

Automated and Connected Driving Challenges

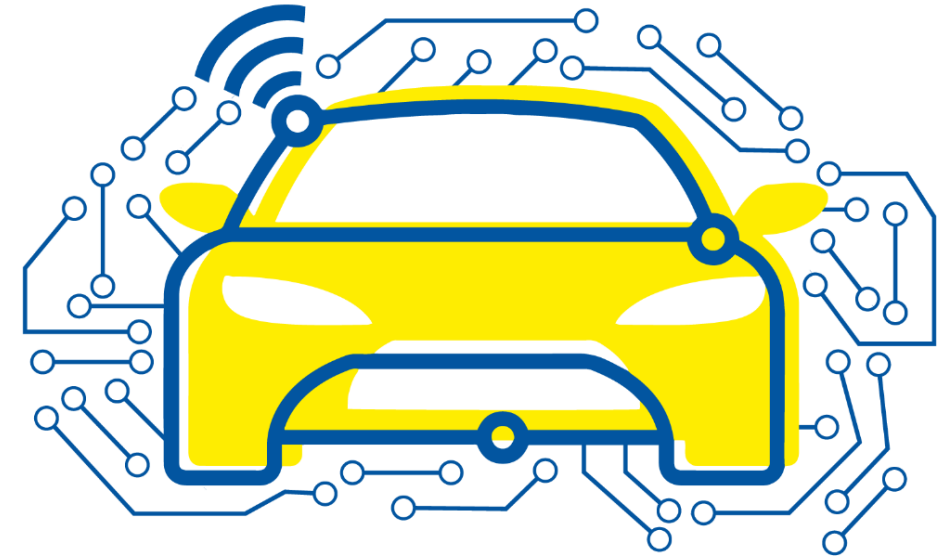
Section 2 – Sensor Data Processing

Localization

Combination Localization Approaches

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Localization – Combination of Approaches

Motivation

Requirements for fully automated driving

- Centimeter accuracy



Image: univdatos.com

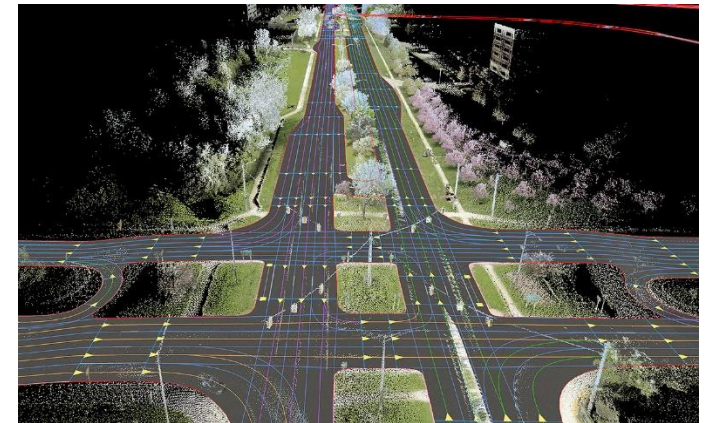


Image: [autonews](https://autonews.com)



Localization – Combination of Approaches

Motivation

Requirements for fully automated driving

- Centimeter accuracy
- High frequency
- Reliability & Robustness

Weaknesses of individual localization techniques

- Unreliable availability (GNSS, landmarks)
- Error accumulation (odometry, inertial)

Strengths of individual localization techniques

- High accuracy for short distances at high frequency (odometry, inertial)
- High accuracy for longer distances at low frequency (GNSS, landmarks)

→ **Complementing strengths and weaknesses**

→ **Combination of global and relative localization techniques can help meet the requirements**



Image: [univdatos.com](https://www.univdatos.com)

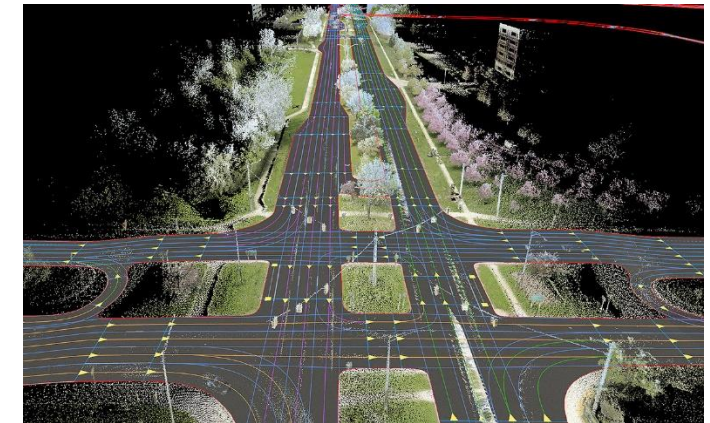


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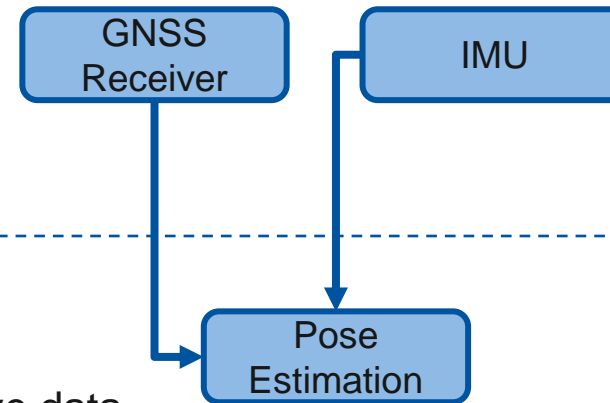


Localization – Combination of Approaches

Terminology & Categorization

Sensor-level Fusion

- Input: raw sensor data (e.g. GNSS + IMU)
- Data fusion function specific to the respective data
- Minimal information loss before fusion





Localization – Combination of Approaches

Terminology & Categorization

Sensor-level Fusion

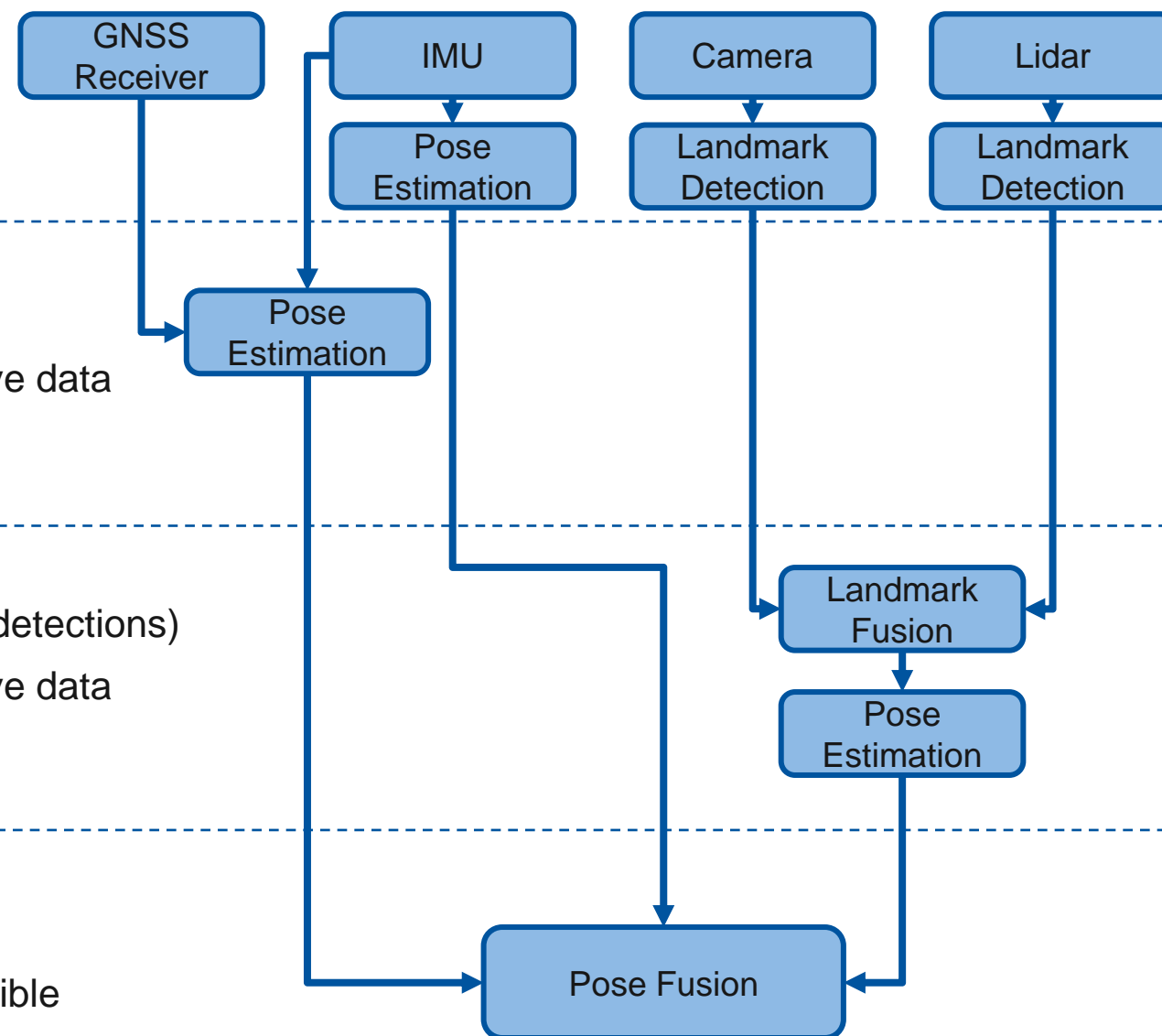
- Input: raw sensor data (e.g. GNSS + IMU)
- Data fusion function specific to the respective data
- Minimal information loss before fusion

Feature-level Fusion

- Input: intermediate features (e.g. landmark detections)
- Data fusion function specific to the respective data
- Some information loss before fusion

Pose-level Fusion

- Input: pose estimates
- Generic fusion for all sources of poses possible
- Largest information loss before fusion





Localization – Combination of Approaches

Fusion Approaches

Kalman-Filter

- Algorithm for state estimation based on noisy and incomplete measurements
- Continual update of current state estimate with new measurements
- Applicable to various tasks: pose estimation, object tracking
- Relatively easy to implement
- Available in different variations depending, e.g., on system dynamics and noise distributions (see [Tao2013](#))



Localization – Combination of Approaches

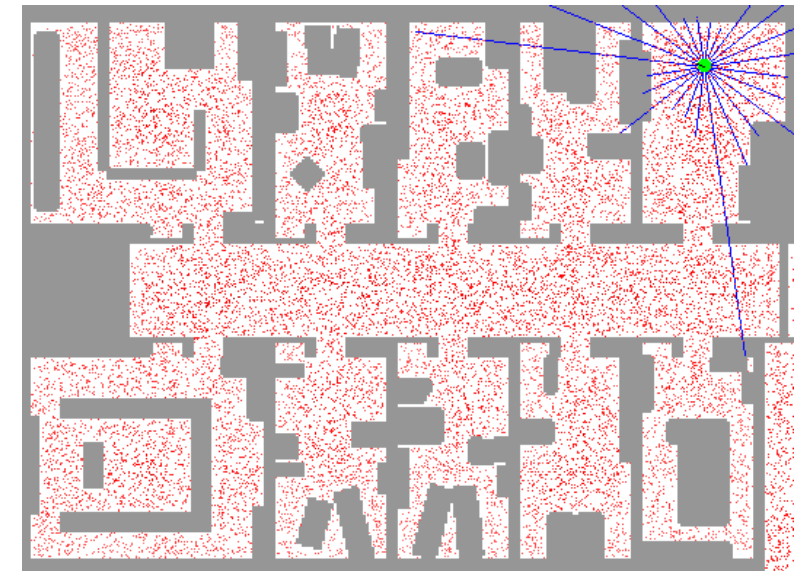
Fusion Approaches

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Particle-Filter

- Algorithm for state estimation based on noisy and incomplete measurements
- System state probability distribution is represented by discrete “particles” which are sampled based on their weight
- Particles’ weights describe their likelihood given the measurements
- Over time, particles are adjusted, resampled, and reweighted.
- Suited for non-linear system dynamics and non-Gaussian noise



Animation: www.washington.edu



Localization – Combination of Approaches

Fusion Approaches

Graph-based fusion approaches

- State variables are represented by nodes in a graph, e.g. poses.
- Generation and optimization of a pose graph, which reconstructs the vehicle trajectory
- Nodes of the graph represent pose estimates or pose measurements, which are connected by edges
- Structure of the graph results in overdetermined optimization problem
 - solution with suitable algorithm (e.g., Gauss-Newton method)
- Popular approach to solving SLAM problems (e. g. [Huang2021](#), [Kümmerle2011](#))
- Adaptation to pose fusion possible (e. g. [Merfels2018](#))

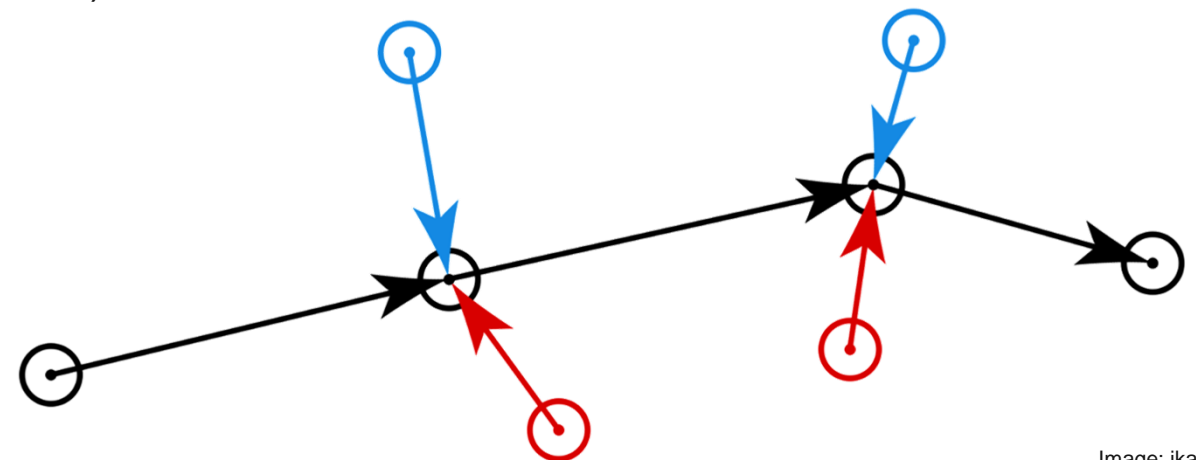


Image: ika