Autonomous Navigation for Flying Robots

Lecture 5.1: State Estimation

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World State (or System State)

- Belief State
  (our belief/estimate of the world state)

- World State
  (real state of the real world)
State Estimation

What parts of the world state are (most) relevant for a flying robot?

- Position
- Velocity
- Obstacles
- Map
- Positions and intentions of other robots/humans
- …
State Estimation

- Cannot observe world state directly
- Need to estimate the world state, but how?
- Infer world state from sensor observations
- Infer world state from executed motions/actions
Sensor Model

- Robot perceives the environment through its sensors

\[ z = h(x) \]

(sensor reading) \hspace{1cm} \text{sensor model (observation function)} \hspace{1cm} \text{world state}

- Goal: Infer the state of the world from sensor readings

\[ x = h^{-1}(z) \]
Motion Model

- Robot executes an action (or control) \( u \) (e.g., move forward at 1m/s)

- Update belief state according to motion model

\[
x' = g(x, u)
\]

current state \( \downarrow \) executed action \( \downarrow \) executed action

motion model \( \downarrow \) executed action

previous state \( \uparrow \) current state \( \uparrow \) current state
Probabilistic Robotics

- Sensor observations are noisy, partial, potentially missing
- All models are partially wrong and incomplete
- Usually we have prior knowledge
Probabilistic Robotics

- Probabilistic sensor models  \( p(z \mid x) \)
- Probabilistic motion models  \( p(x' \mid x, u) \)
- Fuse data between multiple sensors (multi-modal)
  \( p(x \mid z_{\text{vision}}, z_{\text{ultrasound}}, z_{\text{IMU}}) \)
- Fuse data over time (filtering)
  \( p(x \mid z_1, z_2, \ldots, z_t) \)
  \( p(x \mid z_1, u_1, z_2, u_1, \ldots, z_t, u_t) \)
Lessons Learned

- World state vs. (internal) belief state
- Sensor and motion models
- Model uncertainty using probability theory

Next:
Recap on Probability Theory