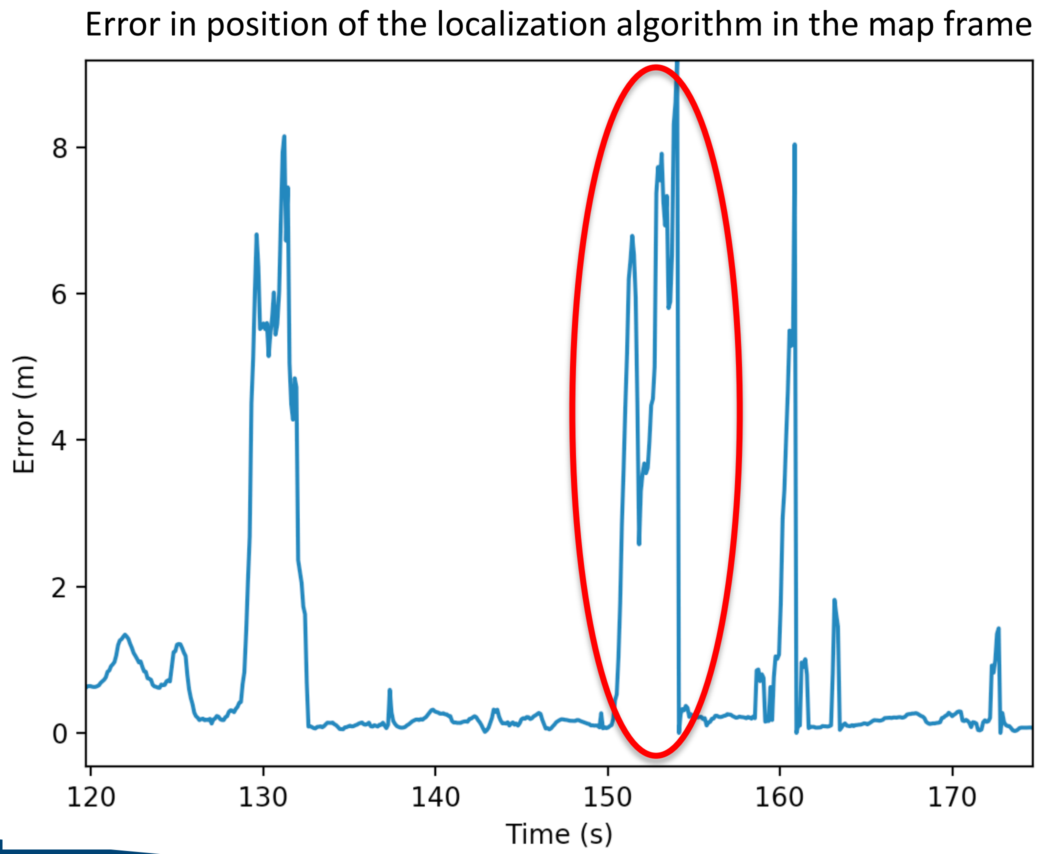
Performance Evaluation of the Localization Algorithm

Turning right with a stop



Turning right without stop

Performance Evaluation of the Localization Algorithm



Reasons for high errors:

1. Making a stop, driving slowly

2. Presence of a big obstacle on the right side of the car (truck for example).

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Conclusion

Goal
Tackle costly methods to localize a car and map its environment

Lidars

Error of 5 to 10 cm

Expensive Tech

High Definition Radars
+
Algorithm

Average error of 8.2 cm
Cheaper than Lidars

High quality GPS

Error of 5 to 10 cm

- Expensive
- Cannot map the surroundings of the car

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Conclusion

Very promising results

- Affordable Solution:
  - ~ 1,000 \$ instead of 10,000 \$
- Accurate Solution:
  - Average error of 8.2 cm.
  - Lidars' error is between 5 to 10 cm.
- Less sensitive to weather conditions
- Improvement possible by using 360 radar information

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Thank you.

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