

Automated and Connected Driving Challenges

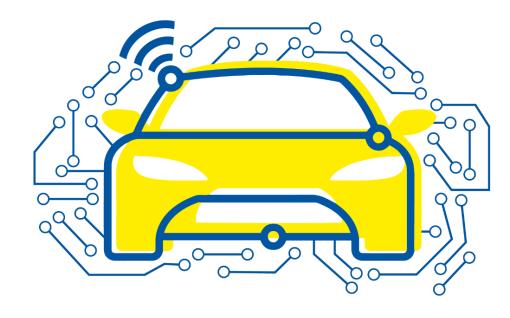
Section 2 – Sensor Data Processing

Localization

Relative Localization

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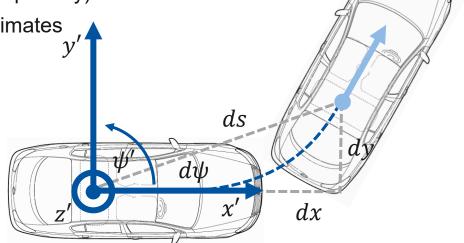
Overview

Relative localization aims to estimate the vehicle pose relative to an initial or previous pose of the vehicle

It is crucial for automated and connected vehicles to ...

• ... be able to localize themselves when global localization is (temporarily) not available

increase robustness and update rate of other localization estimates





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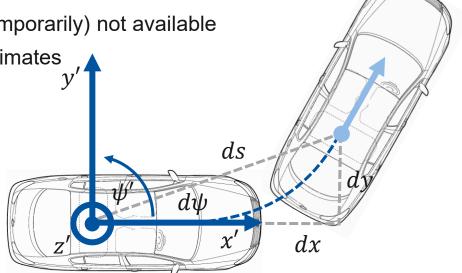
Common Approaches

- Dead Reckoning
 - Odometry, Inertial Navigation, Visual Odometry

Strengths and Weaknesses of Relative Localization Approaches

- + Robustness to challenging environments
- + High precision for close-proximity maneuvering

- Error accumulation / drift
- Lack of global context





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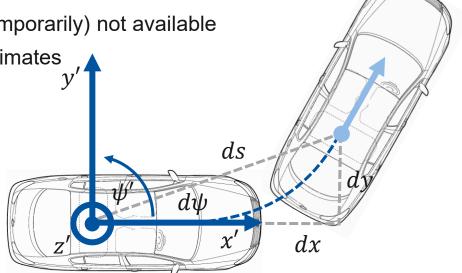
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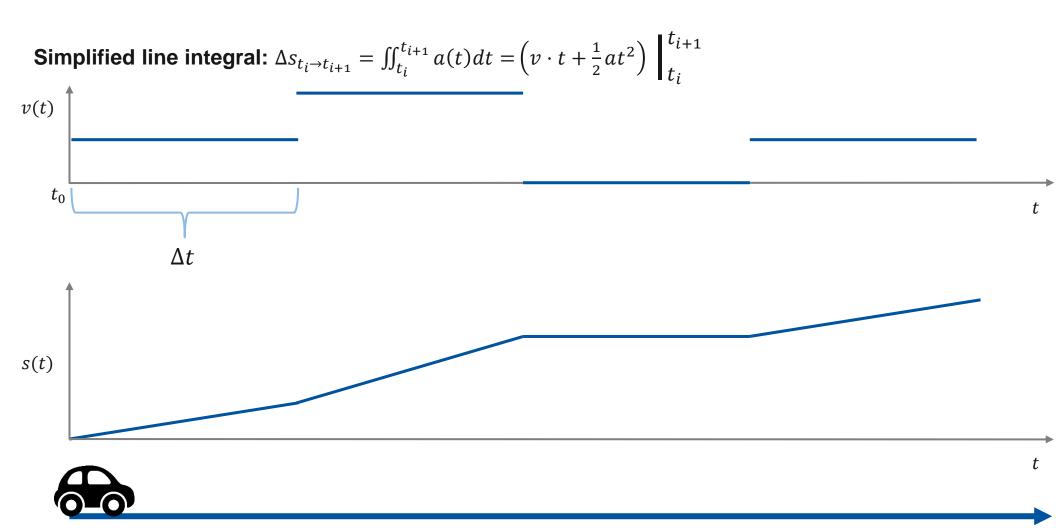
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Example: 1D Dead Reckoning from a standstill





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Odometry

Goal
 Motion estimation based on motion sensors

Sensors
Wheel encoders, steering encoder, magnetometer

• **Velocity estimate** $v(t) = \omega(t) \cdot r_{tire}$ with $\omega(t)$: wheel speed in rad/s

Example use case Dead Reckoning in tunnel









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Example use case Dead Reckoning in tunnel











Inertial Navigation

Goal
 Motion estimation based on inertial sensors

Sensors Accelerometers, gyroscopes

• Velocity estimate $v(t) = \int a(t)dt$

Example use case Improvement of Dead Reckoning in tunnel



Image: Bosch





Sensors	Accelerometers, gyroscopes	
Velocityestimate	$v(t) = \int a(t)dt$	
Example use case	Improvement of Dead Reckoning in tunnel	







Visual Odometry with Cameras

Goal
 Motion estimation based on a sequence of camera images

Sensors
Mono-, Stereo or Omnidirectional Camera



Image: Geiger2011



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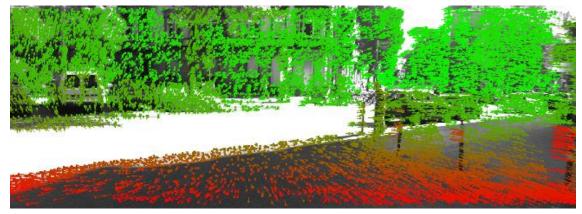
Common approaches

Feature-based approach:

Extraction of image features (i.e. corner, edge or curve) in sequential frames, tracking of associated features and estimation of the relative vehicle movement.

Appearance-based approach:

Based on an observation of changes in the image appearance and intensity on a pixel level instead of extracting features.



mage: Geiger201

Hybrid approach:

Combination of the feature- and appearance-based approach. → In particular useful in environments with few features where a merely feature-based approach might fail.

Source: Agel2016



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Visual Odometry with Lidar sensors

Goal
 Motion estimation based on a sequence of lidar point clouds

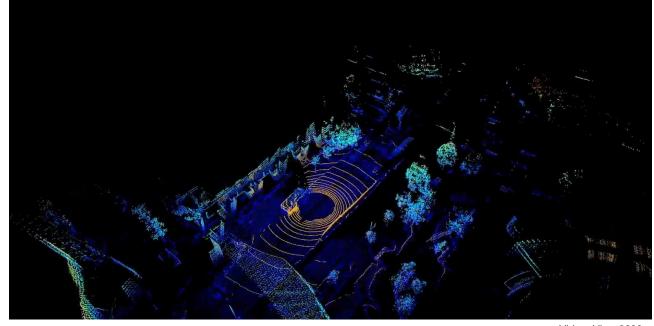
Sensors
 Lidar sensors or pseudo lidar (computed from depth estimates)

Common approaches

Find a transformation between two point clouds that best aligns them, e.g., using the *Iterative Closest Point* (ICP) method.

Feature Tracking

Find a transformation between features found in two different point clouds, e.g., detected landmarks.



Video: Vizzo2023