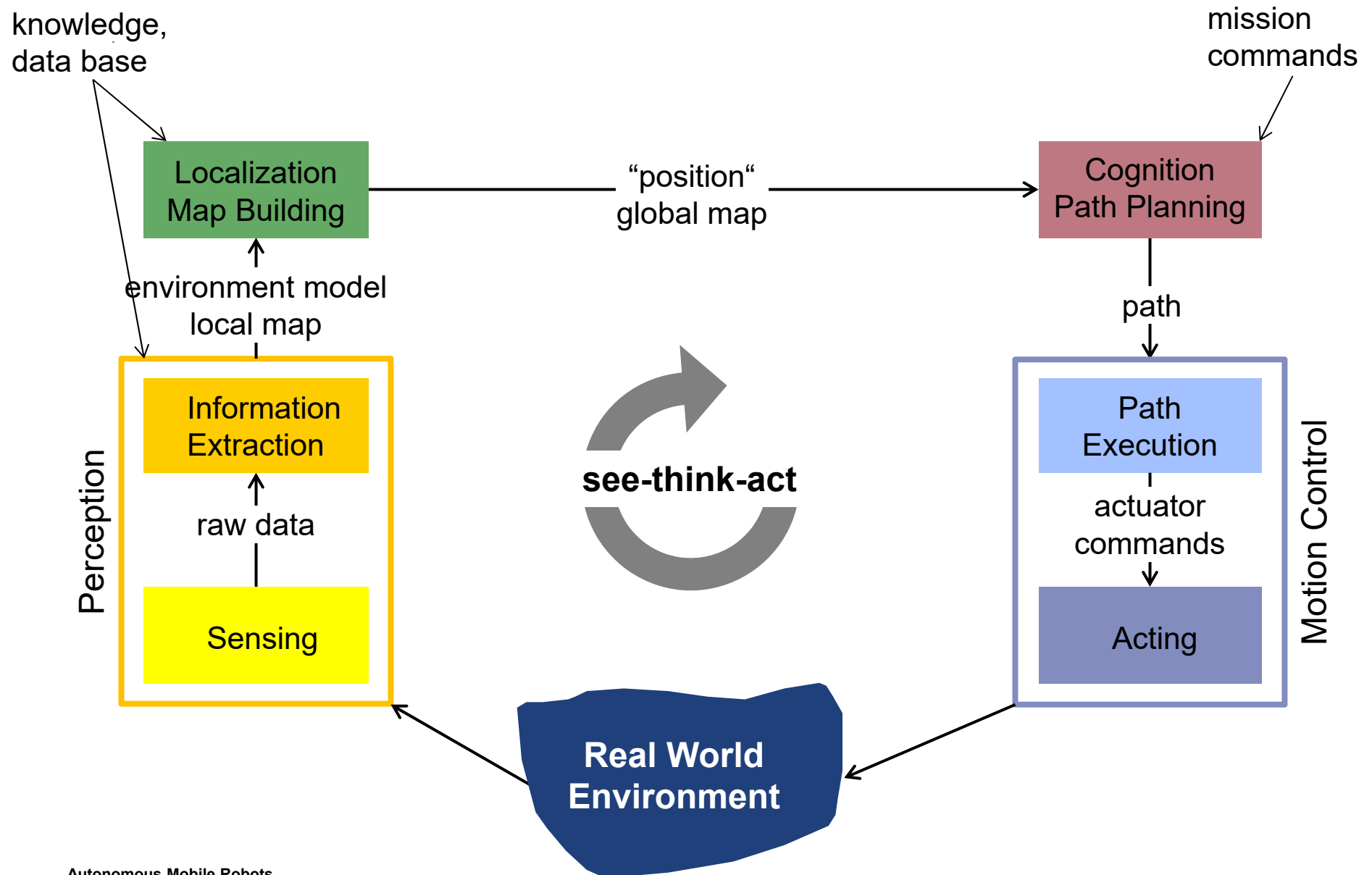


Spring 2018



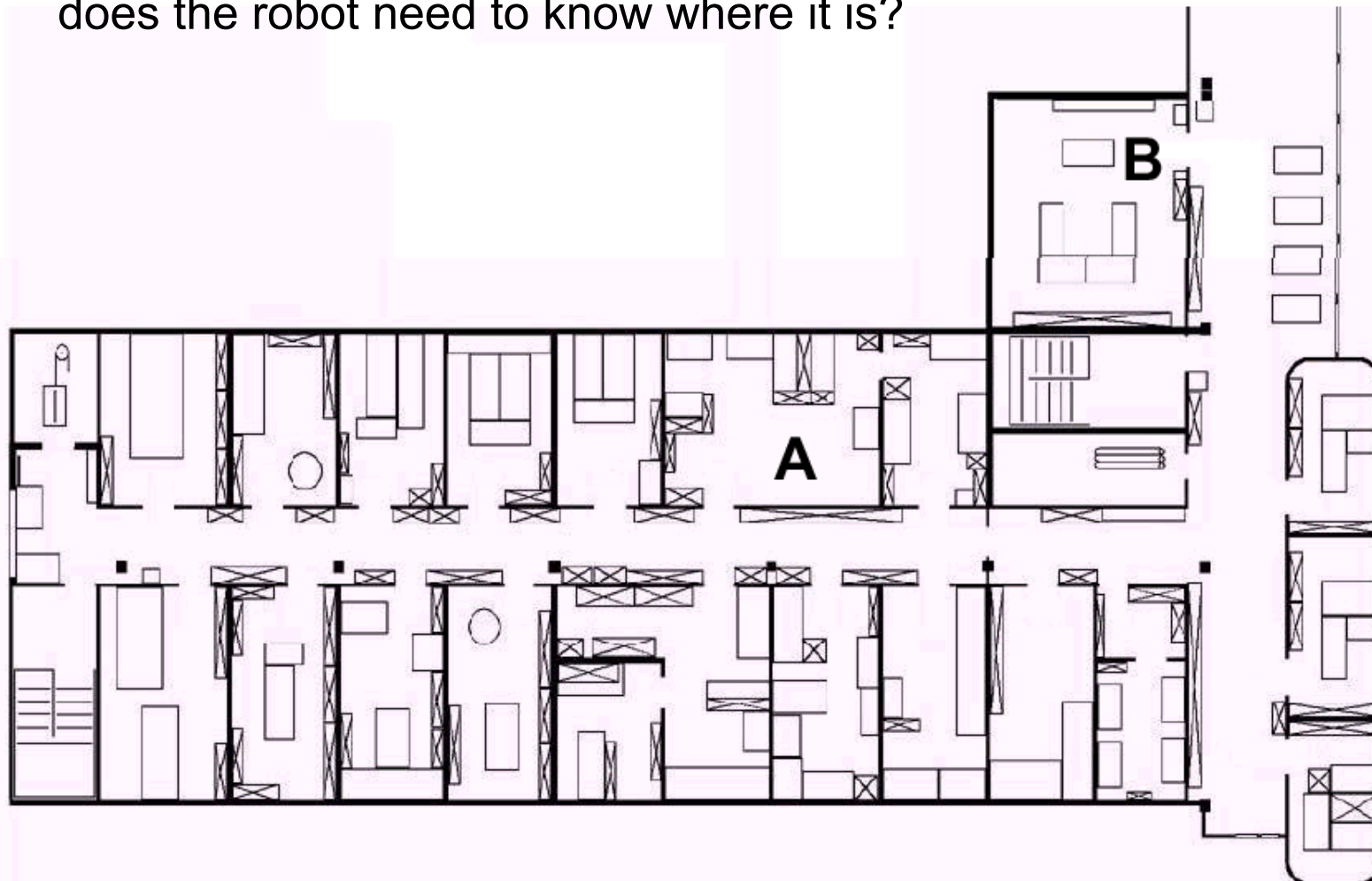
Localization I

Roland Siegwart, Margarita Chli, Juan Nieto, Nick Lawrance



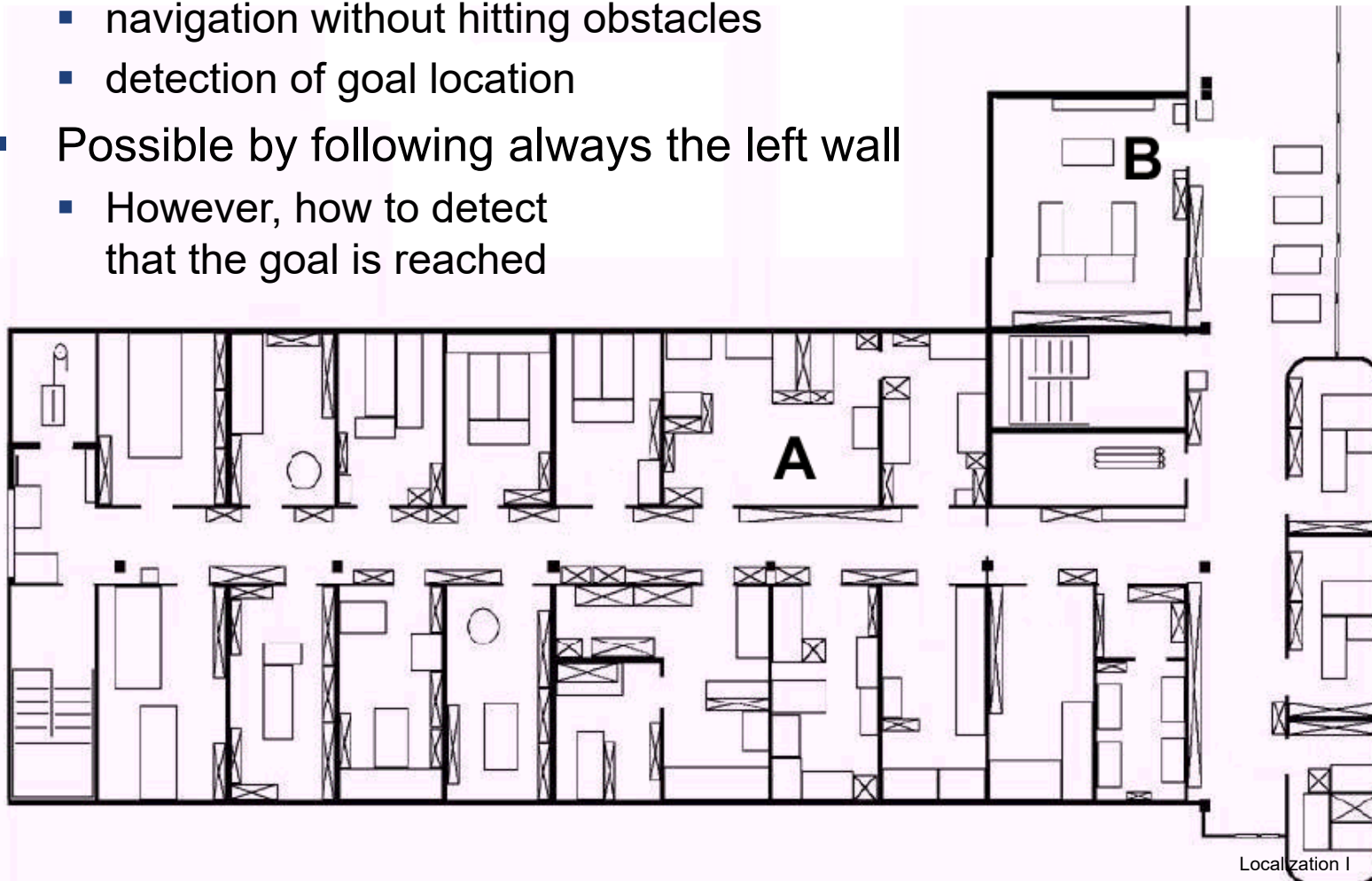
Introduction | Do we need to localize or not?

- To go from A to B:
does the robot need to know where it is?



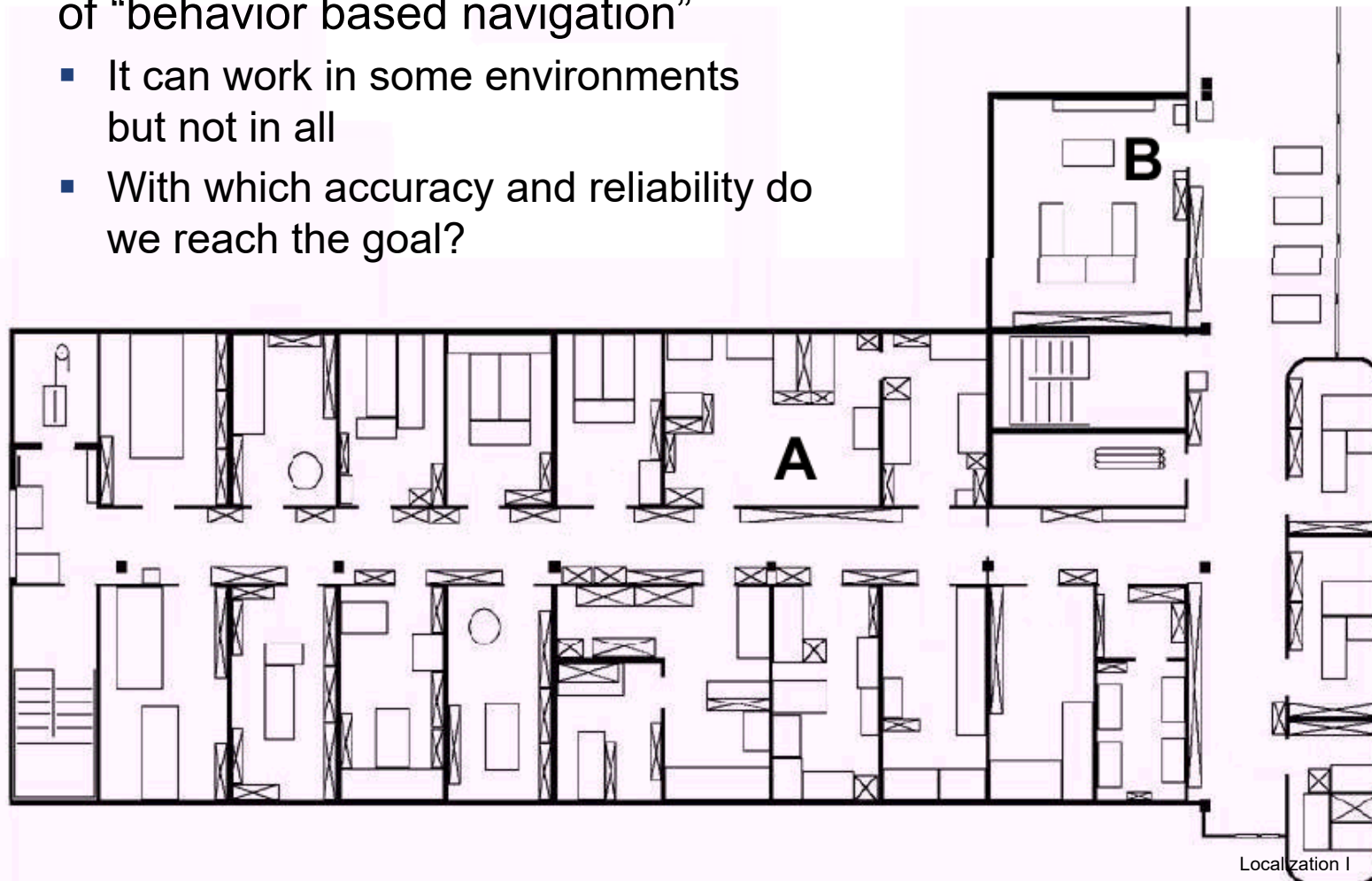
Introduction | Do we need to localize or not?

- How to navigate between A and B
 - navigation without hitting obstacles
 - detection of goal location
- Possible by following always the left wall
 - However, how to detect that the goal is reached



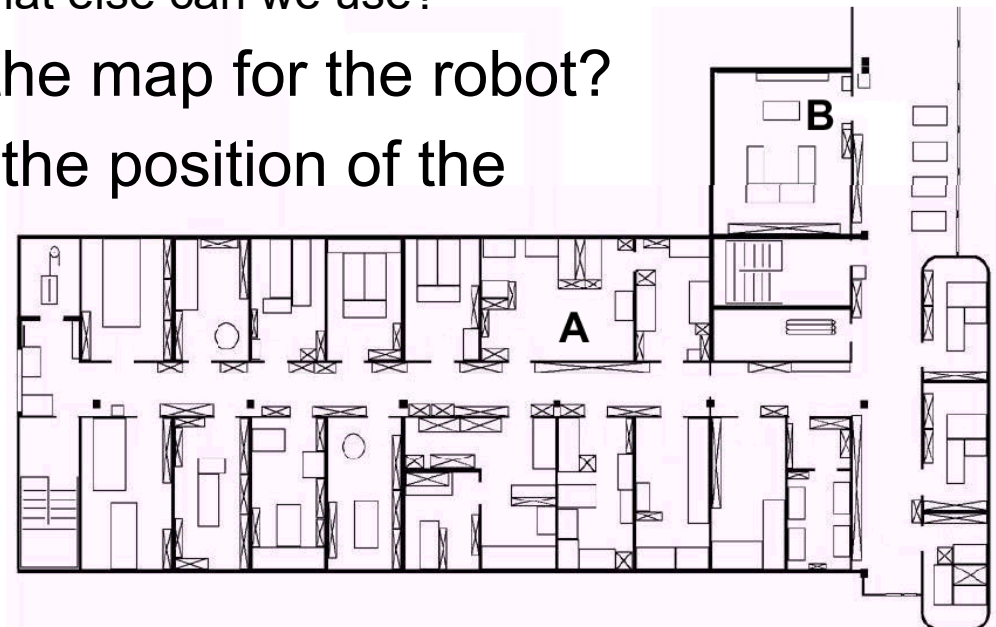
Introduction | Do we need to localize or not?

- Following the left wall is an example of “behavior based navigation”
 - It can work in some environments but not in all
 - With which accuracy and reliability do we reach the goal?



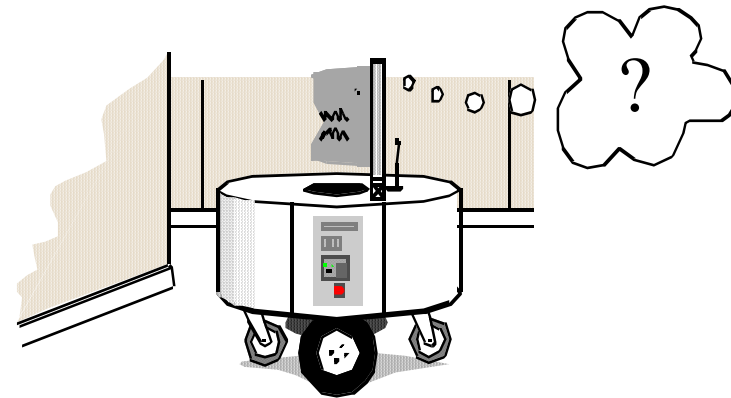
Introduction | Do we need to localize or not?

- As opposed to behavior based navigation is “map based navigation”
 - Assuming that the map is known, at every time step the robot has to know where it is. How?
 - If we know the start position, we can use wheel odometry or dead reckoning. Is this enough? What else can we use?
- But how do we represent the map for the robot?
- And how do we represent the position of the robot in the map?



Introduction | Definitions

- Global localization
 - The robot is not told its initial position
 - Its position must be estimated from scratch
- Position Tracking
 - A robot knows its initial position and “only” has to accommodate small errors in its odometry as it moves



Introduction | How to localize?

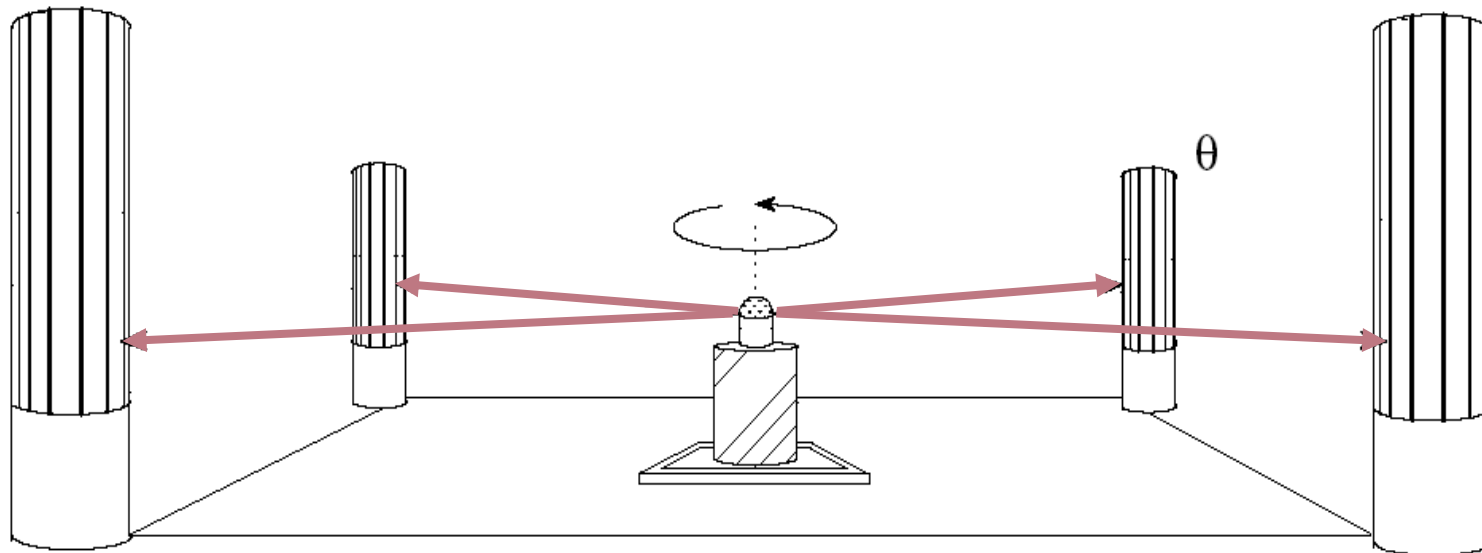
- Localization based on external sensors, beacons or landmarks
- Odometry
- Map Based Localization - without external sensors or artificial landmarks, just use robot onboard sensors
 - Example: Probabilistic Map Based Localization

Introduction | Beacon Based Localization



- Triangulation

- Ex 1: Poles with highly reflective surface and a laser for detecting them
- Ex 2: Coloured beacons and an omnidirectional camera for detecting them (example: RoboCup or autonomous robots in tennis fields)



Introduction | Beacon Based Localization

- KIVA Systems, Boston (MA) (acquired by Amazon in 2011)

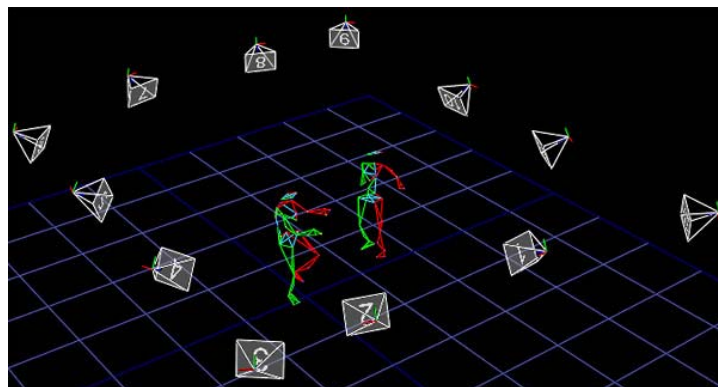


Unique marker with known absolute 2D position in the map

Prof. Raff D'Andrea, ETH

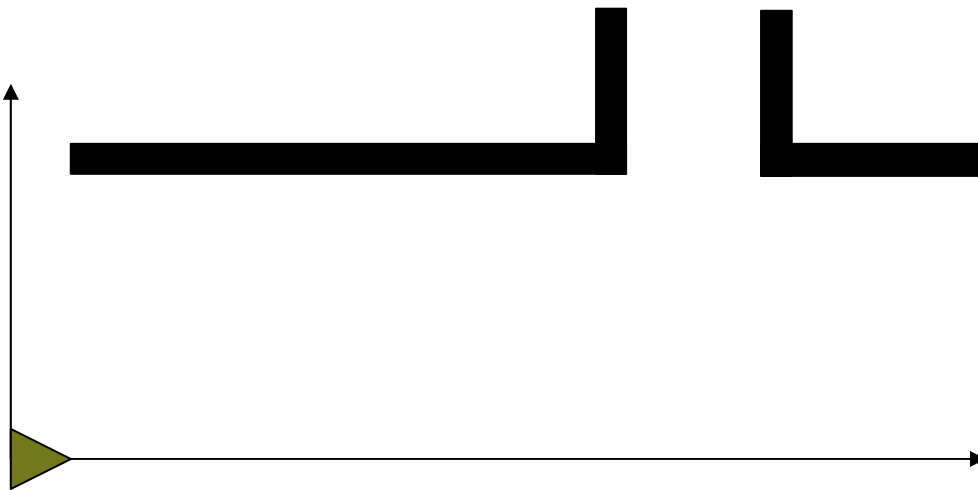
Introduction | Motion Capture Systems

- High resolution (from VGA up to 16 Mpixels)
- Very high frame rate (several hundreds of Hz)
- Good for ground truth reference and multi-robot control strategies
- Popular brands:
 - VICON (10kCHF per camera),
 - OptiTrack (2kCHF per camera)



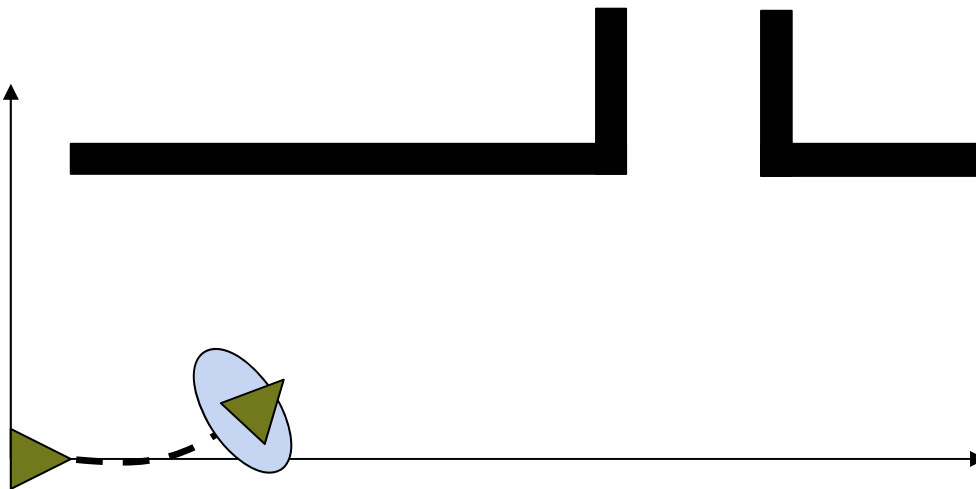
Introduction | Map-based localization

- Consider a mobile robot moving in a known environment.



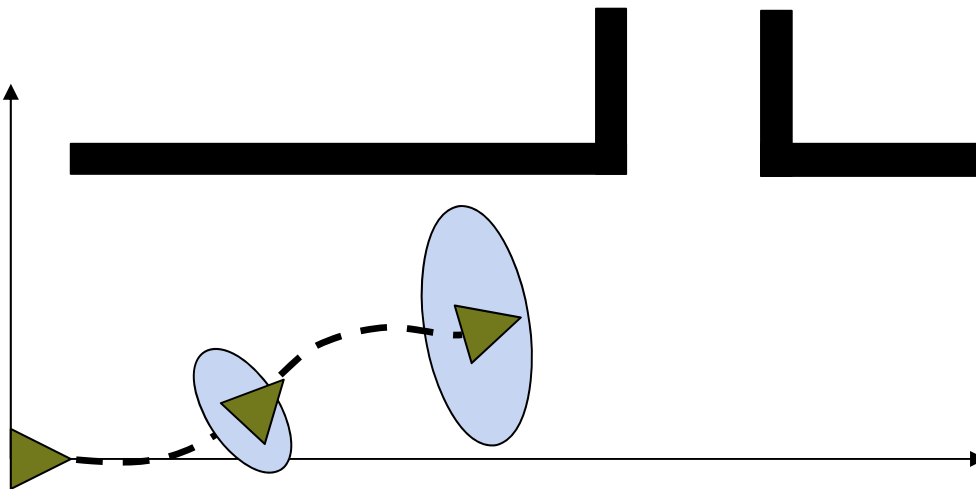
Introduction | Map-based localization

- Consider a mobile robot moving in a known environment.
- As it starts to move, say from a precisely known location, it can keep track of its motion using odometry.



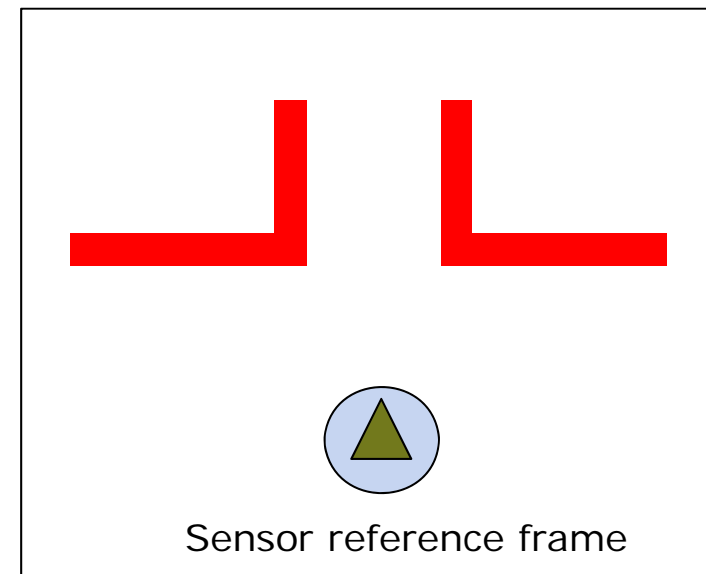
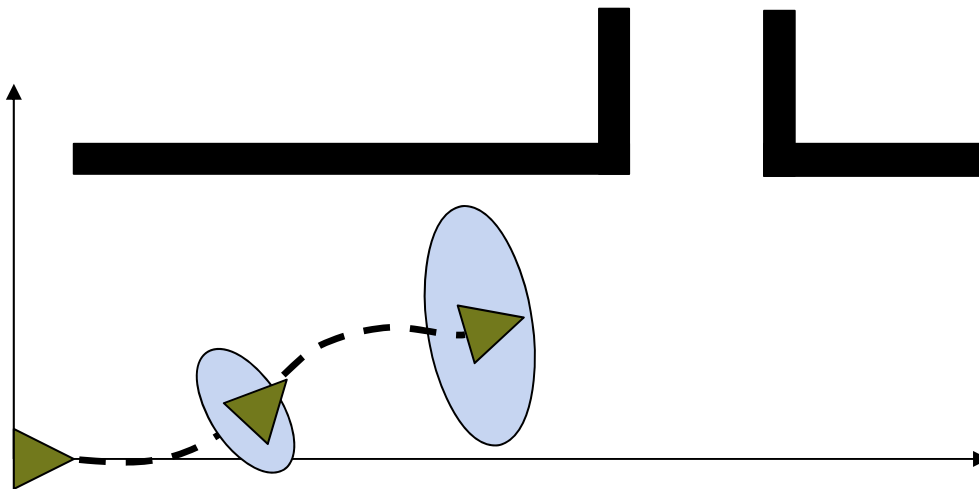
Introduction | Map-based localization

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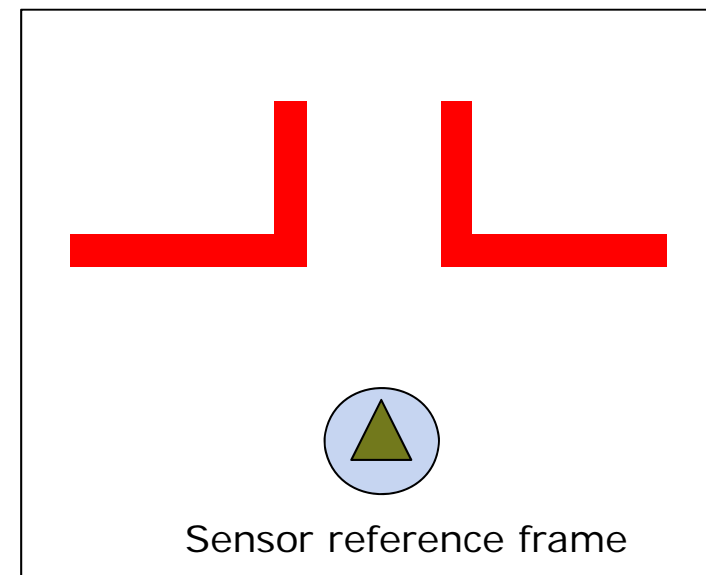
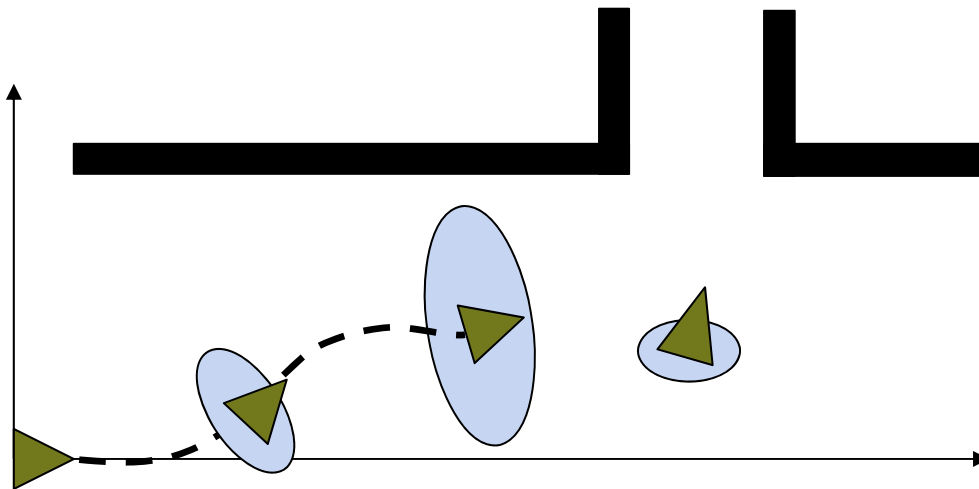
Introduction | Map-based localization

- Consider a mobile robot moving in a known environment.
- As it starts to move, say from a precisely known location, it can keep track of its motion using odometry.



Introduction | Map-based localization

- Consider a mobile robot moving in a known environment.
- As it starts to move, say from a precisely known location, it can keep track of its motion using odometry.
- The robot makes an observation and updates its position and uncertainty

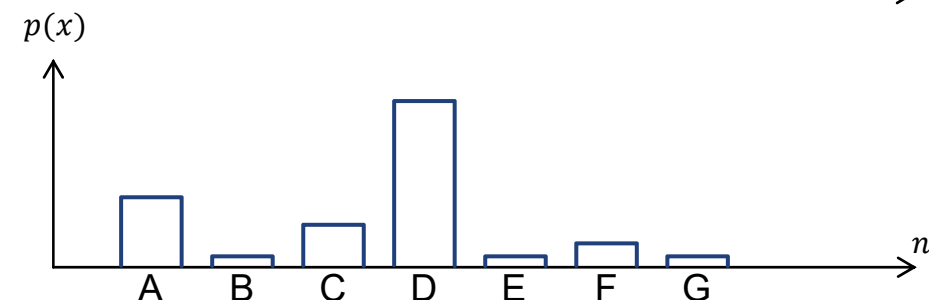
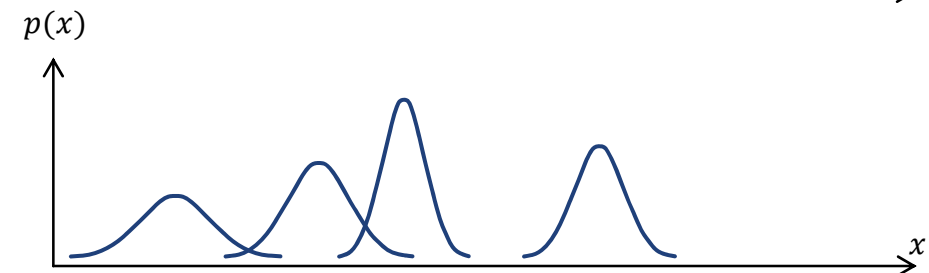
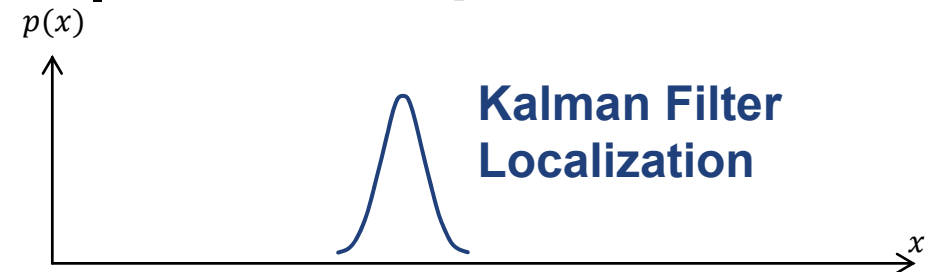


Ingredients | Probabilistic Map-based localization

- Probability theory → error propagation, sensor fusion
- Belief representation → discrete / continuous (map/position)
- Motion model → odometry model
- Sensing → measurement model

Probabilistic localization | Belief Representation

- Continuous map with single hypothesis probability distribution $p(x)$
- Continuous map with multiple hypotheses probability distribution $p(x)$
- Discretized metric map (grid k) with probability distribution $p(k)$
- Discretized topological map (nodes n) with probability distribution $p(n)$



Belief Representation | Characteristics

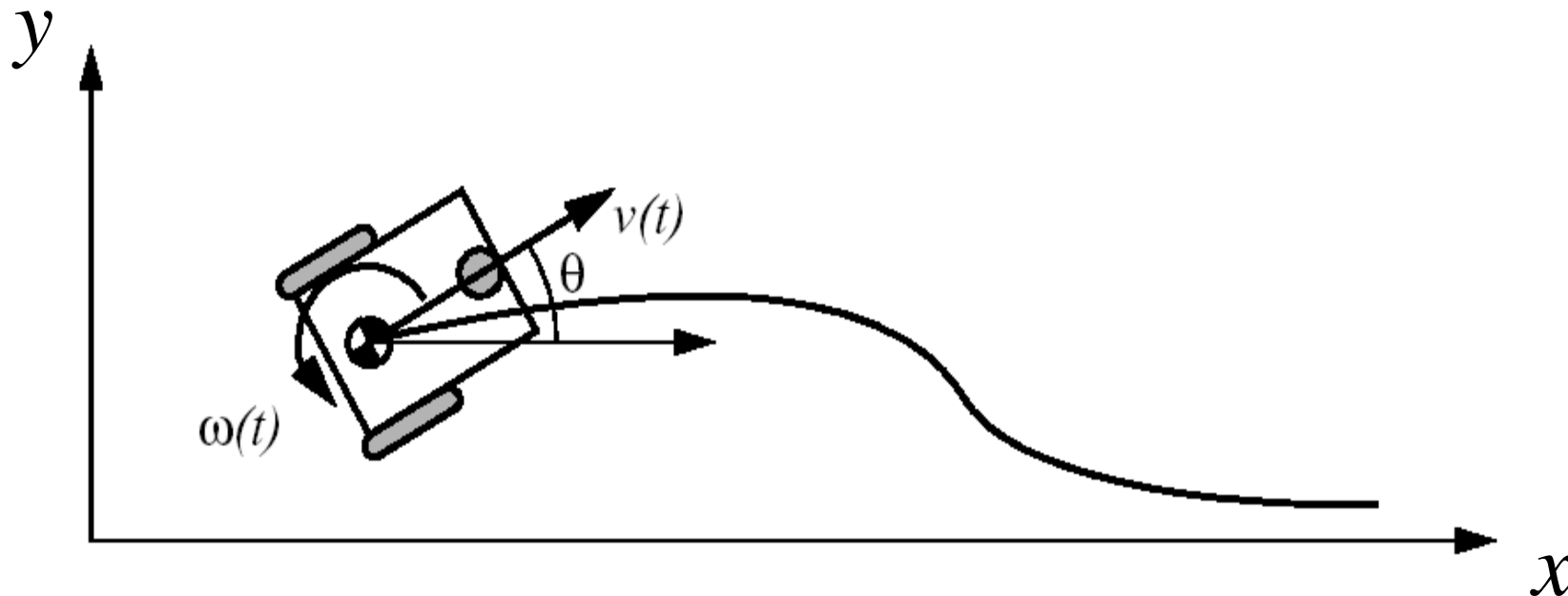
- Continuous
 - Precision bound by sensor data
 - Typically single hypothesis pose estimate
 - Lost when diverging (for single hypothesis)
 - Compact representation and typically reasonable in processing power.
- Discrete
 - Precision bound by resolution of discretisation
 - Typically multiple hypothesis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

Odometry

- Definition
 - Dead reckoning (also deduced reckoning or odometry) is the process of calculating vehicle's current position by using a previously determined position and estimated speeds over the elapsed time
- Robot motion is recovered by integrating proprioceptive sensor velocities readings
 - Pros: Straightforward
 - Cons: Errors are integrated -> unbound
- Heading sensors (e.g., gyroscope) help to reduce the accumulated errors but drift remains

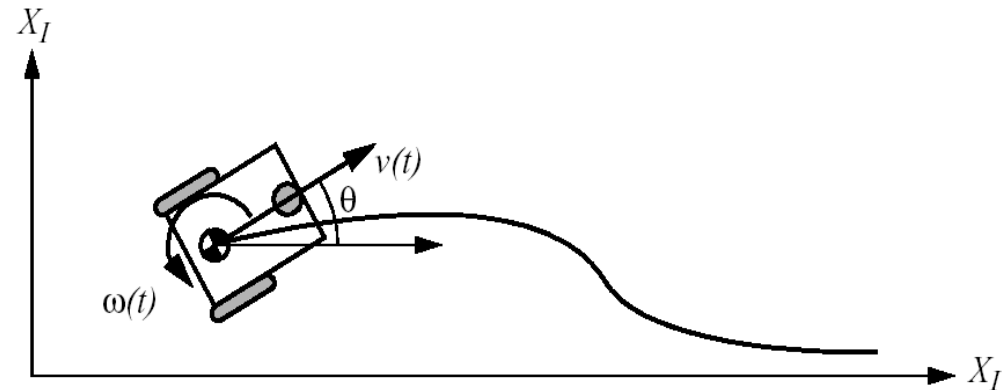
Odometry | The Differential Drive Robot

$$x = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad \hat{x}_t = x_{t-1} + \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta \theta \end{bmatrix} = f(x_{t-1}, u_t)$$



Odometry | Wheel Odometry

■ Kinematics



$$\hat{x}_t = f(x_{t-1}, u_t) = \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \theta_{t-1} \end{bmatrix} + \begin{bmatrix} \Delta s \cos(\theta + \frac{\Delta\theta}{2}) \\ \Delta s \sin(\theta + \frac{\Delta\theta}{2}) \\ \Delta\theta \end{bmatrix}$$

→ This term comes from the application of the Instantaneous Center of Rotation

Can you demonstrate these equations?

$$\Delta s = \frac{\Delta s_r + \Delta s_l}{2}$$

$$\Delta\theta = \frac{\Delta s_r - \Delta s_l}{b}$$

Odometry | Error Propagation

- Error model $P_t = F_{x_{t-1}} \cdot \Sigma_{x_{t-1}} \cdot F_{x_{t-1}}^T + F_{\Delta S} \cdot \Sigma_{\Delta S} \cdot F_{\Delta S}^T$

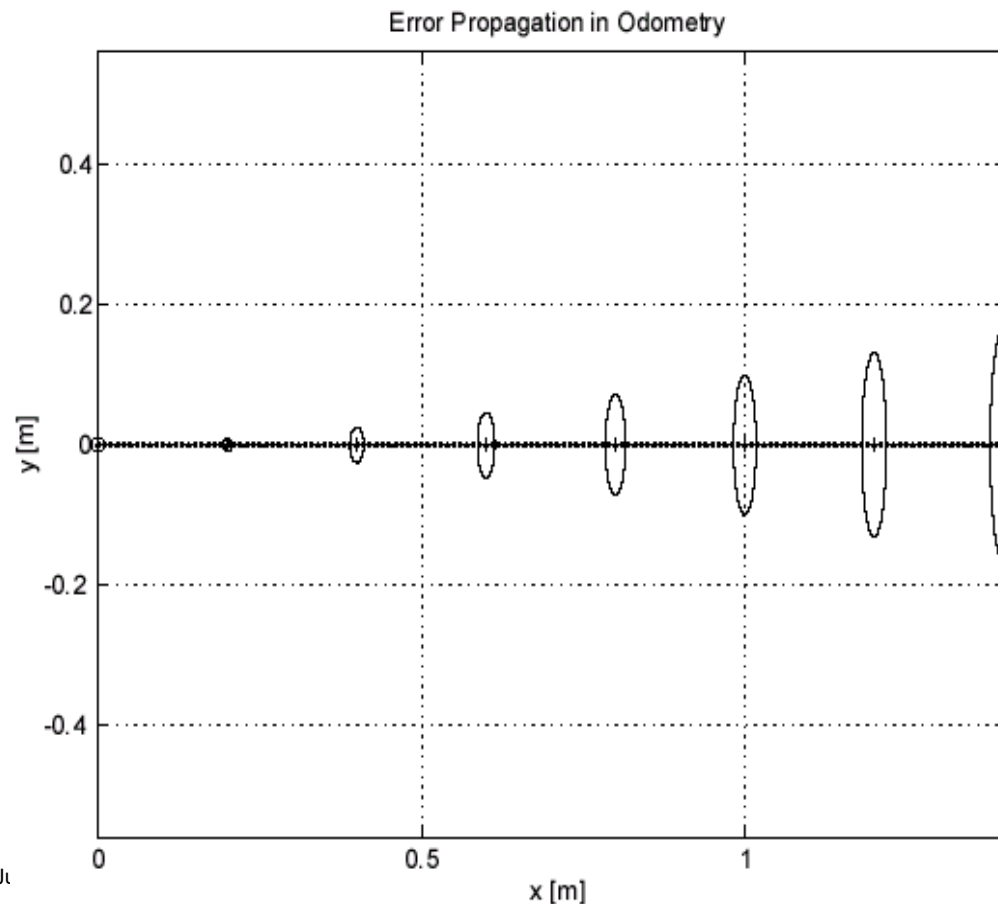
$$\Sigma_{\Delta S} = \begin{bmatrix} k_r |\Delta s_r| & 0 \\ 0 & k_l |\Delta s_l| \end{bmatrix}$$

$$F_{x_{t-1}} = \nabla f_{x_{t-1}} = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} & \frac{\partial f}{\partial \theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\Delta s \sin(\theta + \Delta \theta / 2) \\ 0 & 1 & \Delta s \cos(\theta + \Delta \theta / 2) \\ 0 & 0 & 1 \end{bmatrix}$$

$$F_{\Delta S} = \begin{bmatrix} \frac{1}{2} \cos\left(\theta + \frac{\Delta \theta}{2}\right) - \frac{\Delta s}{2b} \sin\left(\theta + \frac{\Delta \theta}{2}\right) & \frac{1}{2} \cos\left(\theta + \frac{\Delta \theta}{2}\right) + \frac{\Delta s}{2b} \sin\left(\theta + \frac{\Delta \theta}{2}\right) \\ \frac{1}{2} \sin\left(\theta + \frac{\Delta \theta}{2}\right) + \frac{\Delta s}{2b} \cos\left(\theta + \frac{\Delta \theta}{2}\right) & \frac{1}{2} \sin\left(\theta + \frac{\Delta \theta}{2}\right) - \frac{\Delta s}{2b} \cos\left(\theta + \frac{\Delta \theta}{2}\right) \\ \frac{1}{b} & -\frac{1}{b} \end{bmatrix}$$

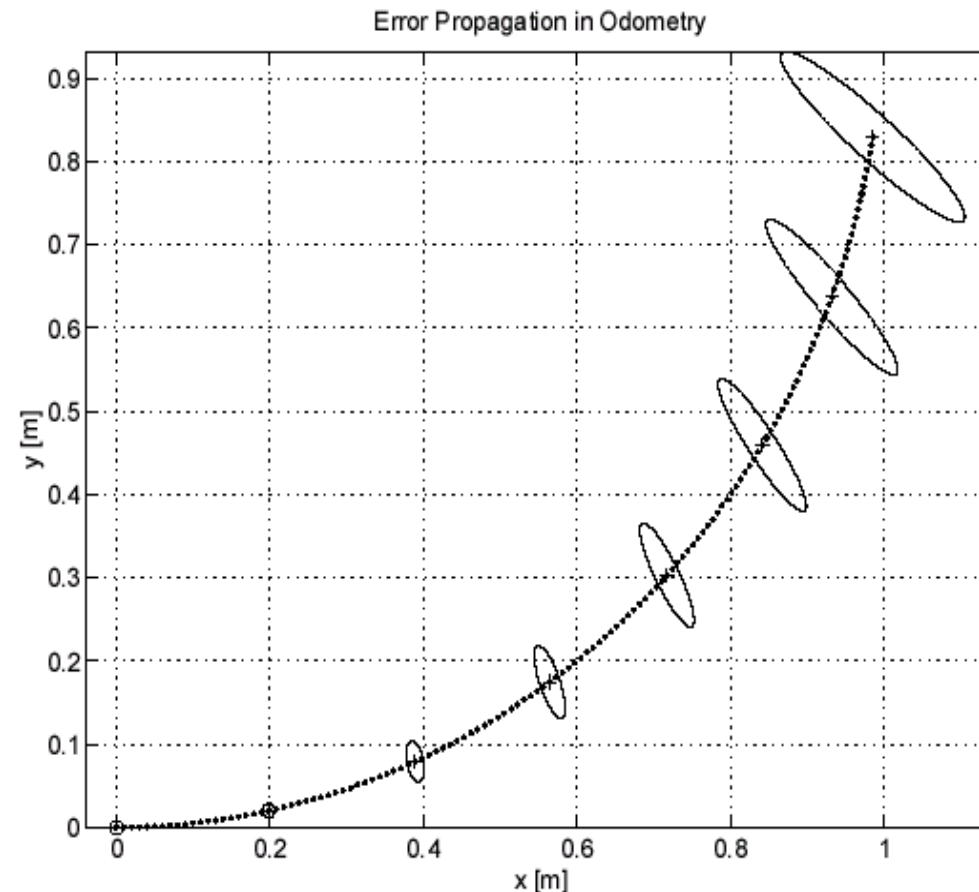
Odometry | Growth of Pose uncertainty for Straight Line Movement

- Note: Errors perpendicular to the direction of movement are growing much faster!



Odometry | Growth of Pose uncertainty for Movement on a Circle

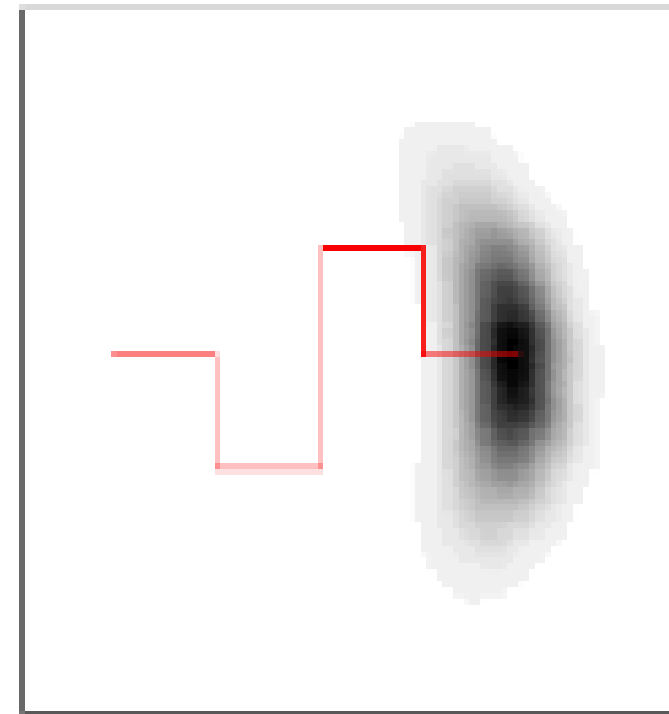
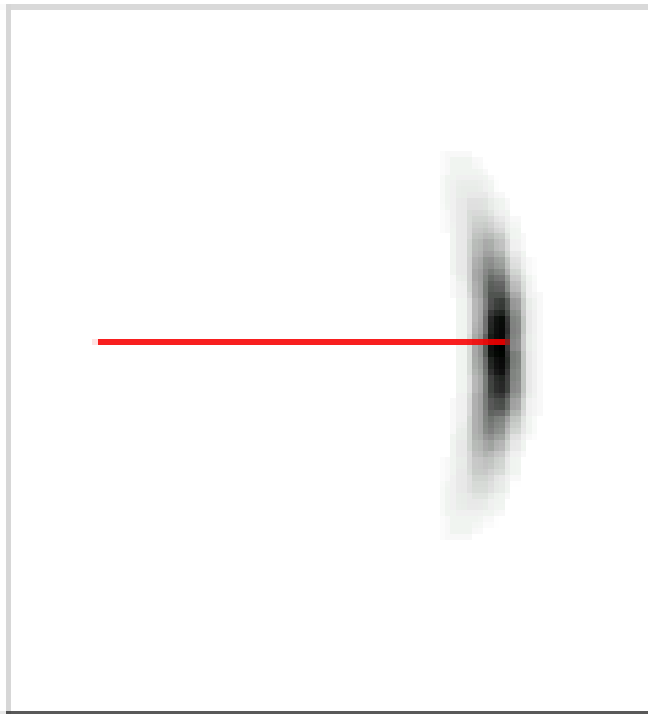
- Note: Errors ellipse does not remain perpendicular to the direction of movement!



Odometry | Example of non-Gaussian error model

- Note: Errors are not shaped like ellipses!

Courtesy AI Lab, Stanford



[Fox, Thrun, Burgard, Dellaert, 2000]

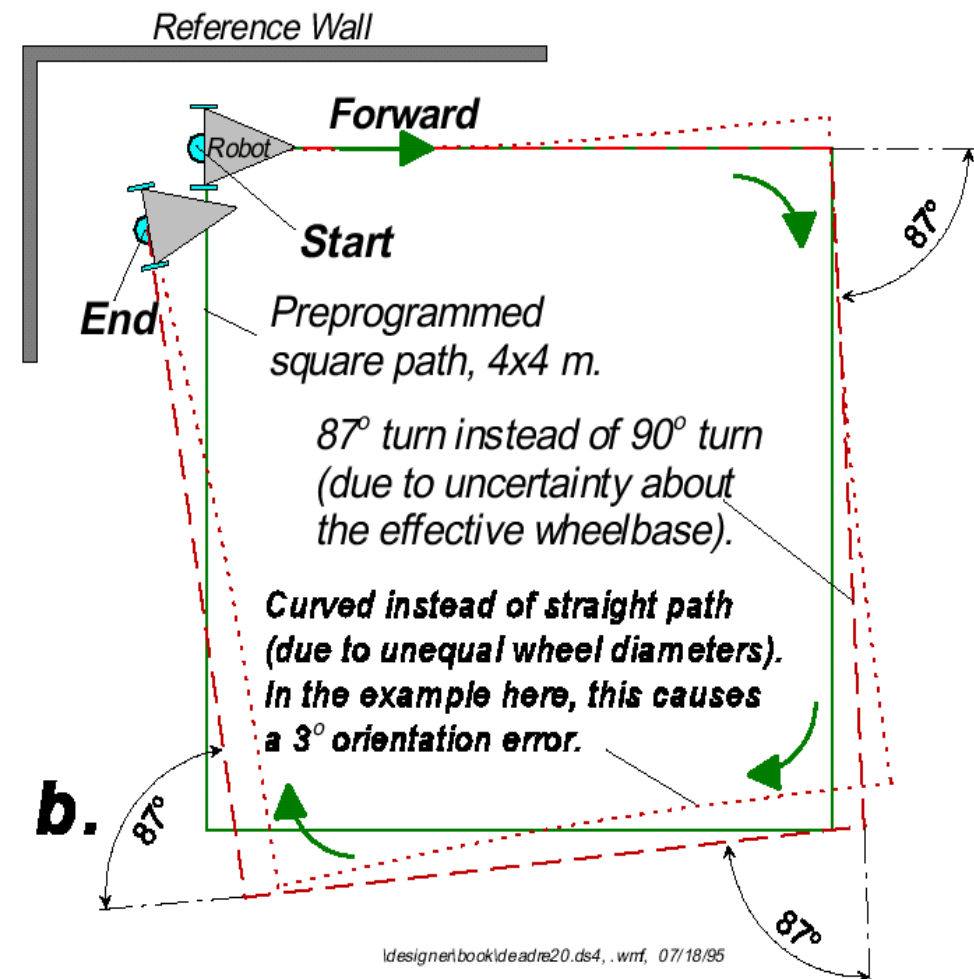
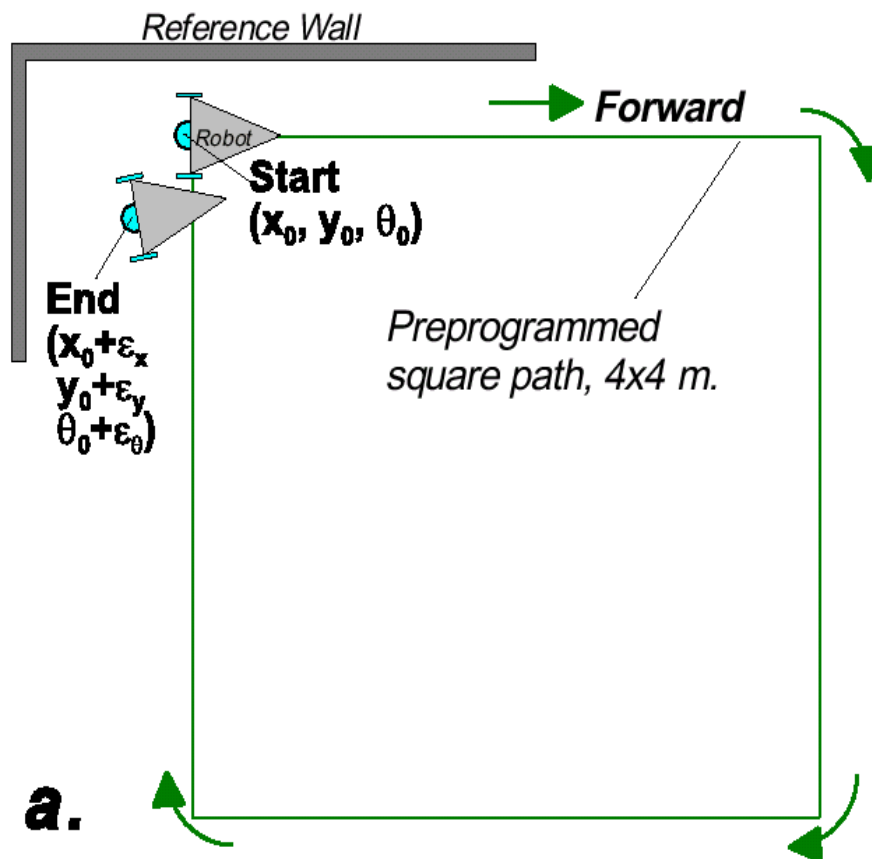
Odometry | Error sources

- Deterministic
- (Systematic)
- Deterministic errors can be eliminated by proper calibration of the system.
- Non-Deterministic errors are random errors. They have to be described by error models and will always lead to uncertain position estimate.
- Major Error Sources in Odometry:
 - 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 (non deterministic)
 - Unequal floor contact (slippage, non planar ...) (non deterministic)

Odometry | Calibration of systematic errors

[Borenstein 1996]

- The unidirectional square path experiment



Odometry | Calibration of Errors II

[Borenstein 1996]

- The bi-directional square path experiment

