# Localization for Autonomous Driving Brief tutorial to have fun with localization

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#### Abstract

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#### Acknowledgements

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#### Abbreviations

ADAS Advanced Driver Assistance Systems

CKF Cubature Kalman Filter EKF Extended Kalman Filter

GNSS Global Navigation Satellite System HD High Definition (as in HD maps)

IMU Inertial Measurement Unit

KF Kalman Filter

LIDAR Light Detection and Ranging MCL Monte Carlo Localization

PF Particle Filter

RADAR Radio Detection and Ranging
RBPF Rao-Blackwellized Particle Filter

SLAM Simultaneous Localization and Mapping

UKF Unscented Kalman Filter

V2X Vehicle-to-Everything Communication

#### Overview

# Course chapters

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☐ Types of localization problems
☐ State estimation challenges
☐ Sensor types and characteristics
☐ Sources of uncertainty in robotics
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☐ Bayes' theorem
☐ Conditional probability
☐ Markov assumption
☐ Joint and marginal probabilities
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☐ Linear vs nonlinear systems
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☐ Sigma points
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# Objectives

#### Introduction to Localization

Introduction to Localization
☐ Problem statement and motivation
$\square$ Types of localization problems
☐ State estimation challenges
$\square$ Sensor types and characteristics
$\square$ Sources of uncertainty in robotics

#### 1.1 Problem Statement and Motivation

In robotics and autonomous systems, localization addresses a fundamental question: "Where am I?" This seemingly simple question underlies many complex challenges in autonomous navigation. Imagine waking up in an unfamiliar room – you would use visual cues, memory, and perhaps a map to determine your location. Robots face a similar challenge, but must solve it using sensors and algorithms rather than human intuition.

Localization serves as the cornerstone of autonomous navigation. Without accurate knowledge of its position, a robot cannot effectively plan paths, avoid obstacles, or complete assigned tasks. This becomes particularly critical in applications like autonomous vehicles, where position errors of even a few centimeters can have serious consequences.

#### 1.2 Types of Localization Problems

We can categorize localization problems based on their initial conditions and objectives:

Position Tracking represents the simplest case, where we know the initial position and need to maintain an accurate estimate as the robot moves. Think of using GPS in your car – you start from a known location and track your movement.

Global Localization presents a more challenging scenario where the initial position is unknown. The robot must determine its position from scratch using available sensor information and a map. This is analogous to opening a ride-sharing app in an unfamiliar city and waiting for it to locate you.

The Kidnapped Robot Problem is the most challenging variant, where a well-localized robot is suddenly transported to an unknown location. While this may seem artificial, it tests a system's ability to recover from catastrophic failures or sensor malfunctions.

#### 1.3 Sensor Types and Characteristics

Localization systems typically rely on multiple sensor types, each with distinct advantages and limitations:

- Proprioceptive Sensors measure internal state changes, such as wheel encoders that track rotation or inertial measurement units (IMUs) that detect acceleration and angular velocity. While these sensors provide high-frequency updates, they suffer from cumulative errors through a process called dead reckoning.
- Exteroceptive Sensors observe the external environment. These include:
  - LIDAR (Light Detection and Ranging) which creates detailed 3D scans of surroundings
  - Cameras that provide rich visual information but require sophisticated processing
  - RADAR which offers reliable distance measurements even in adverse weather
  - GNSS (Global Navigation Satellite System) which provides absolute position but may suffer from urban canyon effects and multipath errors

#### 1.4 Sources of Uncertainty

Understanding uncertainty is crucial for robust localization. Several factors contribute to localization uncertainty:

Motion Uncertainty arises from imperfect robot control and environmental interactions. When a robot moves, wheel slippage, uneven terrain, and mechanical play all introduce errors between commanded and actual motion.

Measurement Uncertainty stems from sensor limitations and noise. For example, LIDAR measurements might be affected by reflective surfaces, while camera images can be distorted by varying lighting conditions.

Environmental Uncertainty relates to the dynamic nature of the real world. Moving objects, changing weather conditions, and modifications to the environment can all affect localization accuracy.

Model Uncertainty comes from our simplified representations of complex physical systems. Our mathematical models of robot motion and sensor behavior are approximations that introduce additional uncertainty.

#### 1.5 The Role of Probability Theory

Given these uncertainties, deterministic approaches to localization often fail in real-world conditions. This necessitates a probabilistic framework that can: - Represent and propa-

gate uncertainty through mathematical models - Fuse information from multiple, imperfect sensors - Handle conflicting measurements and outliers - Provide confidence estimates along with position estimates

This probabilistic approach leads us naturally to the Bayesian filtering framework, which we'll explore in subsequent chapters. The framework provides a mathematical foundation for combining prior knowledge, motion predictions, and sensor measurements to maintain an estimate of the robot's position over time.

Understanding these foundational concepts is crucial as we progress to more advanced topics in localization. The challenges and considerations introduced here will inform our discussion of specific algorithms and implementations throughout the course.

Would you like me to elaborate on any of these sections or move on to the probability theory foundations?

# **Probability Theory Foundations**

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☐ Random variables and probability distributions
☐ Bayes' theorem
☐ Conditional probability
☐ Markov assumption
☐ Joint and marginal probabilities
☐ Gaussian distributions

# Bayesian Filtering Framework

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## Particle Filtering

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 □ Importance sampling
 □ Particle representation
 □ Sequential Importance Sampling (SIS)
 □ Resampling techniques
 □ Sample degeneracy and impoverishment
 □ Adaptive particle filtering

## **Advanced Topics**

□ Advanced Topics
 □ Multi-hypothesis tracking
 □ SLAM basics
 □ Sensor fusion techniques
 □ Loop closure
 □ Global vs local localization

# MATLAB Implementation: Kalman Filter

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☐ Visualization and analysis
□ Performance evaluation

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☐ Visualization tools
□ Performance metrics

## **Practical Applications**

□ Practical Applications
 □ Vehicle localization case studies
 □ Robot navigation examples
 □ Integration with mapping
 □ Real-world challenges
 □ Best practices and optimization

# Project Work

Project Work
☐ Implementation exercises
☐ Real dataset analysis
☐ Performance comparison of different filters
☐ Parameter tuning
□ Documentation and presentation