

State Estimation for Localization:

A Look at the Odometry State Estimator

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WhoAmI

Open Source Robotics Lead @ Samsung Research

- Develop and Maintain 50+ ROS 1 and ROS 2 packages
- ROS2 Technical Steering Committee & Navigation Project Lead

Former Robotics Lead @ Simbe Robotics

I think about production navigation systems; perception, SLAM, planning, and sensor fusion



ROSCon 2018

ROSCon 2019



TechCrunch Sessions 2020



NASA Asteroid Redirect Mission



National Geographic

OVERVIEW

- Kalman Filters
- Non-Linear Filters
- Robot Localization
- Autoware Odometry



Kalman Filters (1/2)

Filters jobs are to track signals in presence of noise

Filters are smoothers based on data, error estimates, and a model

The Kalman Filter is used in linear systems: Predict and Correct

- Typically constant velocity or acceleration model **A**
- Observation model **H** relates the measurable data to the state
- Process covariance **Q** and measurement covariance **R**
- Measurement **z** taken to estimate the state **$\hat{\mathbf{x}}$**

Predict

$$\begin{aligned}\hat{\mathbf{x}}_{i+1}^- &= \mathbf{A} \hat{\mathbf{x}}_i \\ \mathbf{P}_{i+1}^- &= \mathbf{A} \mathbf{P}_i \mathbf{A}^T - \mathbf{Q}\end{aligned}$$

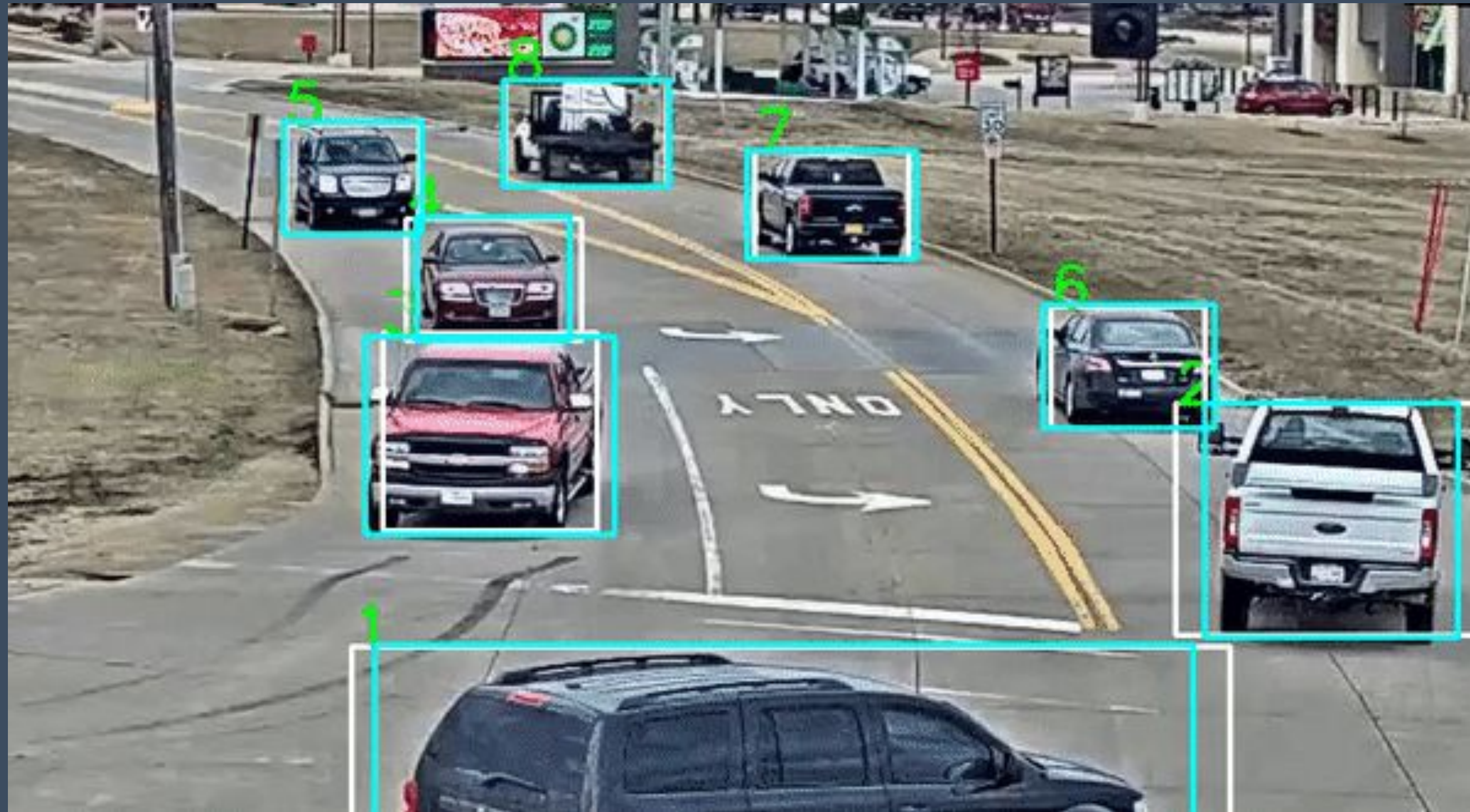


Correct

$$\begin{aligned}\mathbf{K}_{i+1} &= \mathbf{P}_{i+1}^- \mathbf{H}^T (\mathbf{H} \mathbf{P}_{i+1}^- \mathbf{H}^T + \mathbf{R})^{-1} \\ \hat{\mathbf{x}}_{i+1} &= \hat{\mathbf{x}}_{i+1}^- + \mathbf{K}_{i+1} (\mathbf{z}_{i+1} - \mathbf{H} \hat{\mathbf{x}}_{i+1}^-) \\ \mathbf{P}_{i+1} &= (\mathbf{I} - \mathbf{K}_{i+1} \mathbf{H}) \mathbf{P}_{i+1}^-\end{aligned}$$

Kalman Filters (2/2)

Now we can take noisy measurements and track the signal (e.g. the car)



Detections
Tracks

Source: https://nanonets.com/blog/content/images/2019/07/object_tracker_gif.gif

Non-Linear Filters

What happens when your system isn't linear?

Nonlinear filters!

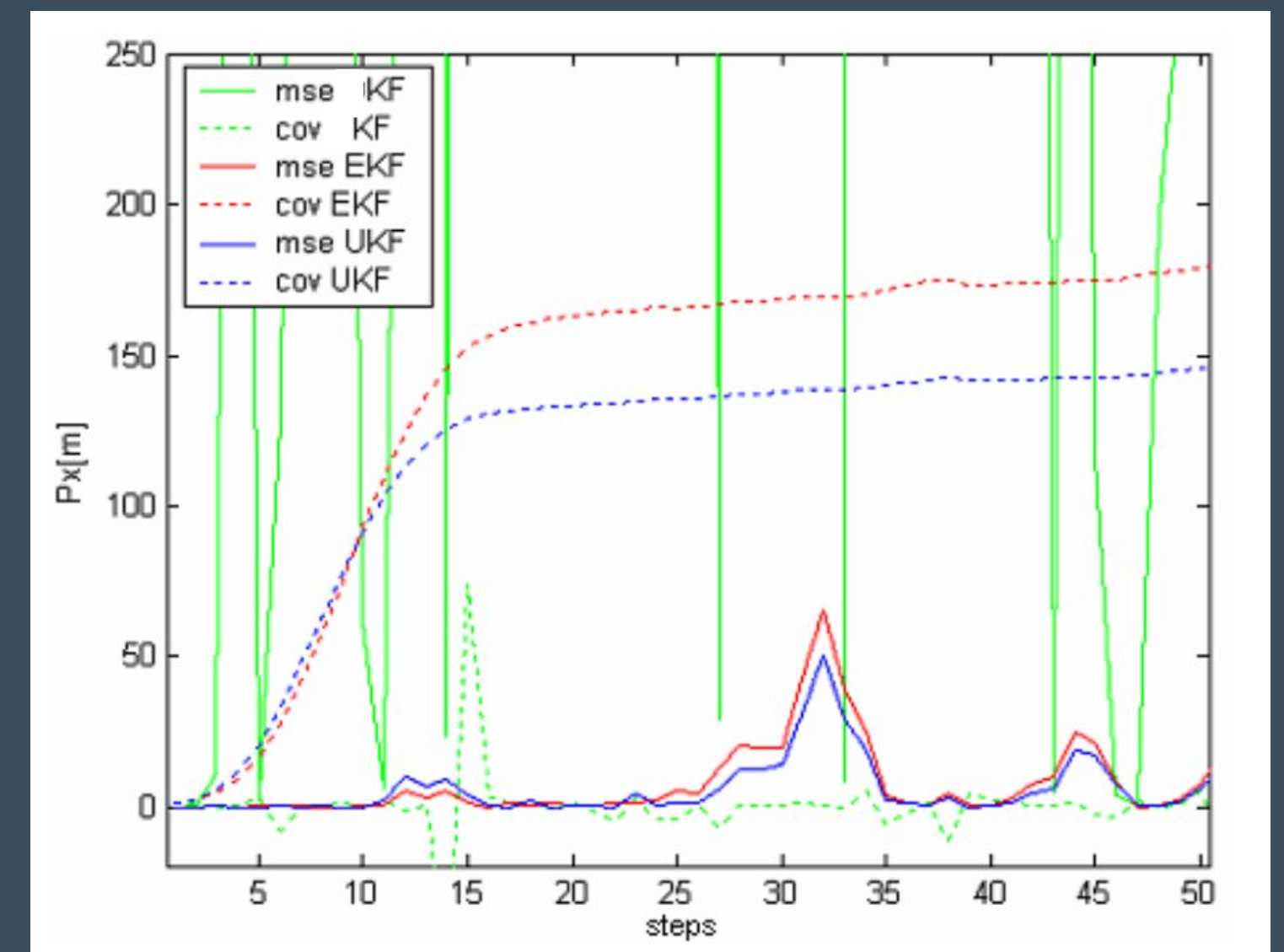
- Extended Kalman Filter (EKF)
- Unscented Kalman Filter (UKF)

EKF:

- Linearizes about the single current estimate (mean, covariance)
- The math is similar, Jacobians to replace $\mathbf{A}\hat{\mathbf{x}}_i$ and $\mathbf{H}\hat{\mathbf{x}}_i$.

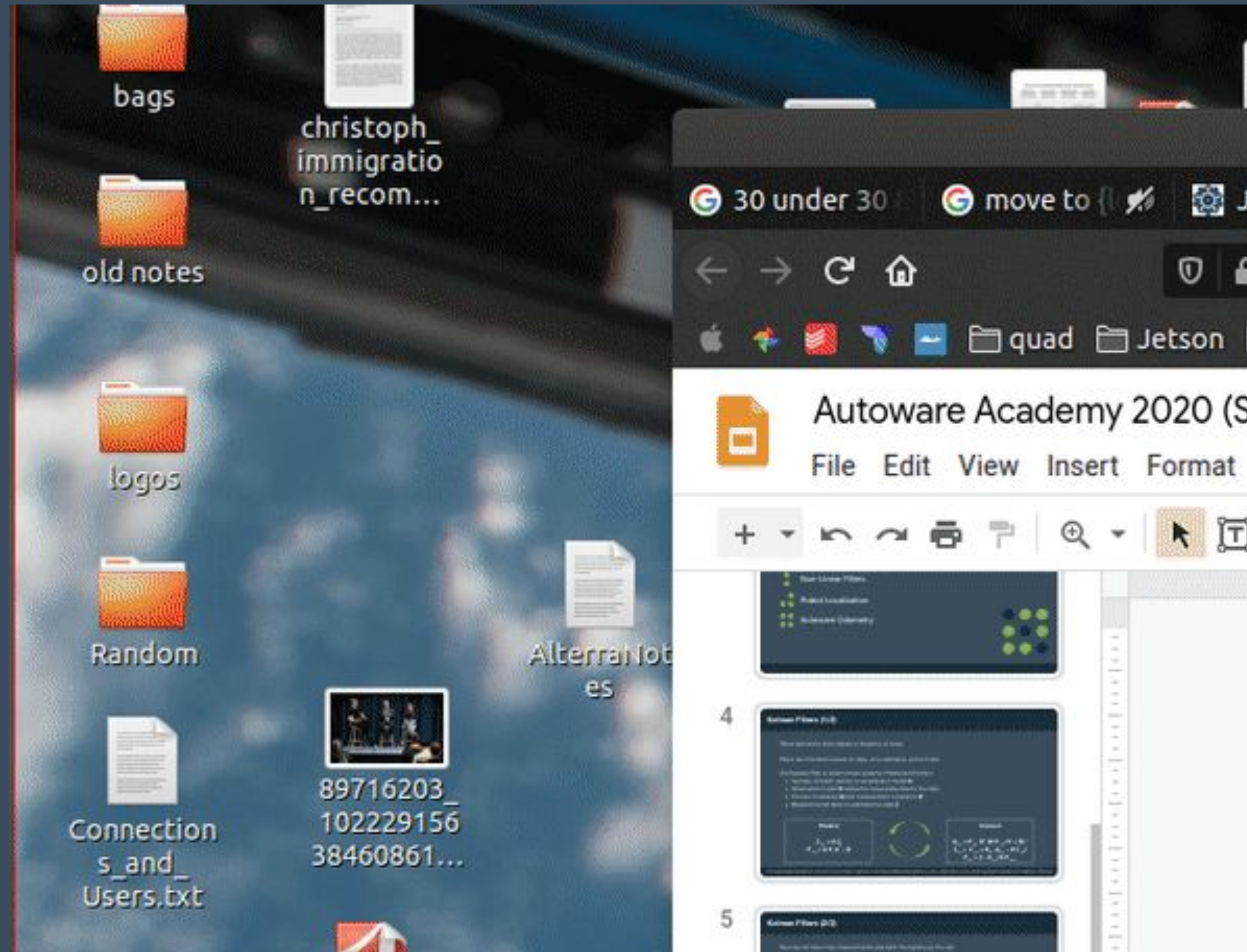
UKF:

- Uses the Unscented Transform for very non-linear systems
- Select “sigma points” in the distribution (many options)
- Transform the points using non-linear function
- New estimate derived from transformed distribution
- Additional accuracy derived from sets of means and covariances



Source: <https://bit.ly/2LU10UG>

EKF vs KF



Real Path

Extended Kalman Filter

Kalman Filter

Uses simulated wheel encoders and GPS updates

<https://gist.github.com/SteveMacenski/50cc1b4fe6e395f974697c501fede78a>

REP 105

Frame Conventions for ROS

- base_link
- odom
- map

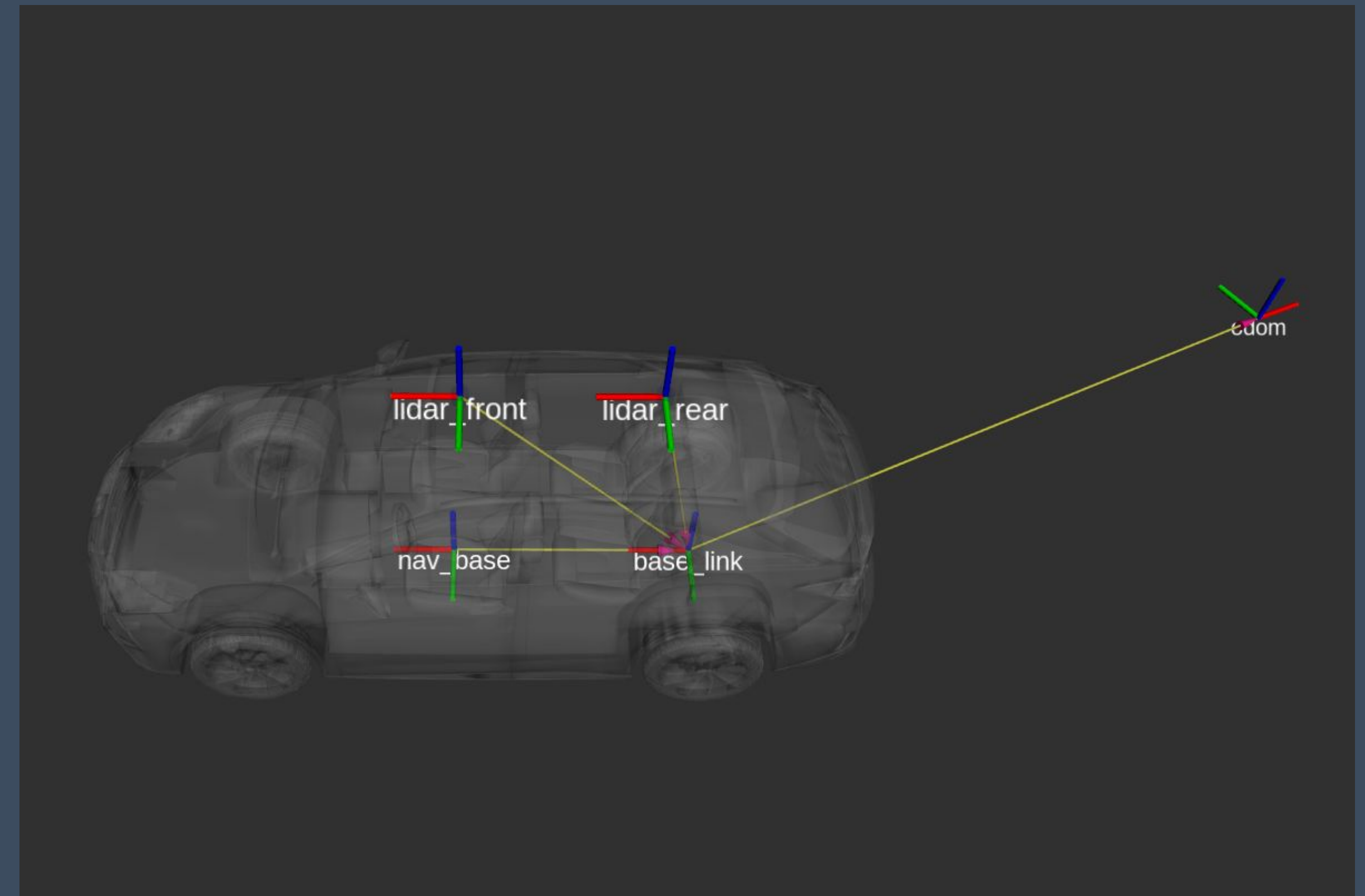
SLAM / Localization (map \rightarrow odom)

- May be discontinuous or cusping
- Accurate globally in space and time
- Sensors: GPS, SLAM, NDT

Odometry (odom \rightarrow base_link)

- Continuous and smooth
- Accurate locally in time / space
- Sensors: wheel encoders, IMUs, VIO

External Transformations Provided by Complete map \rightarrow base_link Tree



Robot Localization (1/2)

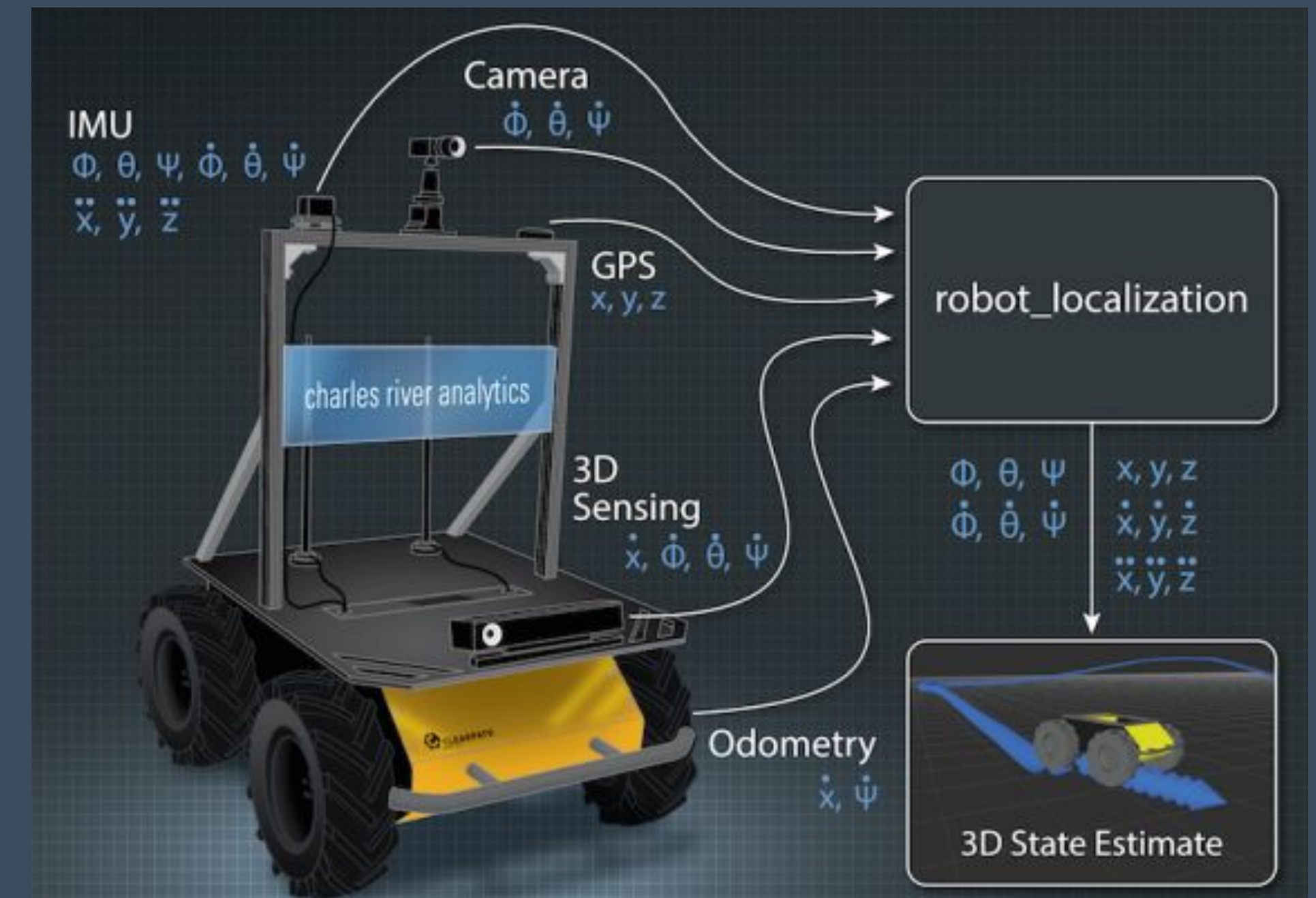
ROS package from Tom Moore while at Charles River Analytics

Robot Localization Non-Linear Filters:

- EKF and UKF
- Many sensors
- Variable rates
- Subset of sensor data

Why is that important?

- Multiple source of the same data coming in
- Sensors are asynchronous
- Data comes in at different rates and qualities
- Some sensor data might be bad
- Turn off bad data better than outlandish covariances



Robot Localization (2/2)

Robot Localization Also Enables GPS Navigation

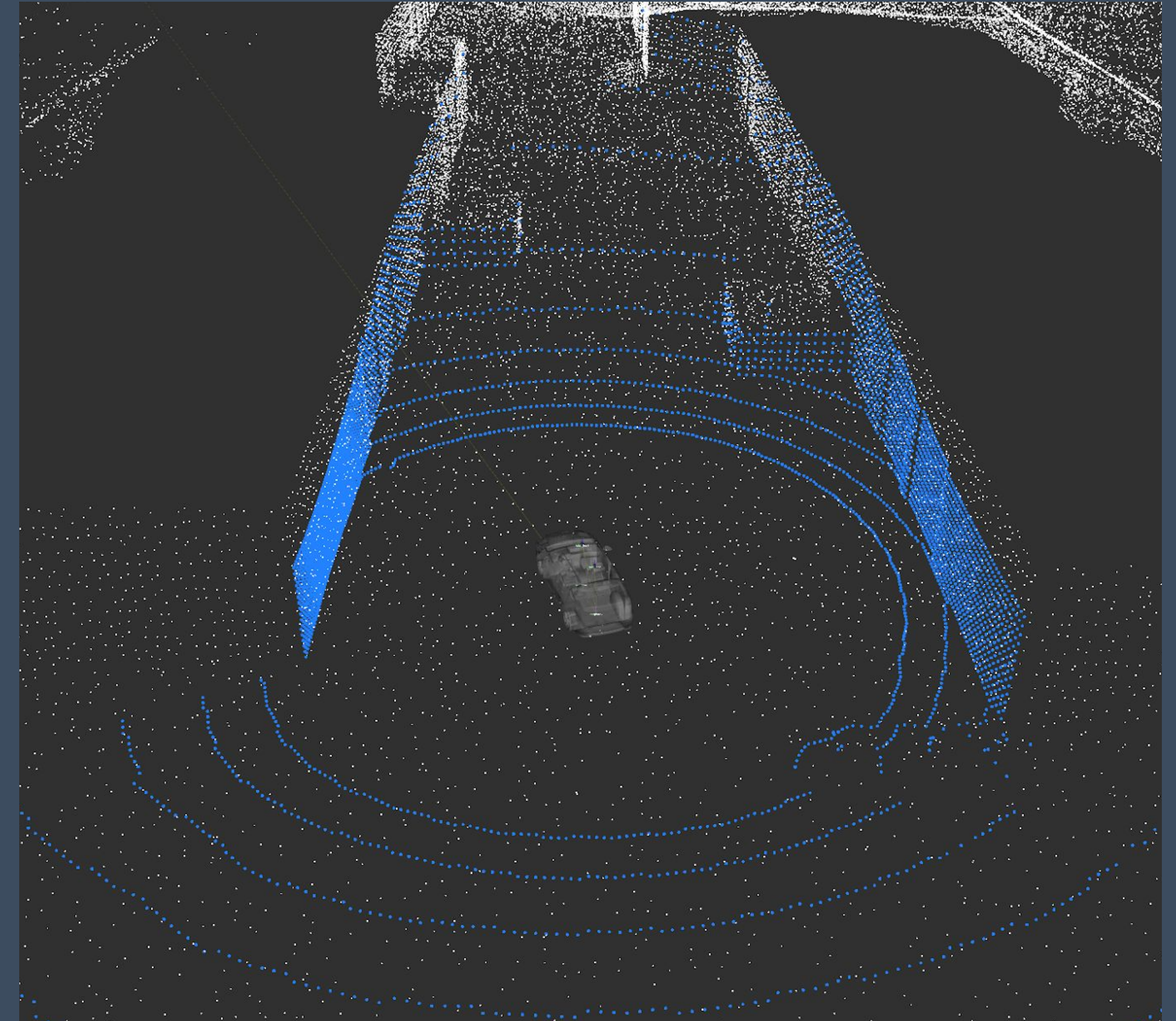
- Nav Sat Transform

It may be used for both local and global filtering

- Filter noisy single global pose sources (NDT)
- Filter multiple global pose sources together
- Filter multiple local sources for odometry

Covariances

- Sensor: measure of confidence in a data source
- Process: measurement of confidence in the model/filter
- Lower is “more confident” - less variance in inputs
- Often implemented as a main diagonal matrix of variances
 - e.g. no “co”-variances (independent)



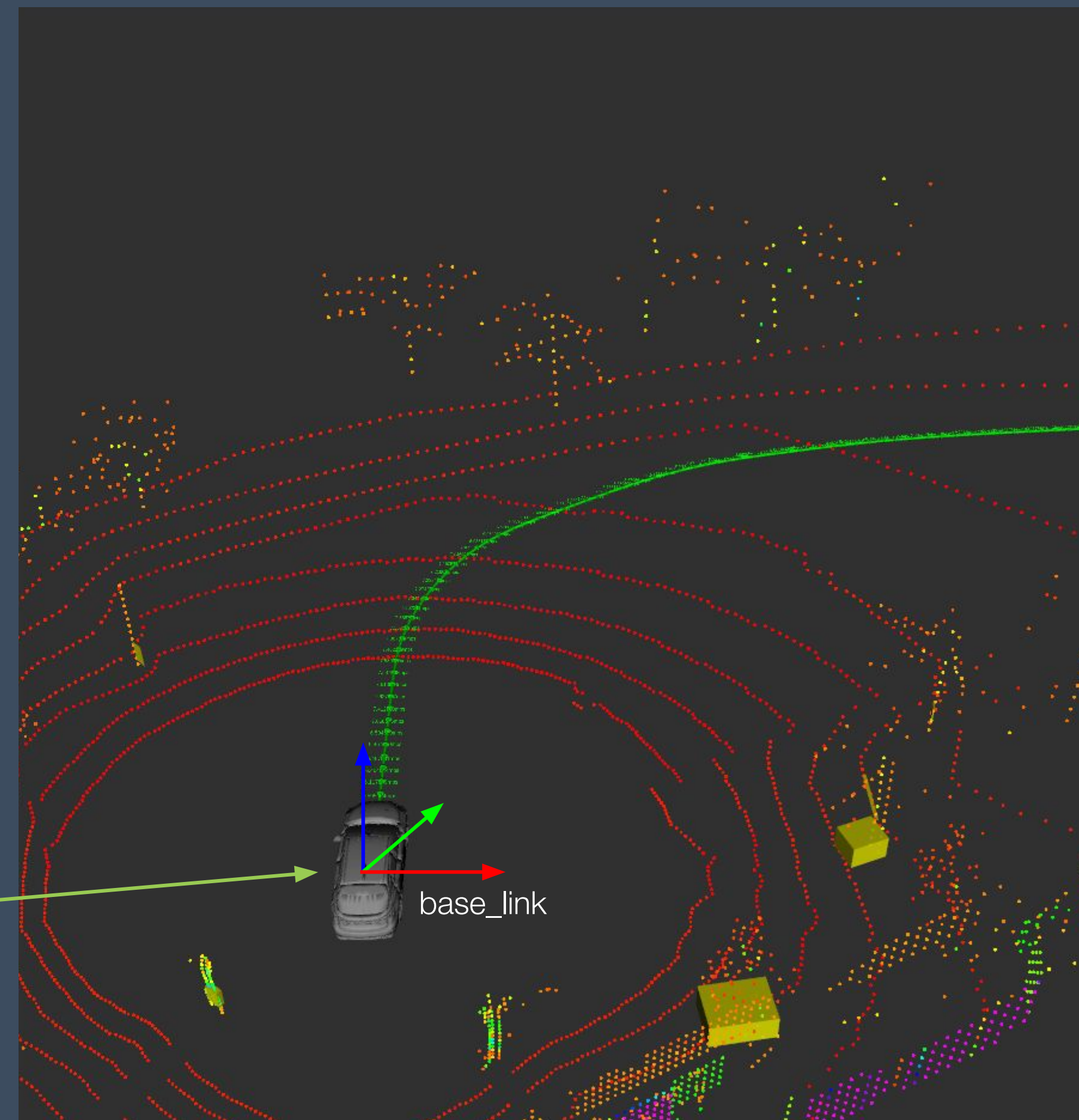
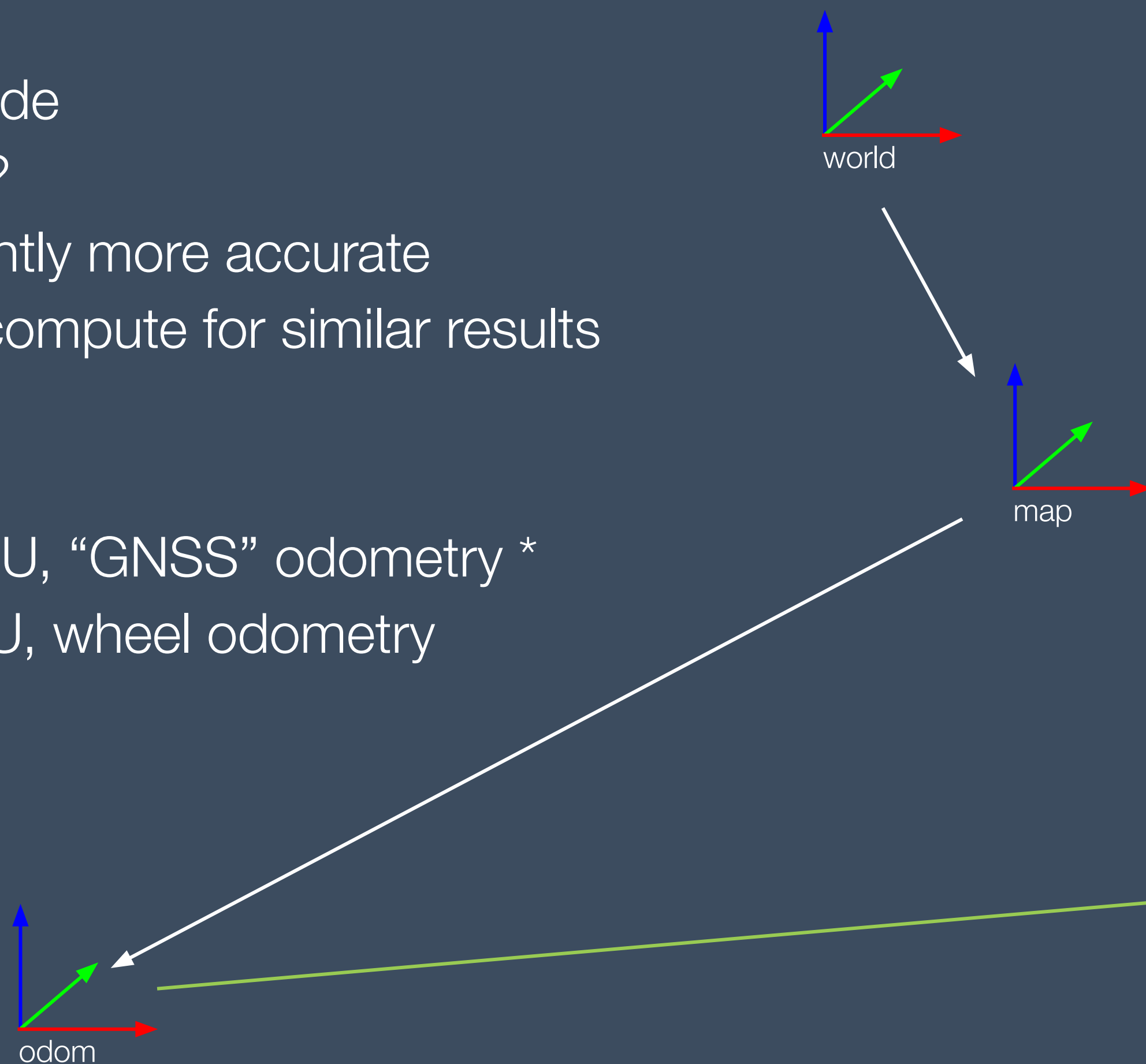
Autoware Odometry

Robot Localization

- Using EKF Node
- Why not UKF?
 - May be slightly more accurate
 - Also more compute for similar results

Sensors

- Simulation: IMU, “GNSS” odometry *
- Hardware: IMU, wheel odometry
- What else?
 - RADAR
 - LIO
 - VIO



* `/gnss/pose` is smoothed odometry, LGSVL doesn't properly represent odometry, GPS is fused for global positioning **only**

Autoware Odometry Configuration

- 50 Hz
- map_frame: map
- odom_frame: odom
- base_link_frame: base_link
- world_frame: odom
- Fusing 2 devices: a Pose and an IMU
 - Pose
 - Odometry source from simulator or hardware wheel encoders
 - Fusing XYZ and RPY, no velocities or accelerations
 - IMU
 - IMU source from simulator and hardware
 - Fusing RPY, angular velocities, and accelerations
 - Generally not recommended: Only RPY and no accelerations
- Default process and initial covariances

```
pose0: /gnss/pose
pose0_config: [true,  true,  true,
               true,  true,  true,
               false, false, false,
               false, false, false,
               false, false, false]
pose0_queue_size: 10
pose0_nodelay: false
pose0_differential: false
pose0_relative: true
```

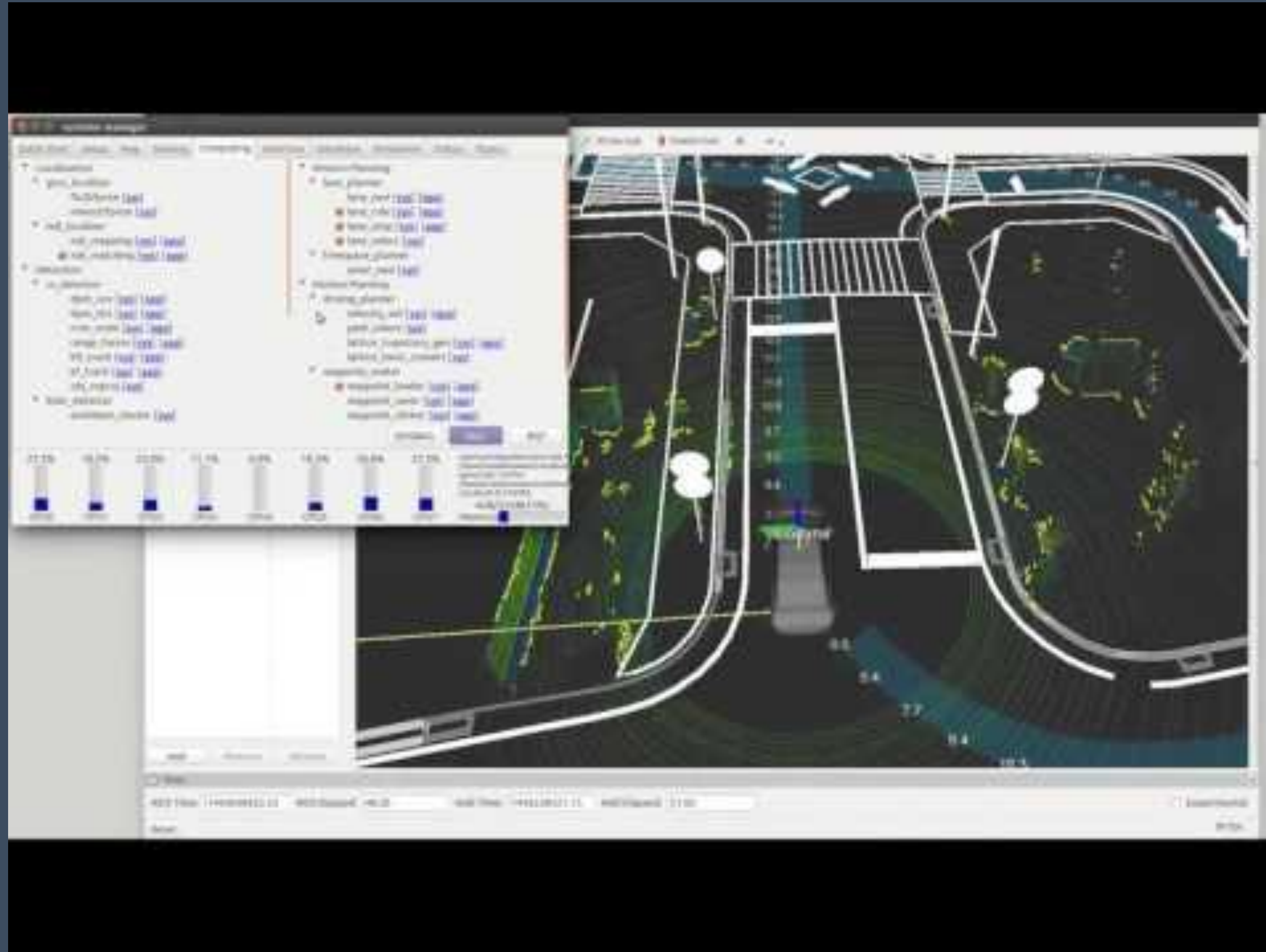
```
imu0: /imu/imu_raw
imu0_config: [false, false, false,
              true,  true,  true,
              false, false, false,
              true,  true,  true,
              true,  true,  true]
imu0_nodelay: false
imu0_differential: false
imu0_relative: false
imu0_queue_size: 10
imu0_remove_gravitational_acceleration: true
```


RECAP

- Kalman Filters
- Non-Linear Filters
- Robot Localization
- Autoware Odometry



Demo



GitLab: <https://gitlab.com/autowarefoundation/autoware.auto>

Documentation: <https://autoware.readthedocs.io/>



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