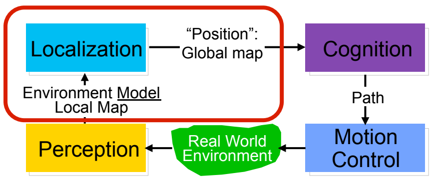
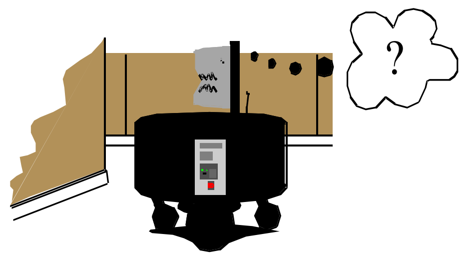
Localization

where am I? – errors and odometry





Bookkeeping

2

- Homework 2
- Quiz 3
- Assignment 3
- Upcoming:
  - Projects
  - Projects
  - Odometry
  - Projects
- Reading: SNS 5.1–5.4 (we will cover 5.2 in class)

Homeworks and Quizzes

3

- Homework
  - Thank you!
  - Scheduling
  - Group work
  - Lectures
  - Unfortunately, no consensus
  - Suggestions are welcome!
- Quiz

Assignment 3

4

- Build LED circuit
  - Breadboard-based building
  - Find partners OR AA batteries
- Build motor
  - Very simple conceptually
- Writeup
  - Circuit diagram, explanations of current, efficiency of motors, …
  - 1-1.5 pages not counting diagrams
- In-class workshop
  - 12th November

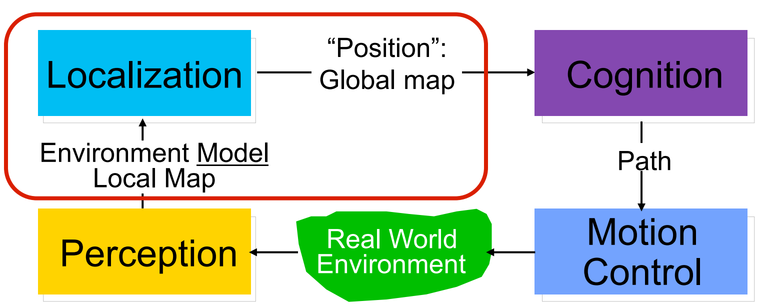
Assignment 3

5

- Provided:
  - AA Battery
  - Battery case
  - Breadboard
  - LED
    - Current:
      - 20 mA (milliamps)
    - Forward Voltages:
      - Red/Orange 1.9–2.0 V
      - Green: 2.9–3.1 V
      - Blue/White/Pink/Violet: 3.0–3.2 V
  - Resistor
    - 100 ohm
  - Magnet
  - Copper wire
- Not provided
  - Paper clips
  - Bobby pins
  - Safety pins
  - Cardboard tubes
  - Instructions
- Things we have in lab
  - Wire stripping
  - Scissors
  - Jumper cables
  - Soldering station

Odometry

6



- Localization: where in the environment am I?
- What does this need?

Localization and Map Building

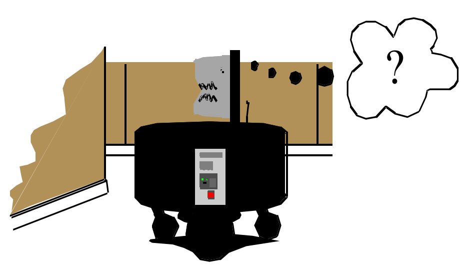
7

- Noise and aliasing
- Odometric position estimation
  - And an example: differential drive
- To localize or not to localize
- Belief representation
- Map representation
- Probabilistic map-based localization
- Other examples of localization system
- Autonomous map building

Localization: Where am I?

8

- Belief representation
- Odometry, dead reckoning
- Localization based on external sensors, beacons or landmarks
- Probabilistic Map-Based Localization



Challenges of Localization

9

- Knowing absolute position (e.g. GPS) is not sufficient
- Localization in human-scale as relates to environment
- Planning in *Cognition* needs >1 position as input
- Perception and motion plays an important role
  - Sensor noise
  - Sensor aliasing
  - Effector noise
  - Odometric position estimation

Sensor Noise

10

- Sensor noise mainly influenced by environment
  - e.g. surfaces, illumination, background noise
- Or by the measuring principle of the sensor
  - "…condenses the essentials of a method or an instrument"
  - e.g. interference between ultrasonic sensors
- Sensor noise *drastically* reduces useful sensor readings
  - Solution(s):
  - Use multiple readings
  - Employ temporal and/or multi-sensor fusion

Sensor Aliasing

11

- Robots: non-uniqueness of sensors readings is the norm
  - What does that mean?
- With multiple sensors have:
  - Many-to-one mapping from environmental states to robot's perceptual inputs
  - Example:
- So: information from sensors usually insufficient to identify the robot's position from a single reading
  - Robot's localization is usually based on a series of readings
  - Sufficient information is recovered by the robot over time

Effector (Actuator) Noise

12

- Odometry, dead reckoning
  - Position update is based on proprioceptive sensors
  - Odometry: wheel sensors only
  - Dead reckoning: also heading sensors
- How?
  - Sense movement with wheel encoders and/or heading sensors
  - Integrate that into model to get the position
    - Pros: Straightforward, easy
    - Cons: Errors are integrated → unbound
- Extra sensors onlyreduce accumulated errors
  - Same problem

Odometry: Error sources

13

deterministic (systematic) ⟷ non-deterministic (non-systematic)

- Deterministic errors can be eliminated with calibration
- Random errors: described by error models
  - Will always leading to uncertain position estimate
- Major Error Sources:
  - Limited resolution during integration (time increments, measurement resolution …)
  - Misalignment of the wheels (deterministic)
  - Unequal wheel diameter (deterministic)
  - Variation in the contact point of the wheel
  - Unequal floor contact (slipping, not planar …)

Classification of Errors

14

- **Range error:** integrated path length (distance) of movement
  - Sum of the wheel movements
- **Turn error:** similar to range error, but for turns
  - Difference of the wheel motions
- **Drift error:** difference in the error of the wheels → error in angular orientation

Over long periods of time, turn and drift errors far outweigh range errors!

Classification of Errors

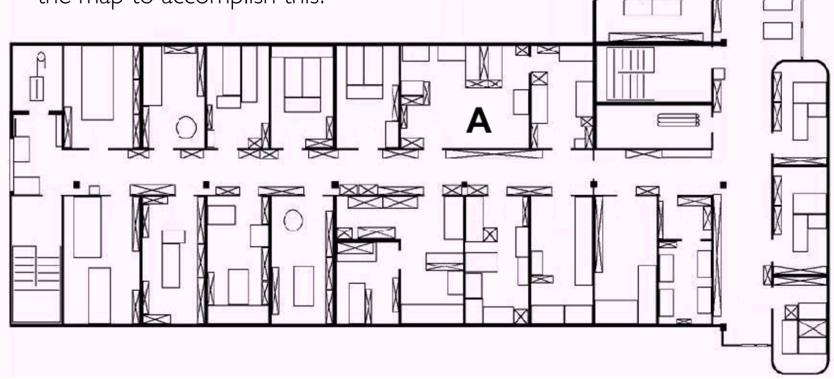
15

- Over long periods of time, turn and drift errors outweigh range errors!
  - Consider moving forward on a straight line along the **x** axis. The error in the **y**-position introduced by a move of **d** meters will have a component of **d**$\sin\Delta\theta$, which can be quite large as the angular error $\Delta\theta$ grows.

To localize or not?

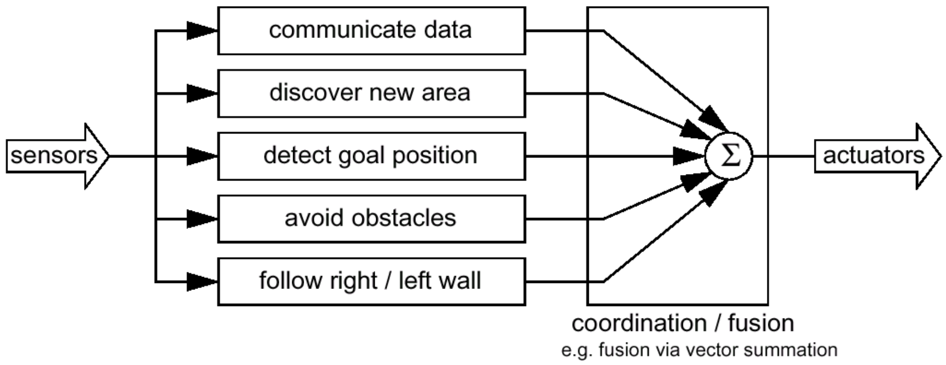
24

- How to navigate between A and B
  - navigation without hitting obstacles
  - detection of goal location
- Do you need to know where you are in " the map to accomplish this?



Behavior Based Navigation

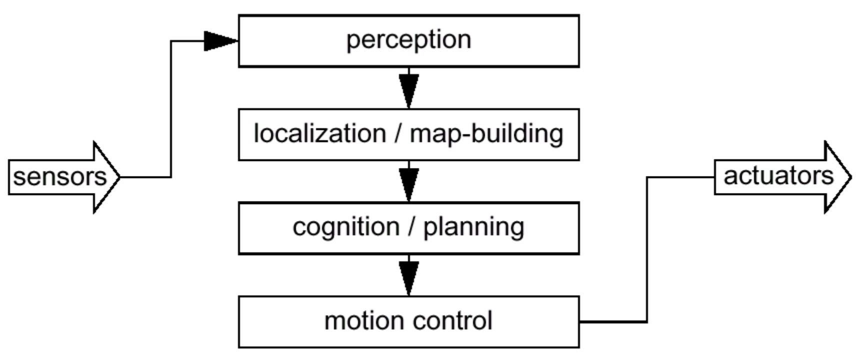
25



Model Based Navigation

5.3

26



Belief Representation

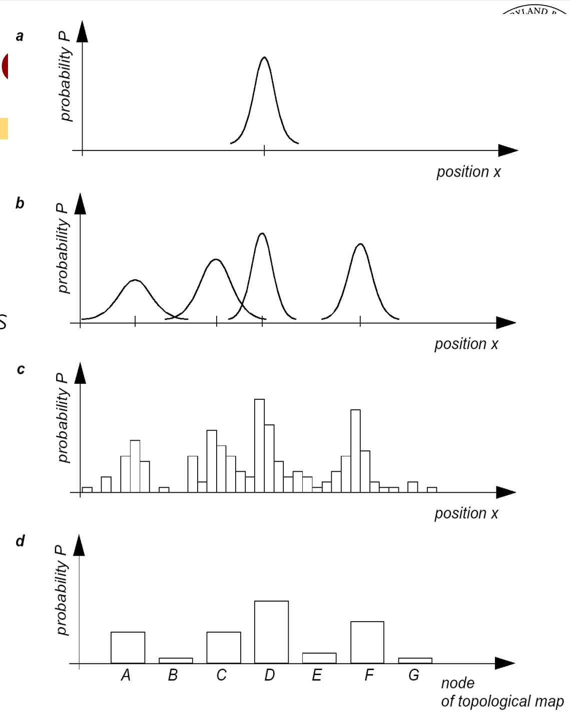
27

- a) Continuous map with *single hypothesis*
- b) Continuous map with *multiple hypothesis*
- d) Discretized map with probability distribution
- d) Discretized topological map with probability distribution

Belief Repr

28

- a) Continuous map with *single hypothesis*
- b) Continuous map with *multiple hypothesis*
- d) Discretized map with probability distribution
- d) Discretized topological map with probability distribution



Characteristics

29

Belief Representation can be…

- Continuous
  - Precision bound by sensor data
  - Typically single hypothesis pose estimate
  - Lost when diverging (for single hypothesis)
  - Compact representation and typically reasonable in processing power.
- Discrete
  - Precision bound by resolution of discretisation
  - Typically multiple hypothesis pose estimate
  - Never lost (when diverges converges to another cell)
  - Important memory and processing power needed. (not the case for topological maps)