Distributed Intelligent Systems – W4

An Introduction to Localization Methods for Mobile Robots

Outline

- Positioning systems
  - Indoor
  - Outdoor

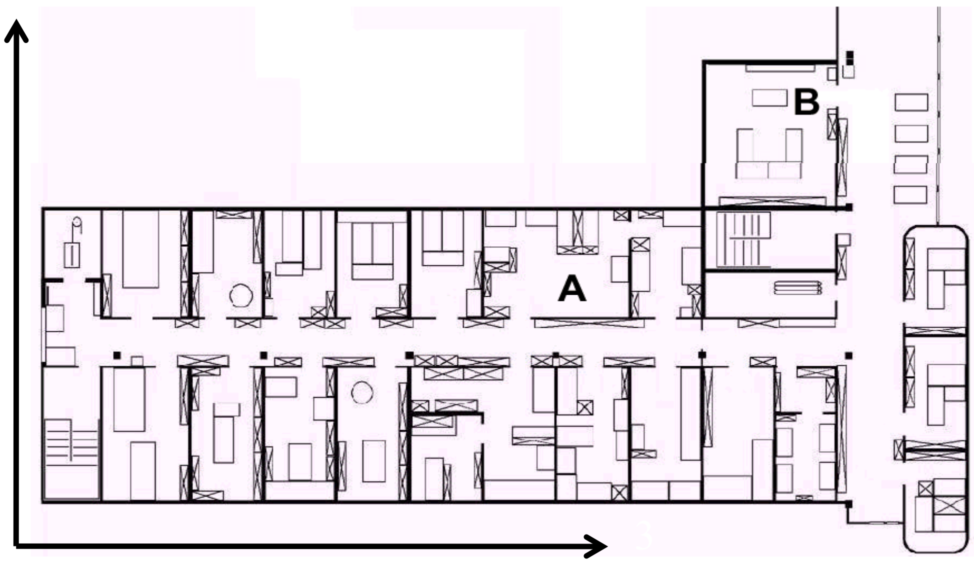
- Robot localization using proprioceptive sensors without uncertainties
  - Kinematic models
  - Odometry

- Robot localization with uncertainties
  - The 1D problem: error sources and accelerometer-based odometry
  - Fusion of proprioceptive and exteroceptive sensory data for 1D localization

Robot Localization

- Key task for:
  - Path planning
  - Mapping
  - Referencing
  - Coordination

- Type of localization
  - Absolute coordinates
  - Local coordinates
  - Topological information



Positioning Systems

Classification axes

- Indoor vs. outdoor techniques
- Absolute vs. relative positioning systems
- Line-of-sight vs. non-line-of-sight
- Underlying physical principle and channel
- Positioning available on-board vs. off-board
- Scalability in terms of number of nodes

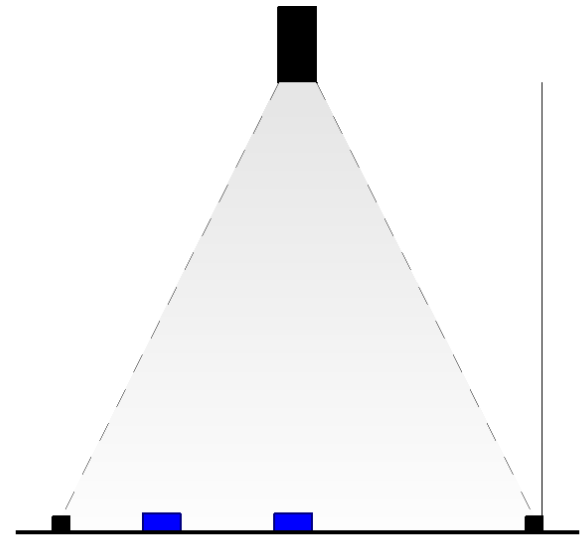
Selected Indoor Positioning Systems

- Overhead cameras and Motion Capture Systems (MCSs)
- Impulse Radio Ultra Wide Band (IR-UWB)
- Infrared (IR) + RF technology

EPFL

2D Single- or Multi-Camera Systems

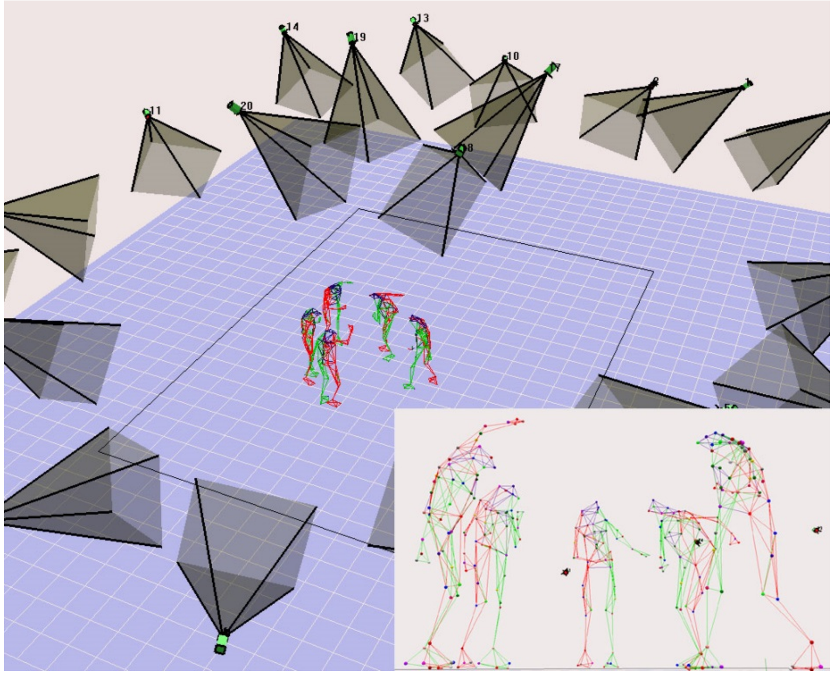
- Tracking objects with one (or more) overhead cameras
- Absolute positions/poses, available outside the robot/sensor
- Active, passive, or no markers
- Open-source software available (e.g., SwisTrack, developed at DISAL)
- Major issues: light, calibration



Performance 1 camera system	
Accuracy	~ 1 cm (2D)
Update rate	~ 20-100 Hz
# agents	~ 100
Area	~ 10 m^2

3D Multi-Camera Systems

- Called also Motion Capture System (MCS)
- 10-50 cameras
- mm accuracy
- Up to a few hundred Hz update, 2 ms latency
- 6D pose estimation of objects
- 4-5 passive markers per object to be tracked needed
- A few hundreds m^3 motion arena
- Open-source and markerless systems exist (but less reliable)



Coordinated ball (Prof. D'Andrea, ETHZ):
http://www.youtube.com/watch?v=hyGJBV1xnJI
Aggressive maneuver (Prof. Kumar, UPenn):
http://www.youtube.com/watch?v=geqip_0Vjec

IR-UWB System - Technology

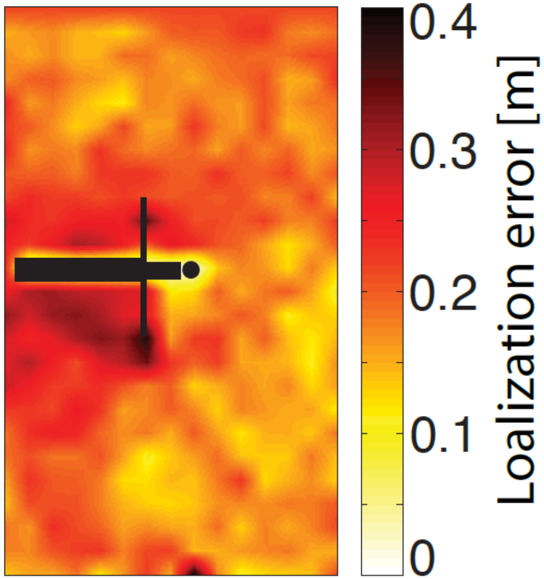
- Impulse Radio Ultra-Wide Band
- Based on time-of-flight (TDOA, Time Difference of Arrival)
- 6 - 8 GHz central frequency
- Very large bandwidth (>0.5GHz)
  → high material penetrability
- Fine time resolution
  → high theoretical ranging accuracy (order of cm)
- UWB tags (emitters, a few cm, low-power) and multiple synchronized receivers
- Emitters can be unsynchronized but then dealing with interferences not trivial (e.g., Ubisense system synchronized)
- Absolute positions available on the receiving system
- Positioning information can be fed back to tracked devices using a standard narrow-band channel
- Transceiver versions exist (e.g., Eliko system) thanks to progress in UWB chipsets

IR-UWB System – Performances

Ex. State-of-art system (e.g., Ubisense 7000 Series, Compact Tag)

Accuracy	15 cm (3D)
Update rate	34 Hz / tag
# agents	~ 10000
Area	~ 1000 m^2

- Degraded accuracy performance if
  - Inter-emitter interferences
  - Non-Line-of-Sight (NLOS) bias
  - Multi-path



[Prorok and Martinoli, *IJRR*, 2014]

Infrared + Radio – Technology

- Belt of IR emitters (LED) and receivers (photodiode)
- IR LED used as antennas; modulated light (carrier 10.7 MHz), RF chip behind
- Range: measurement of the Received Signal Strength Intensity (RSSI)
- Bearing: signal correlation over multiple receivers
- Measure range & bearing can be coupled with standard RF channel (e.g., 802.11) for heading assessment
- Can also be used for 20 kbit/s IR com channel
- Robot ID communicated with the IR channel (ad hoc protocol)

[Pugh et al., *IEEE Trans. on Mechatronics*, 2009]

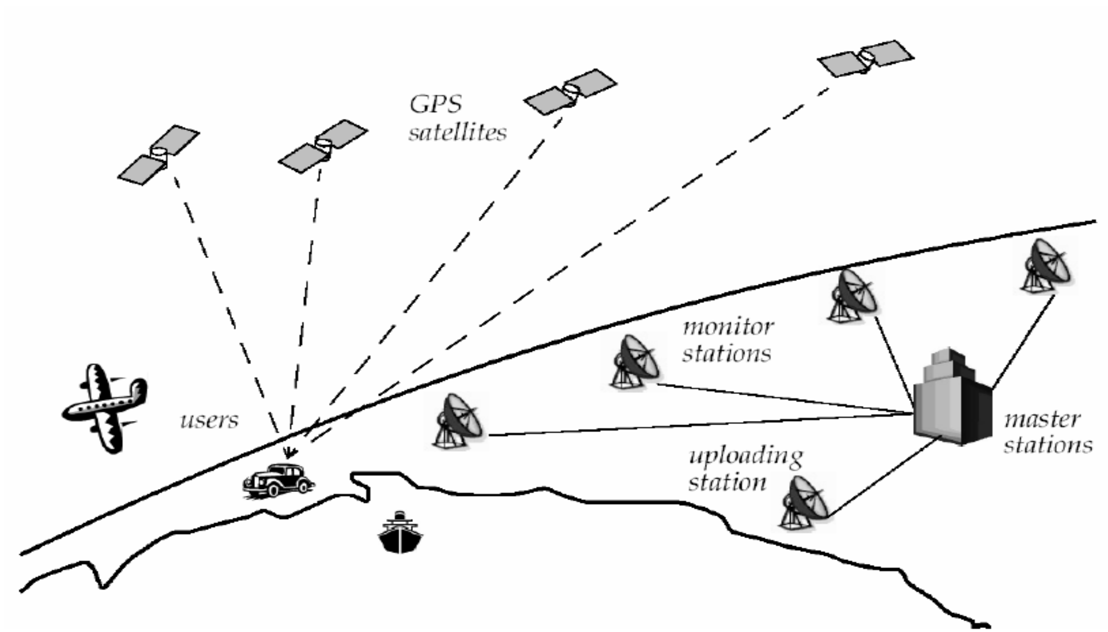
Infrared + Radio – Performances

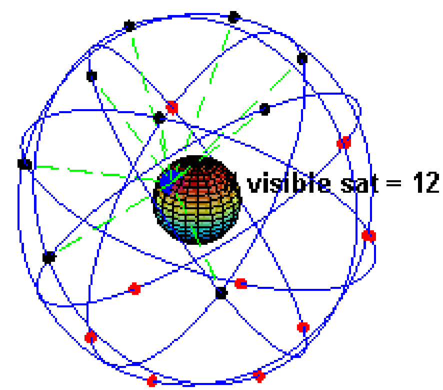
- Range: 3.5 m (extensible to a few m)
- Update frequency 25 Hz with 10 neighboring robots (or 250 Hz with 2); extensible to a few hundred Hz with TDMA schemes
- Accuracy range: <10%, generally decrease 1/d
- Accuracy bearing: $< 10^{o}$
- LOS method
- Extension in 3D possible
- Larger range with more power consumption and dedicated optics; better bearing accuracy with more photodiodes

Selected Outdoor Positioning Techniques

- GPS
- Differential GPS (dGPS)

Global Positioning System





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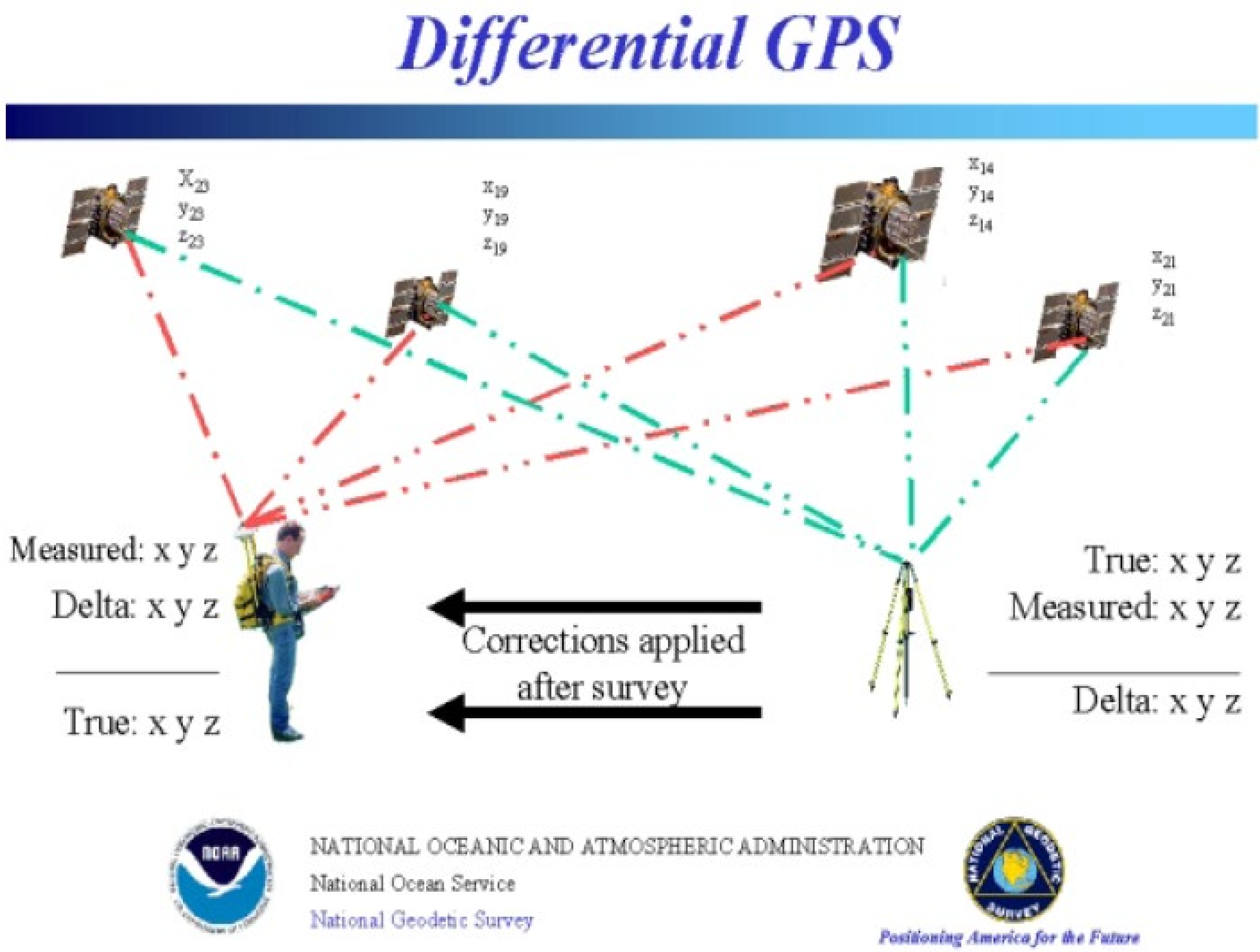
Note: the first and still most prominent example of a GNSS (Global Navigation Satellite System)

Global Positioning System

- Initially 24 satellites (including three spares), 32 as of December 2012, orbiting the earth every 12 hours at a height of 20.190 km.
- Satellites synchronize their transmission (location + time stamp) so that signals are broadcasted at the same time (ground stations updating + atomic clocks on satellites)
- Real time update of the exact location of the satellites:
  - monitoring the satellites from a number of widely distributed ground stations
  - a master station analyses all the measurements and transmits the actual position to each of the satellites
- Location of any GPS receiver is determined through a time of flight measurement (*ns* accuracy!)
- Exact measurement of the time of flight
  - the receiver correlates a pseudocode with the same code coming from the satellite
  - the delay time for best correlation represents the time of flight.
  - quartz clock on the GPS receivers are not very precise
  - the range measurement with (at least) four satellites allows to identify the three values (x, y, z) for the position and the clock correction ΔT
- Recent commercial GPS receiver devices allows position accuracies down to a few meters with best satellite visibility conditions.
- 200-300 ms latency, so max 5 Hz GPS updates

dGPS



Differential GPS
x_{23}
y_{23}
z_{23}
x_{19}
y_{19}
z_{19}
x_{14}
y_{14}
z_{14}
x_{21}
y_{21}
z_{21}
Measured: x y z
Delta: x y z
True: x y z
Corrections applied after survey
True: x y z
Measured: x y z
Delta: x y z
NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
National Ocean Service
National Geodetic Survey
Positioning America for the Future

Odometry

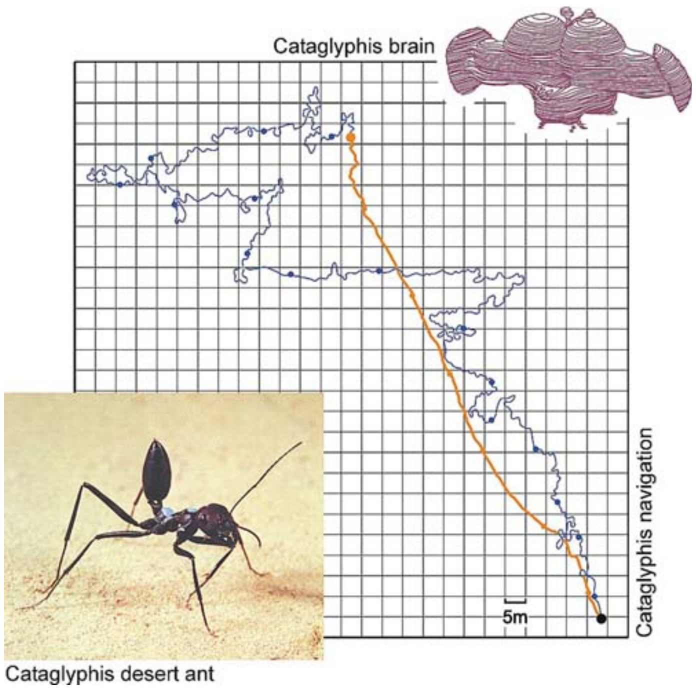
Definition

"Using proprioceptive sensory data influenced by the movement of actuators to estimate change in pose over time"

- Idea: navigating a room with the light turned off
- Start: initial position
- Actuators:
  - Legs
  - Wheels
  - Propeller
- Sensors (proprioceptive):
  - Wheel encoders (DC motors), step counters (stepper motors)
  - Inertial measurement units, accelerometers
  - Nervous systems, neural chains

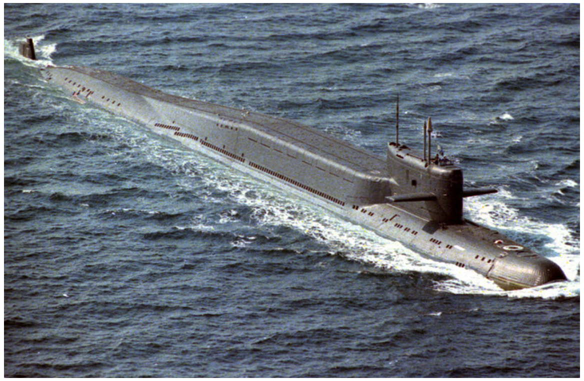
Example of Navigation Heavily Leveraging Odometry

- Example: Cataglyphis desert ant
- Excellent study by Prof. R. Wehner (University of Zuerich, Emeritus)
- Individual foraging strategy
- Underlying mechanisms
  - Dead-reckoning (path integration on neural chains for leg control)
  - Internal compass (polarization of sun light)
  - Local search (around 1-2 m from the nest)
- Extremely accurate navigation: averaged error of a few tens of cm over 500 m path!

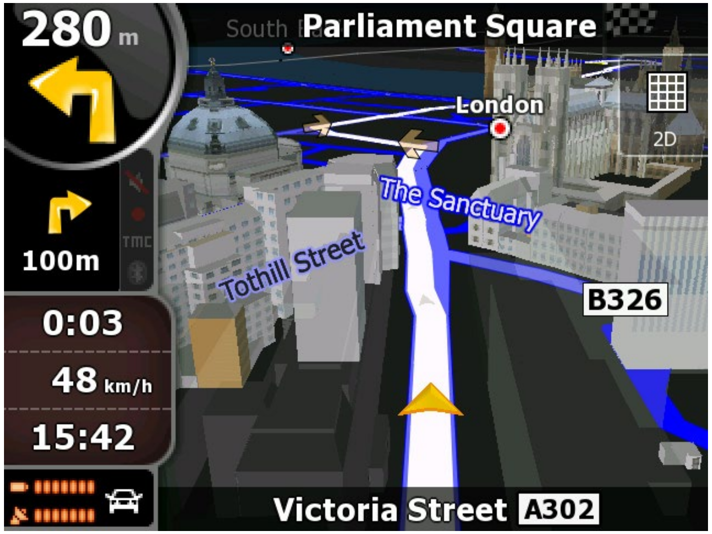


More examples

- Human in the dark
  - Very **bad** odometry sensors
  - $d_{\text{Odometry}} = O(1/\text{m})$
- (Nuclear) Submarine
  - Very **good** odometry sensors
  - $d_{\text{Odometry}} = O(1/10^3\ \text{km})$
- Navigation system in tunnel uses dead reckoning based on
  - Last velocity as measured by GPS
  - Car's odometer, compass



Picture: Courtesy of US Navy

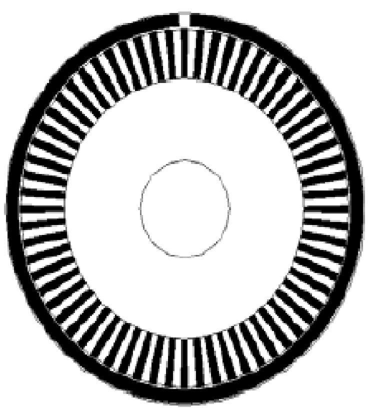


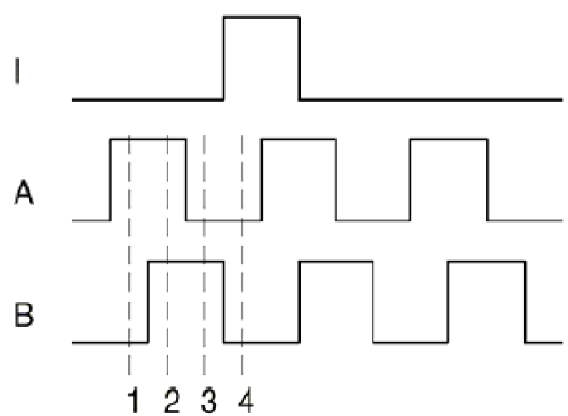
Picture: Courtesy of NavNGo

Odometry using Wheel Encoders or Step Counters

Optical Encoders

- Measure displacement (or speed) of the wheels
- Principle: mechanical light chopper consisting of photo-barriers (pair of light emitter and optical receiver) + pattern on a disc anchored to the motor shaft
- Quadrature encoder: 90º placement of 2 complete photo-barriers, 4x increase resolution + direction of movement
- Integrate wheel movements to get an estimate of the position -> odometry
- Typical resolutions: 64 - 4096 increments per revolution.
- Note: the e-puck is not endowed with wheel encoders but step counters for the stepper motors





State	Ch A	Ch B
S_1	High	Low
S_2	High	High
S_3	Low	High
S_4	Low	Low

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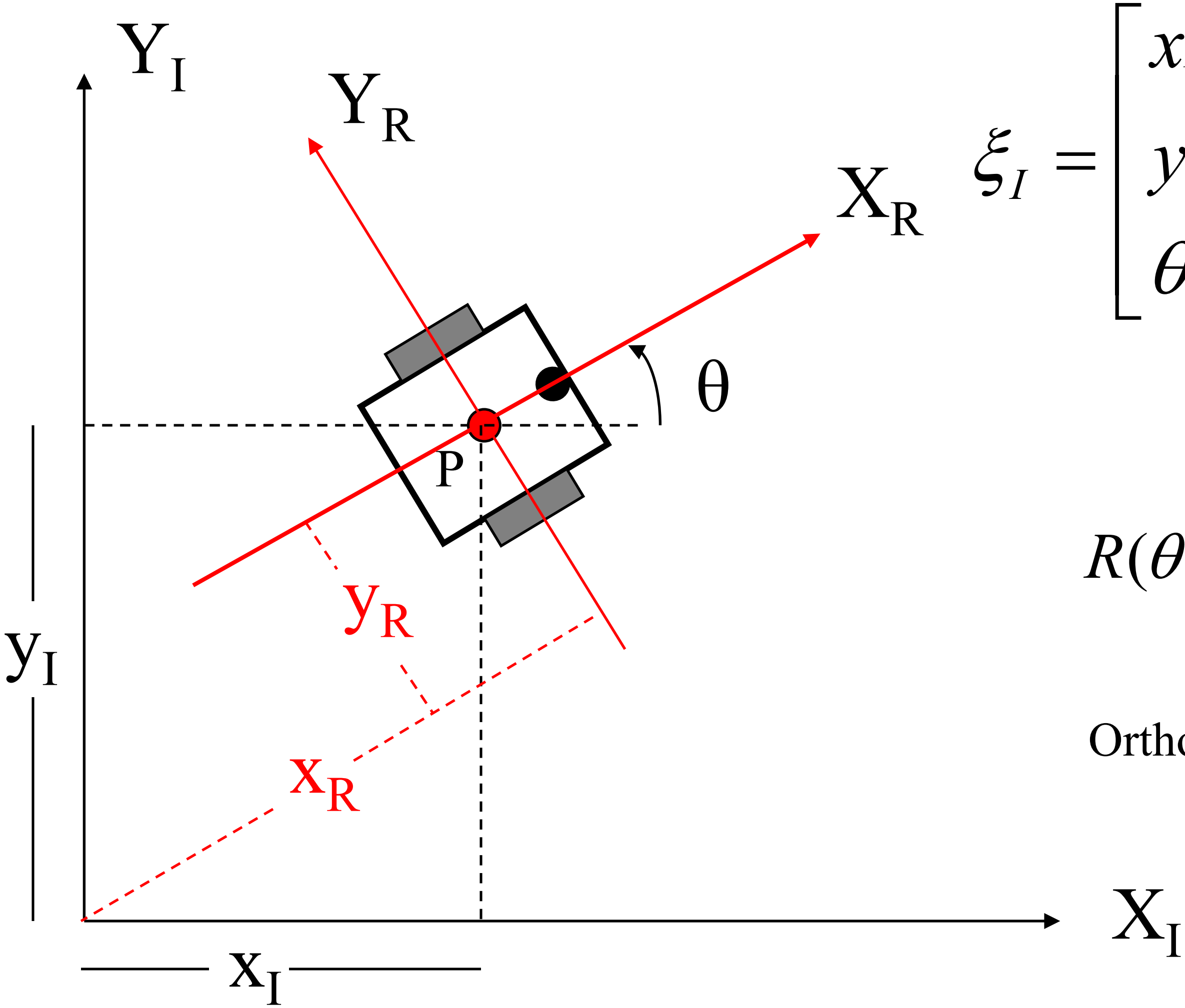
Pose (Position and Orientation) of a Differential-Drive Robot



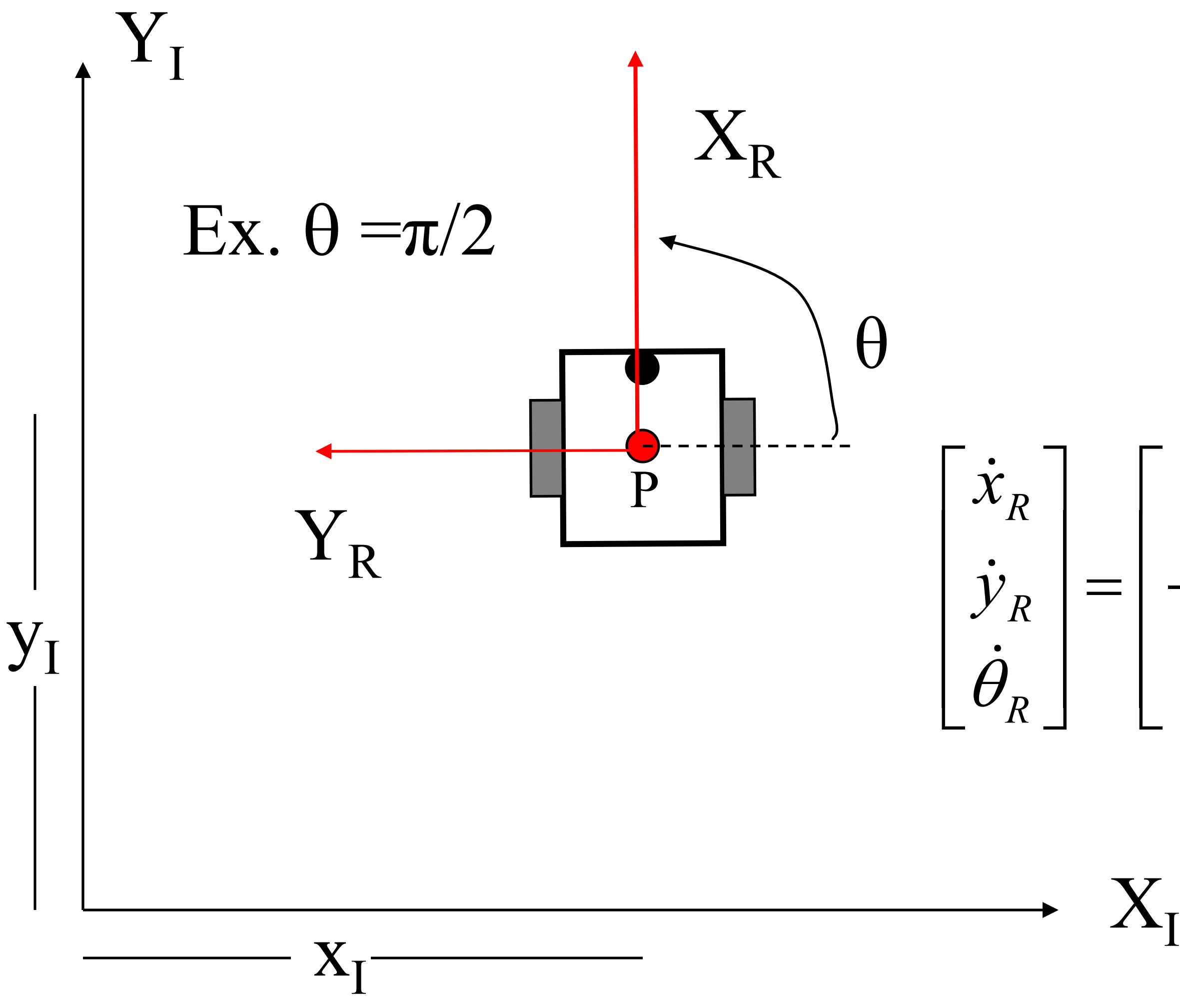
$$\xi_I = \begin{bmatrix} x_I \\ y_I \\ \theta \end{bmatrix} \quad \xi_R = \begin{bmatrix} x_R \\ y_R \\ \theta \end{bmatrix} = R(\theta)\xi_I$$

$$R(\theta) = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Orthogonal Rotation Matrix

From *Introduction to Autonomous Mobile Robots*, Siegwart R. and Nourbakhsh I. R.

Absolute and Relative Motion of a Differential-Drive Robot



$$\dot{\xi}_R = R(\theta)\dot{\xi}_I$$

$$\begin{bmatrix} \dot{x}_R \\ \dot{y}_R \\ \dot{\theta}_R \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{x}_I \\ \dot{y}_I \\ \dot{\theta}_I \end{bmatrix} = \begin{bmatrix} \dot{y}_I \\ -\dot{x}_I \\ \dot{\theta}_I \end{bmatrix}$$

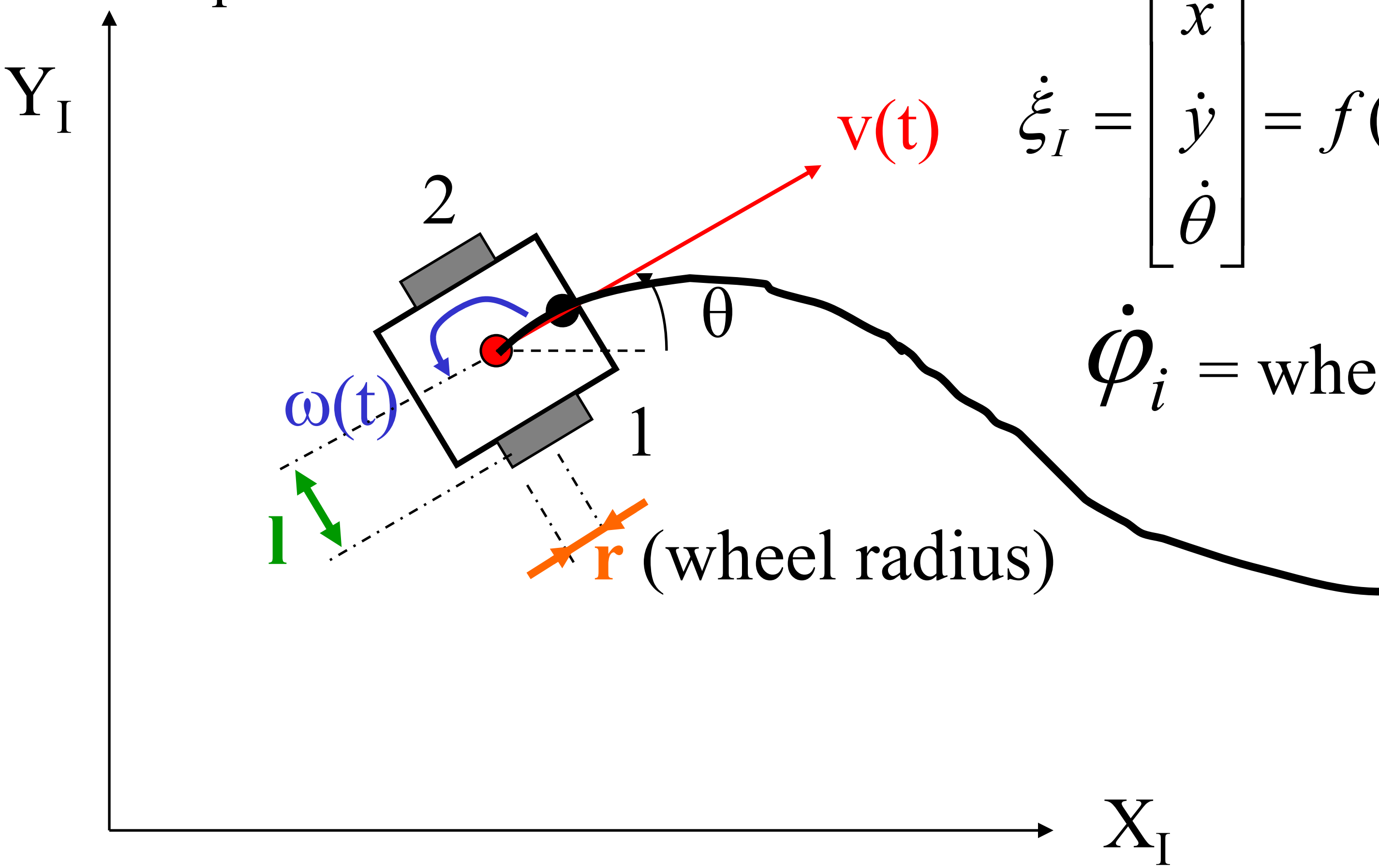
Forward Kinematic Model

How does the robot move given the wheel speeds and geometry?

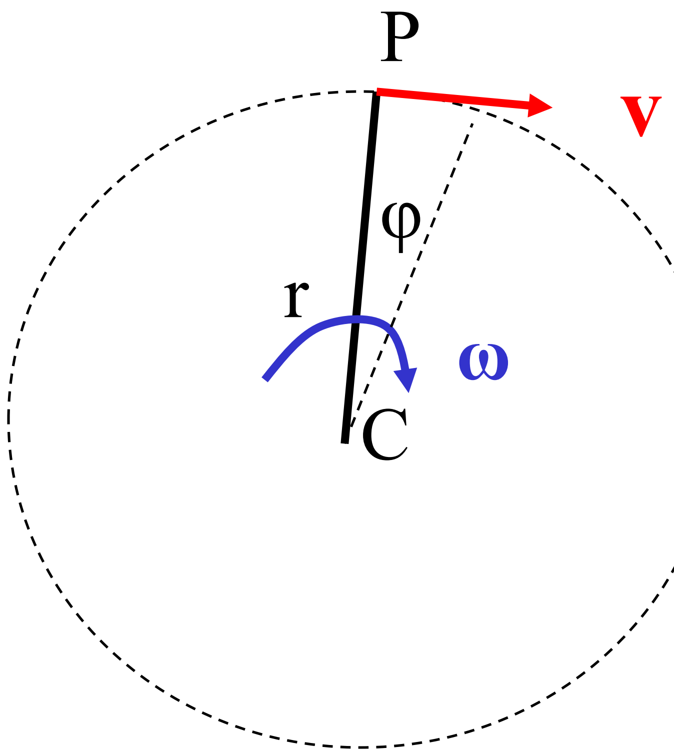
- Assumption: no wheel slip (rolling mode only)!
- In miniature robots no major dynamic effects due to low mass-to-power ratio

$$\dot{\xi}_I = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = f(l, r, \theta, \dot{\varphi}_1, \dot{\varphi}_2)$$

$$\dot{\varphi}_i = \text{wheel i speed}$$



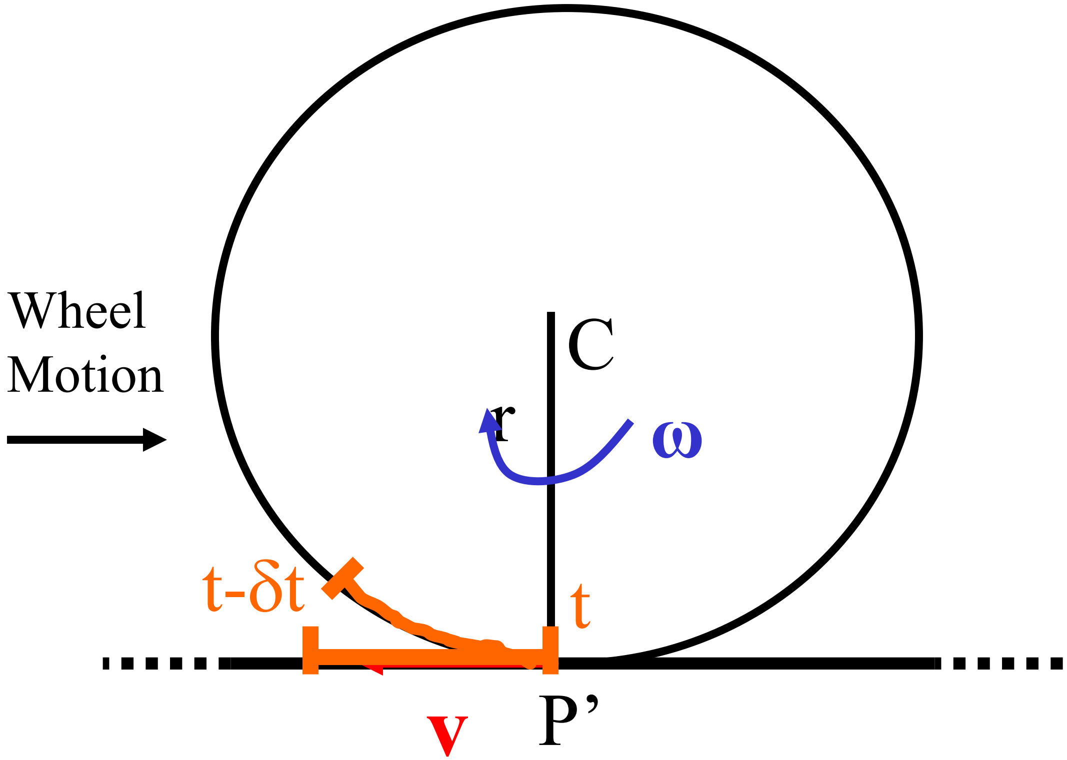
Recap ME/PHY Fundamentals



$$\boxed{v = \omega r = \dot{\varphi} r}$$

v = tangential speed
ω = rotational speed
r = rotation radius
φ = rotation angle
C = rotation center
P = peripheral point

Recap ME/PHY Fundamentals



$$\boxed{v = \omega r = \dot{\varphi} r}$$

v = tangential speed

ω = rotational speed

r = rotation radius

φ = rotation angle

C = rotation center

P = peripheral point

P'= contact point at time t

Rolling!

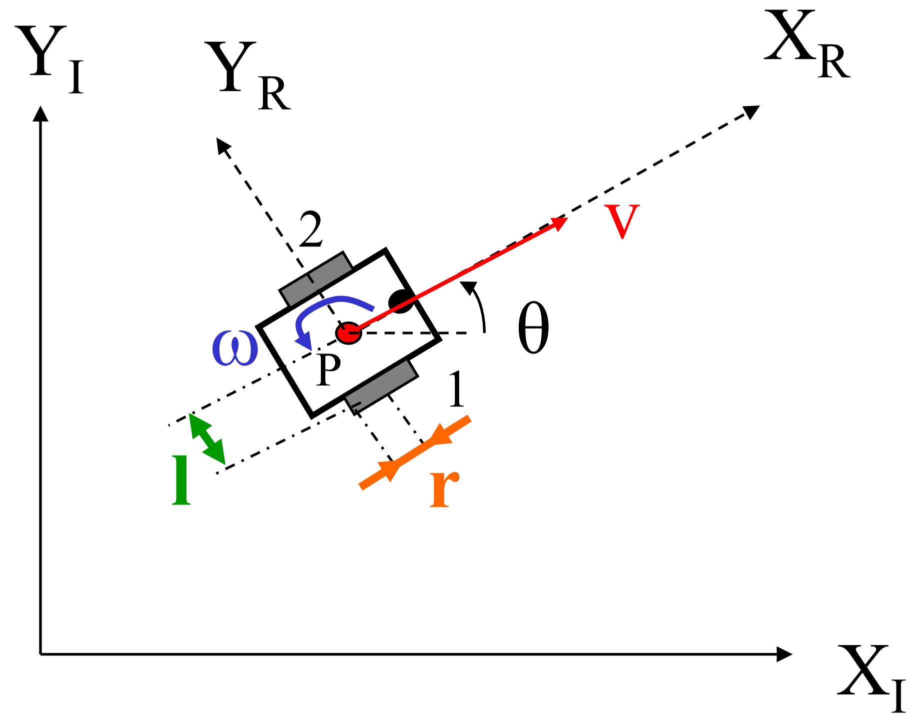
Forward Kinematic Model

Linear speed = average wheel speed 1 and 2:

$$v = \frac{r\dot{\varphi}_1}{2} + \frac{r\dot{\varphi}_2}{2}$$

Rotational speed = sum of rotation speeds (wheel 1 forward speed -> ω anti-clockwise, wheel 2 forward speed ω clockwise):

$$\omega = \frac{r\dot{\varphi}_1}{2l} + \frac{-r\dot{\varphi}_2}{2l}$$



Idea: linear superposition of individual wheel contributions

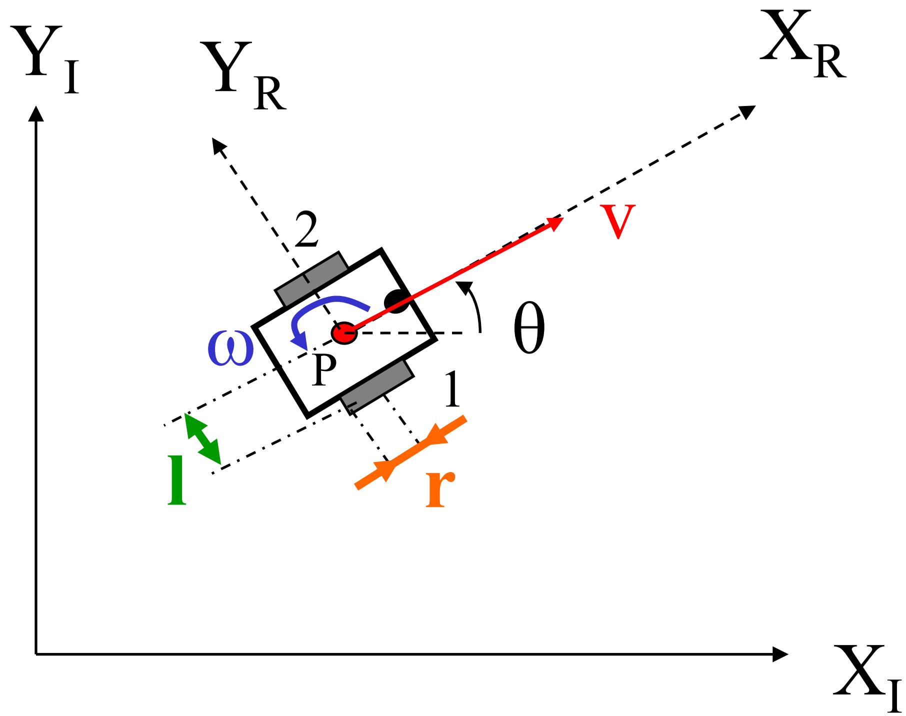
Forward Kinematic Model

1. $\dot{x}_R = v = \frac{r\dot{\varphi}_1}{2} + \frac{r\dot{\varphi}_2}{2}$

2. $\dot{y}_R = 0$

3. $\dot{\theta}_R = \omega = \frac{r\dot{\varphi}_1}{2l} + \frac{-r\dot{\varphi}_2}{2l}$

4. $\dot{\xi}_I = R^{-1}(\theta)\dot{\xi}_R$



$$\dot{\xi}_I = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{r\dot{\varphi}_1}{2} + \frac{r\dot{\varphi}_2}{2} \\ 0 \\ \frac{r\dot{\varphi}_1}{2l} + \frac{-r\dot{\varphi}_2}{2l} \end{bmatrix}$$

Odometry

- Given our absolute pose over time, we can calculate the robot pose after some time *t* through integration
- Given the kinematic forward model, and assuming no slip on both wheels

$$\xi_I(T) = \xi_{I_0} + \int_0^T \dot{\xi}_I dt = \xi_{I_0} + \int_0^T R^{-1}(\theta)\dot{\xi}_R dt$$

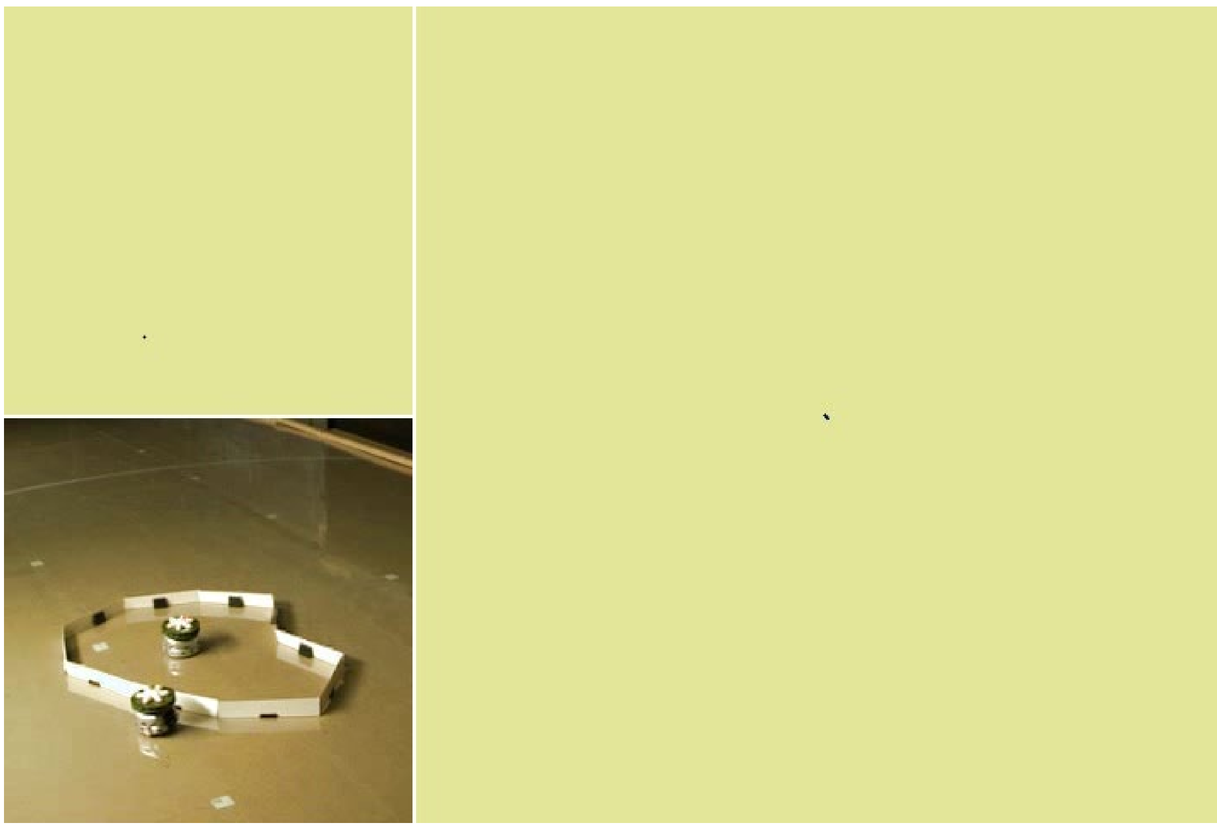
- Given an initial pose ξ_{I0}, after time T, the pose of the vehicle will be $\xi_I(T)$
- $\xi_I(T)$ computable with wheel speed 1, wheel speed 2, and parameters r and l

Localization Uncertainities in Odometry

Deterministic Error Sources

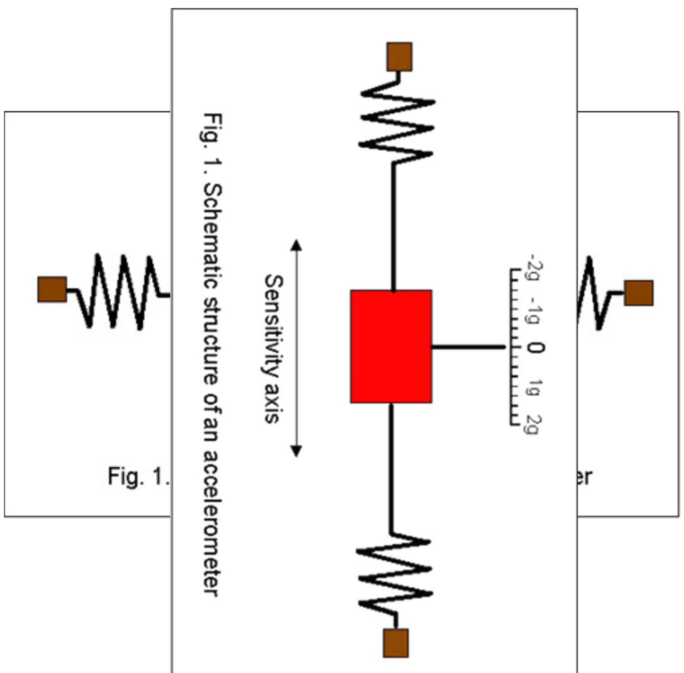
- Limited encoder resolution
- Wheel misalignment and small differences in wheel diameter

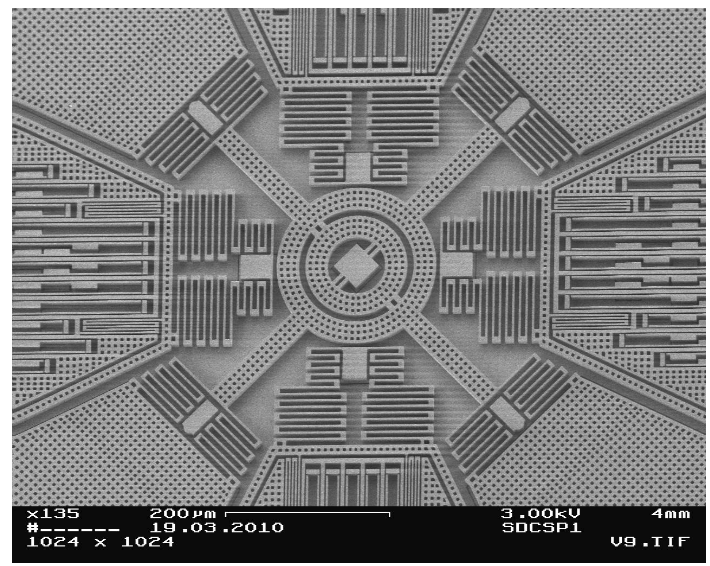
➢ Can be fixed by calibration



Non-Deterministic Error Sources

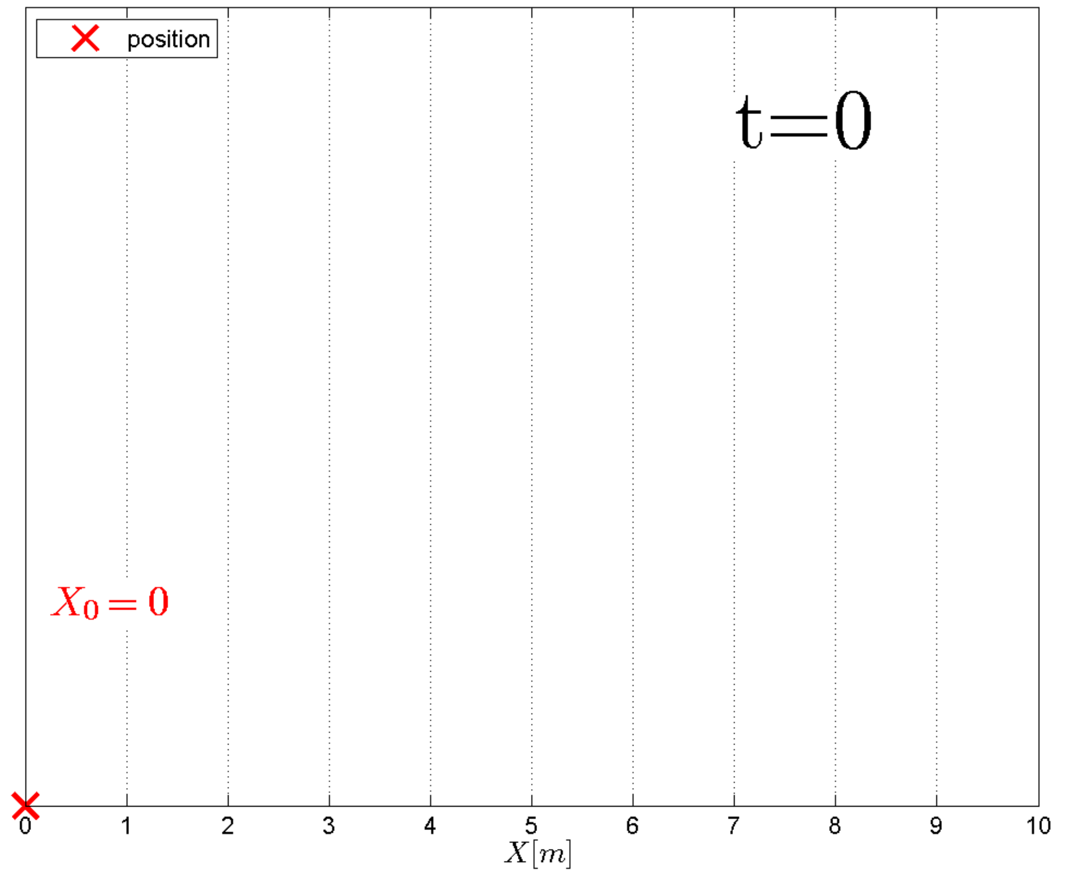
- From Week 3 (s.17): no deterministic prediction possible → we have to describe them probabilistically
- Example: accelerometer-based odometry

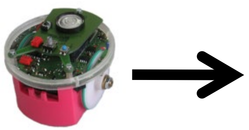




MEMS-Based accelerometer (e.g., on e-puck)

Odometry in 1D





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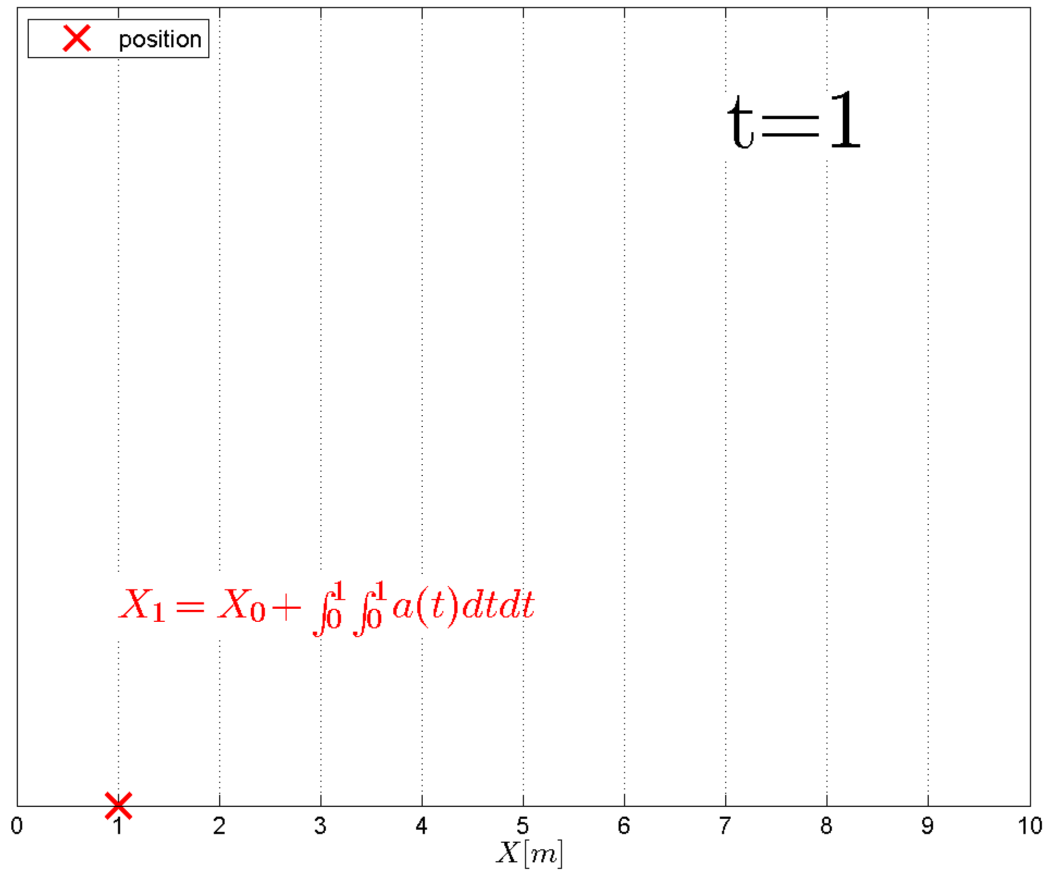

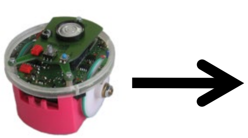

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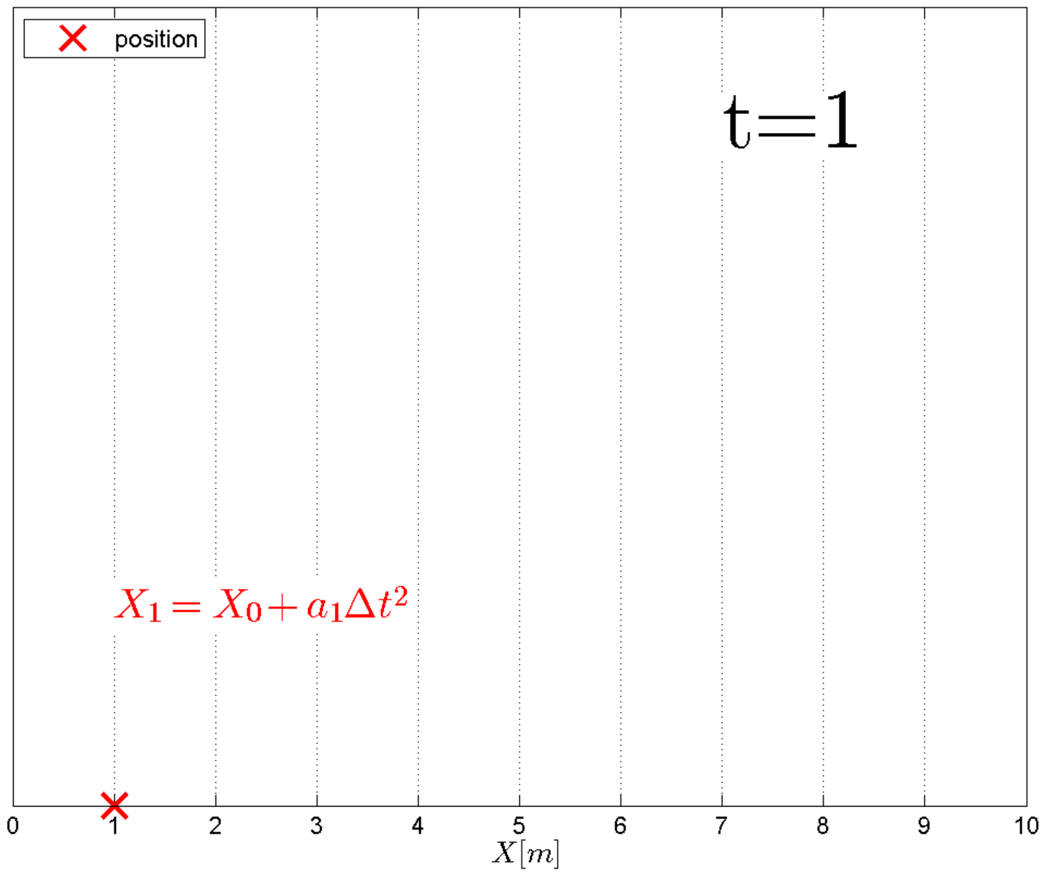
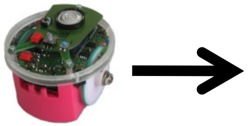
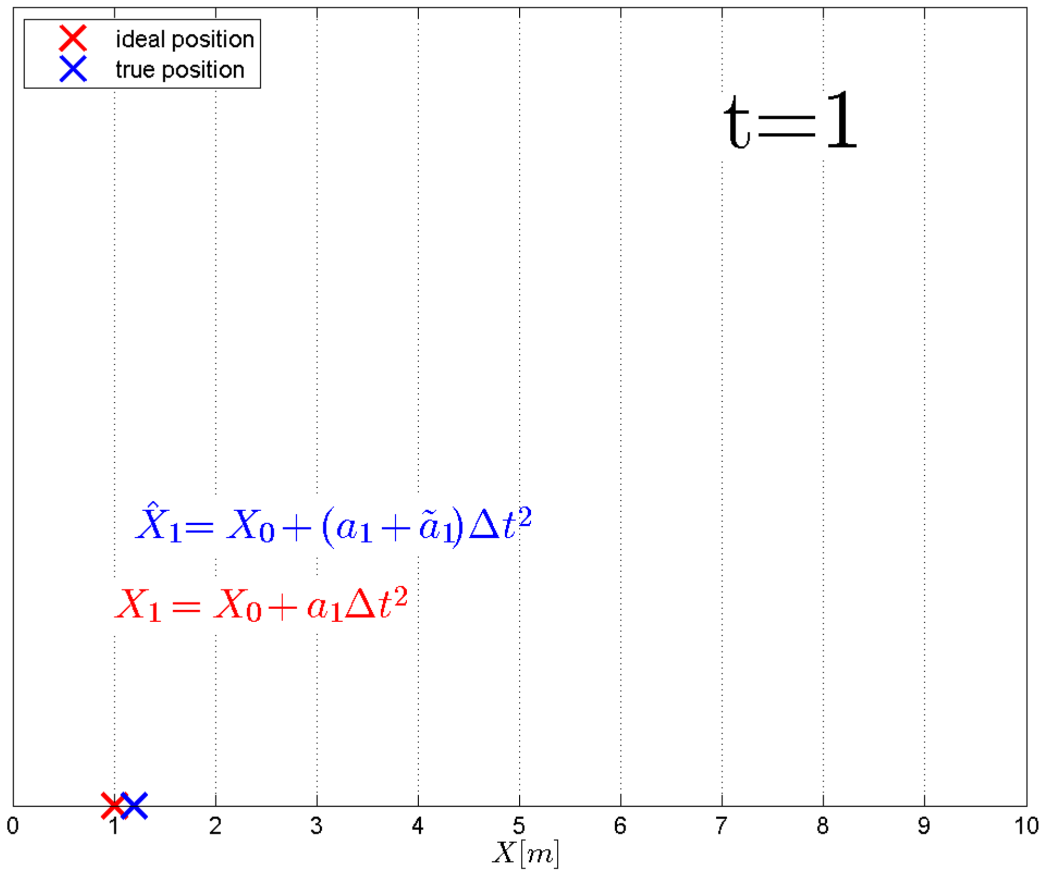
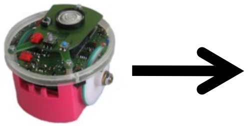


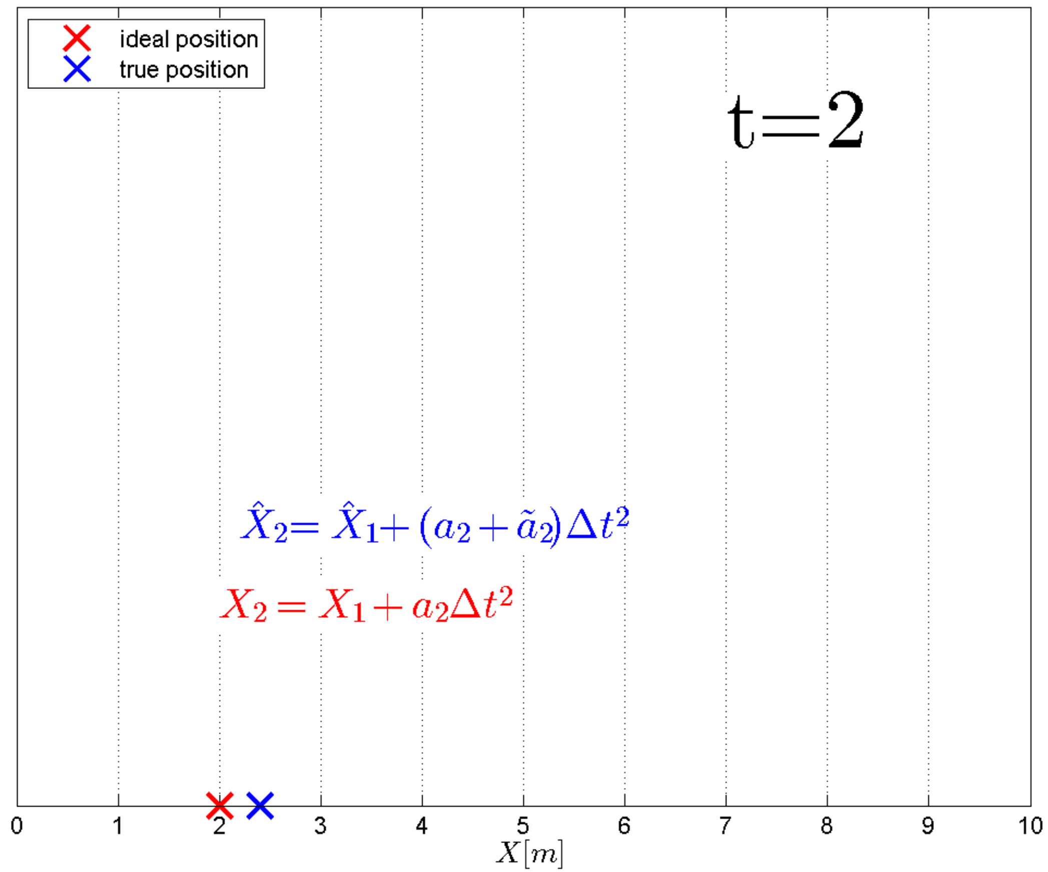


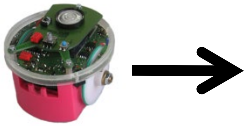
Odometry in 1D





Odometry in 1D





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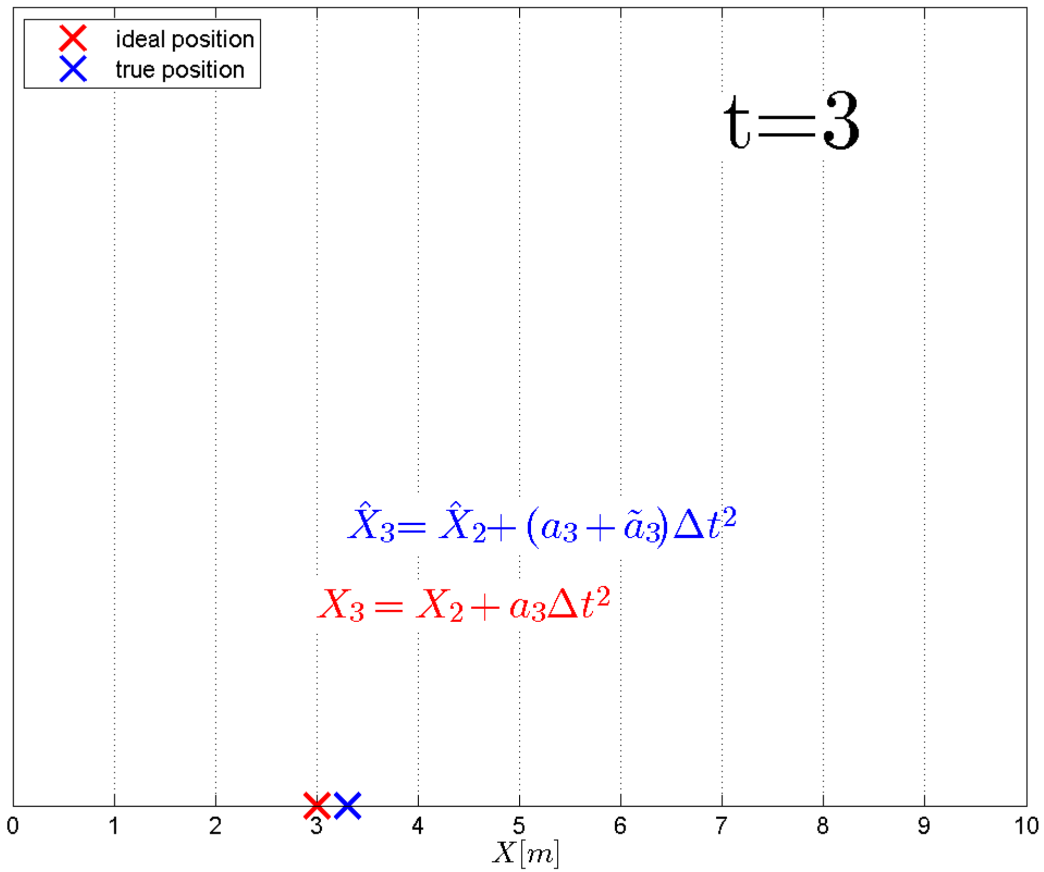
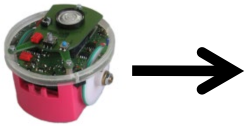
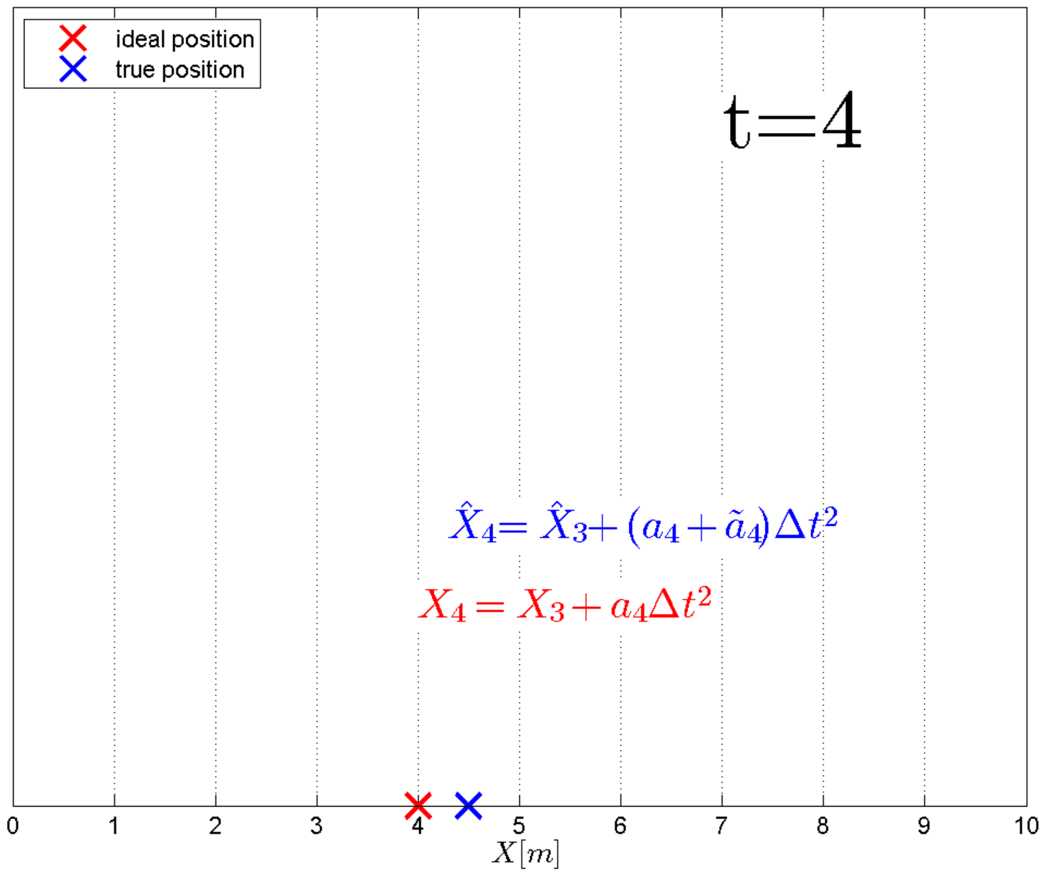
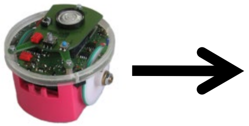


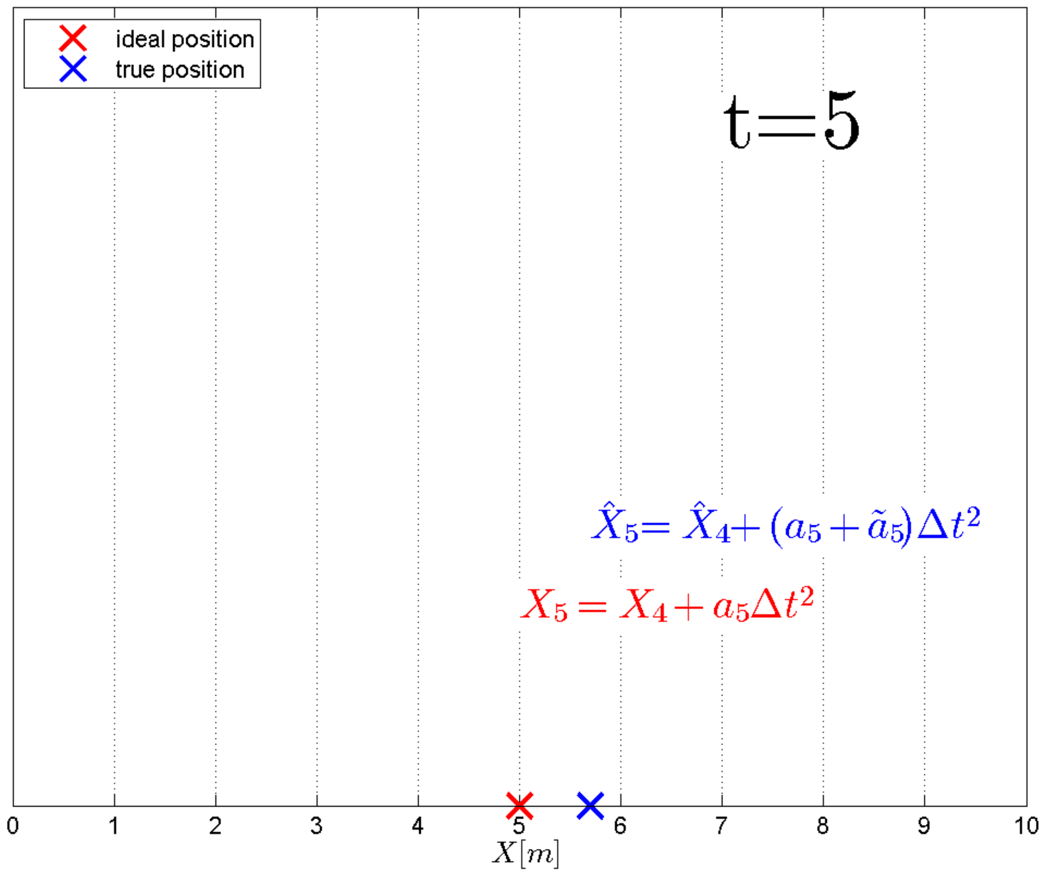


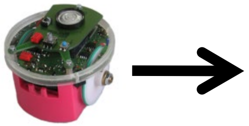
Odometry in 1D





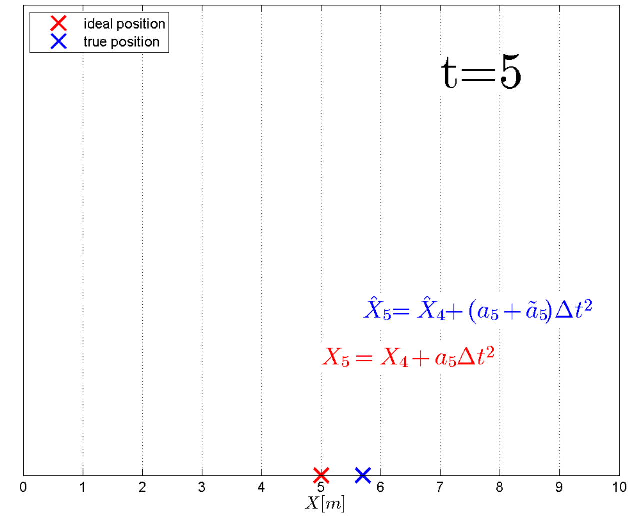
Odometry in 1D

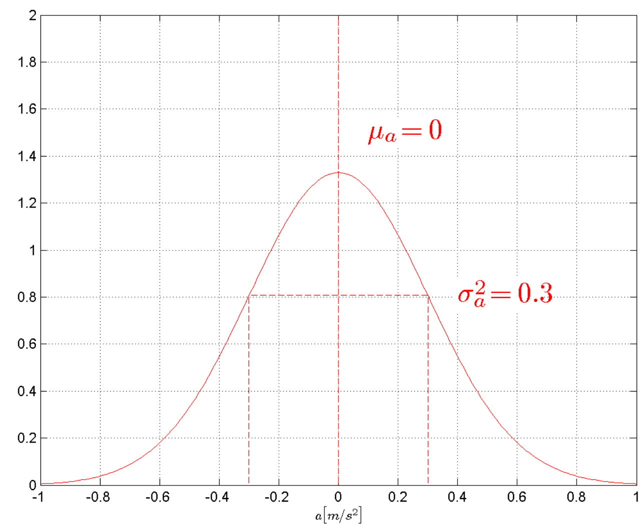




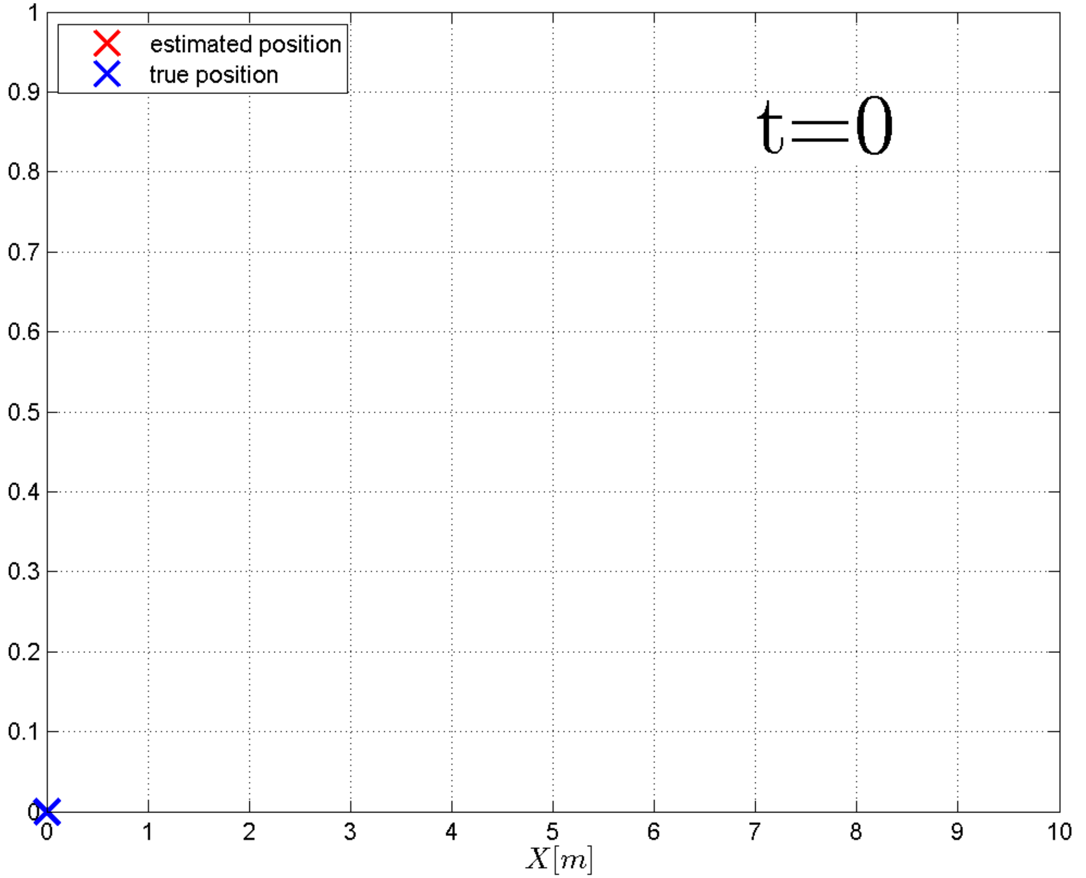
1D Odometry: Error Modeling

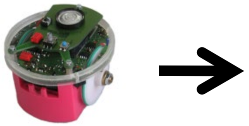
- Error happens!
- Odometry error is cumulative.
  → grows without bound
- We need to be aware of it.
  → We need to model odometry error.
  → We need to model sensor error.
- Multiple independent source of errors with arbitrary distribution combined → Central Limit Theorem → Gaussian assumption reasonable
- Acceleration is random variable A drawn from "mean-free" Gaussian ("Normal") distribution.
  → Position X is random variable with Gaussian distribution.



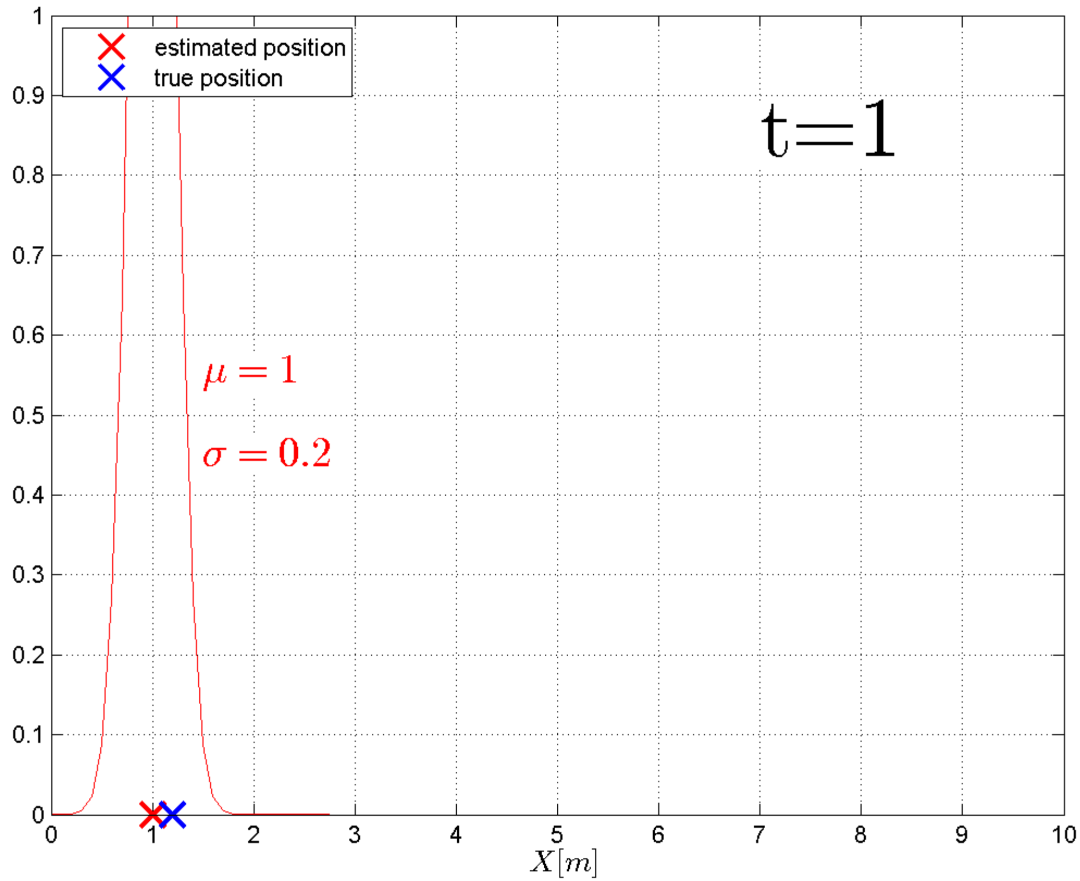


1D Odometry with Gaussian Uncertainty





1D Odometry with Gaussian Uncertainty



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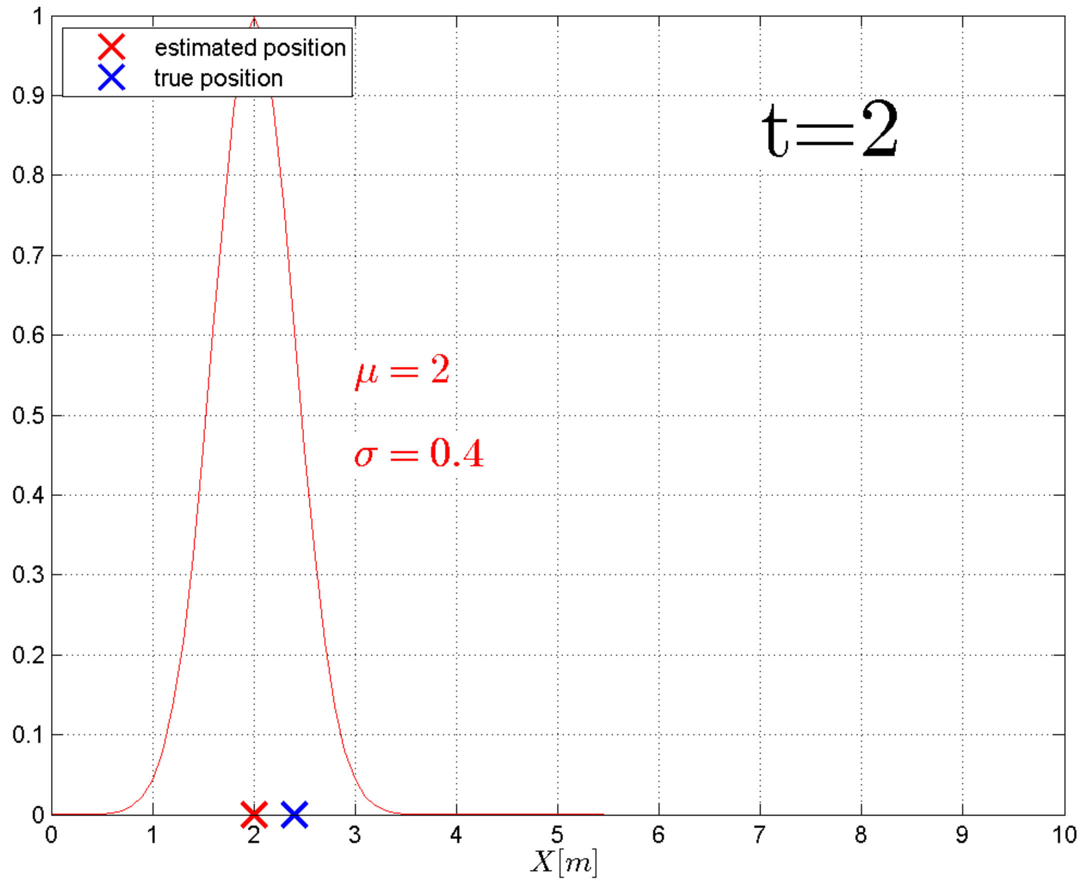

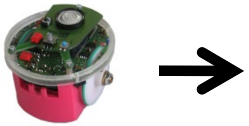

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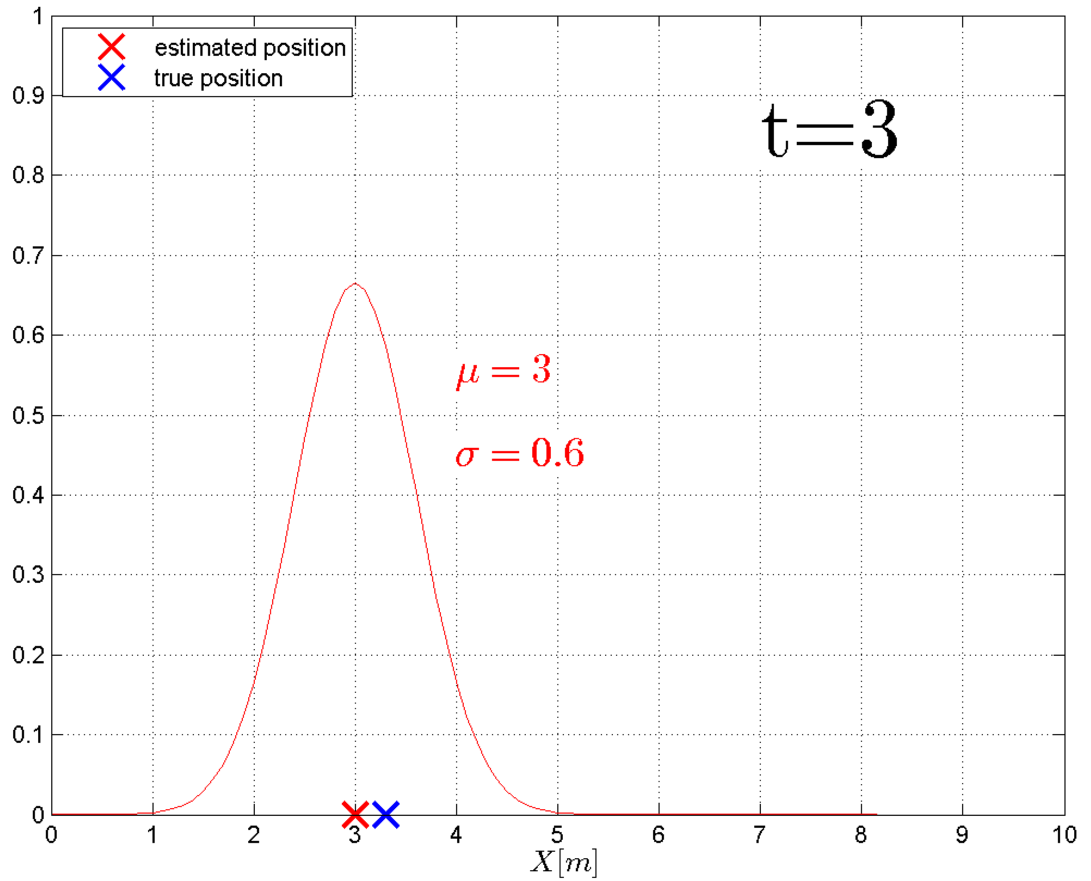

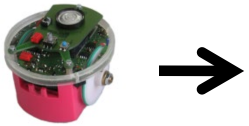

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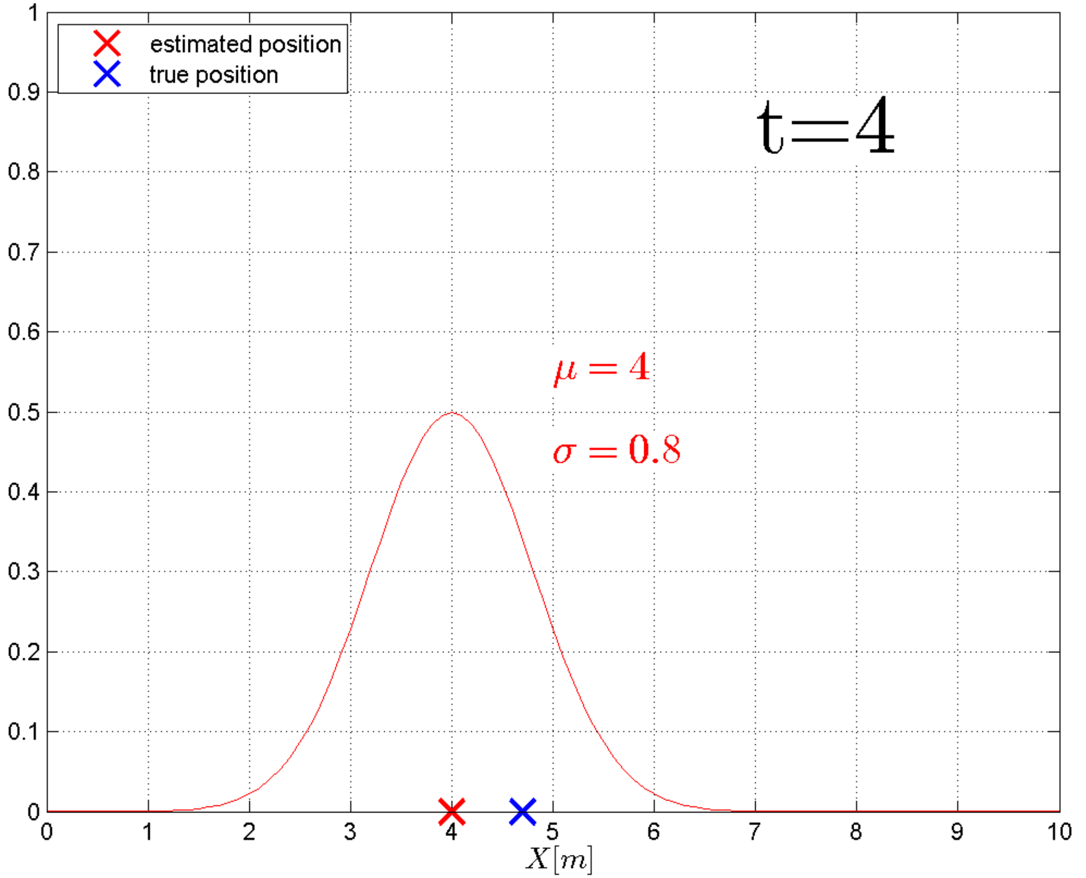

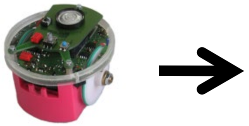

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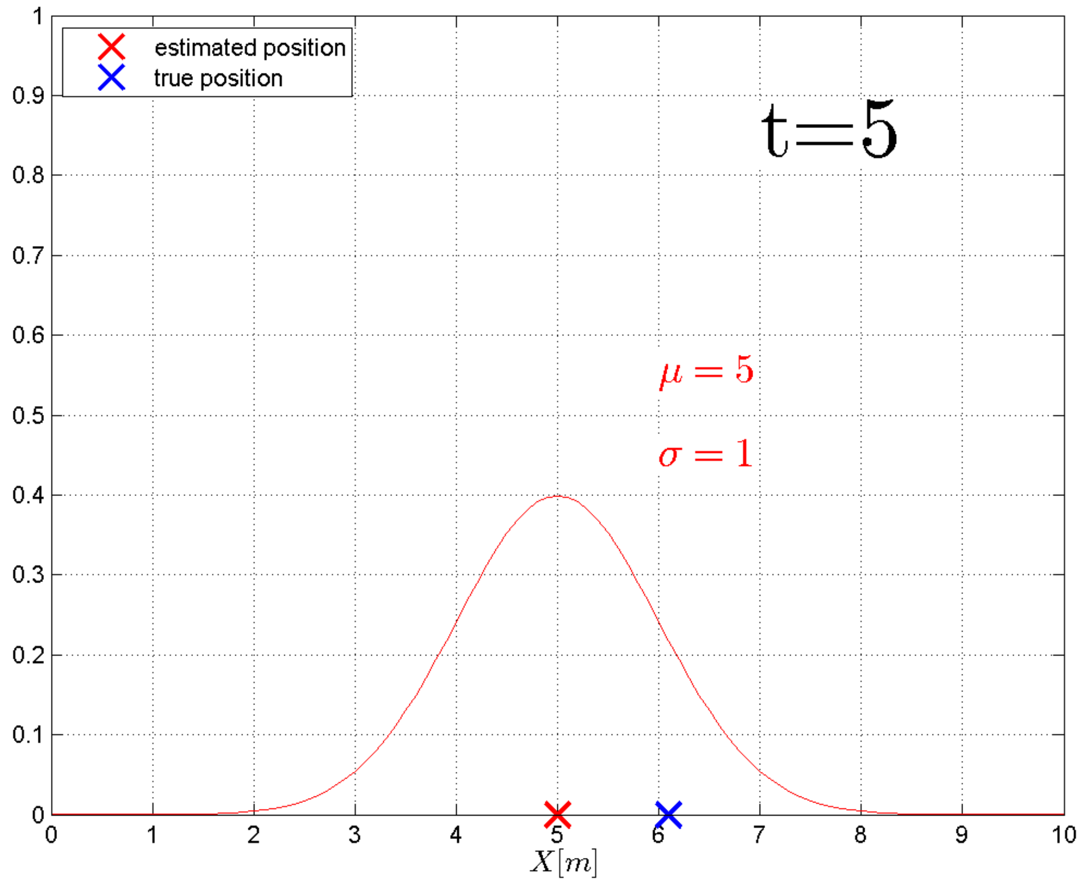
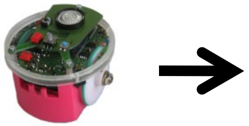




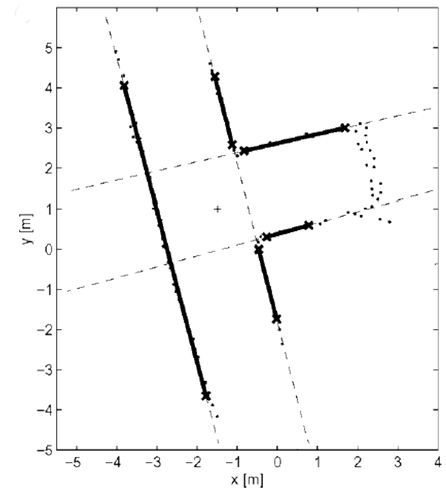
Mitigating Localization Uncertainities in Odometry Through Exteroceptive Sensors – The 1D Case

Features

- Odometry based position error grows without bound.
- Use relative measurement to features ("landmarks") to reduce position uncertainty
- ***Feature***:
  - Uniquely identifiable
  - Position is known
  - We can obtain relative measurements between robot and feature (usually angle or range).
- Examples:
  - Doors, walls, corners, hand rails
  - Buildings, trees, lanes
  - GPS satellites

Automatic Feature Extraction

- High level features:
  - Doors, persons
- Simple visual features:
  - Edges (Canny Edge Detector 1983)
  - Corner (Harris Corner Detector 1988)
  - ***S***cale ***I***nvariant ***F***eature ***T***ransformation (2004)
- Simple geometric features
  - Lines
  - Corners
- “Binary” feature



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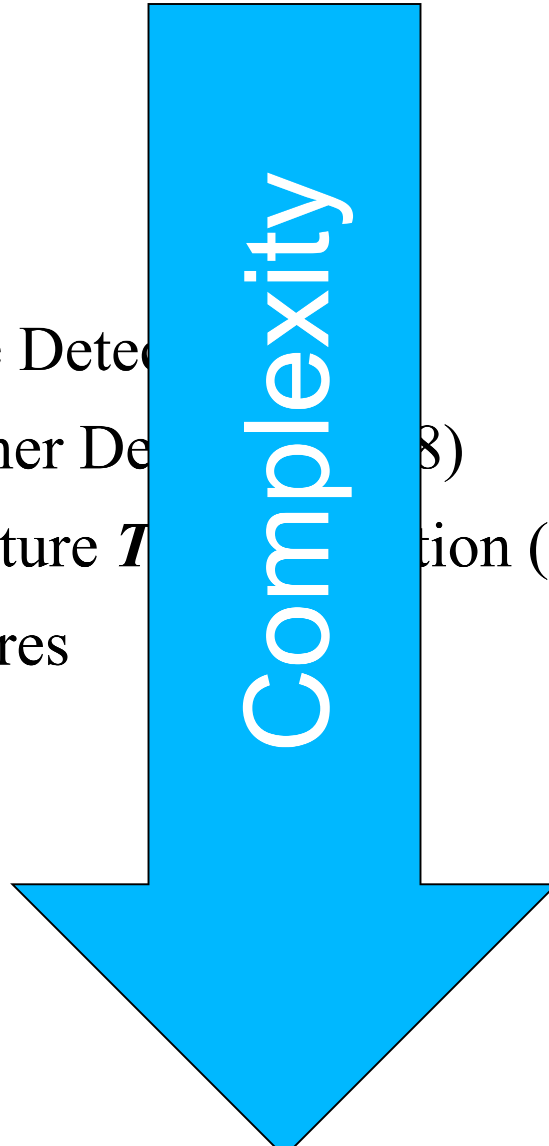
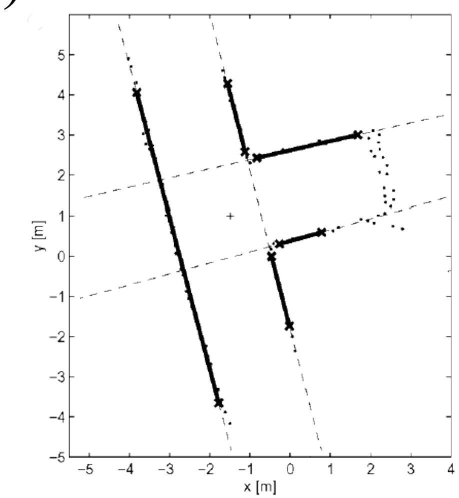
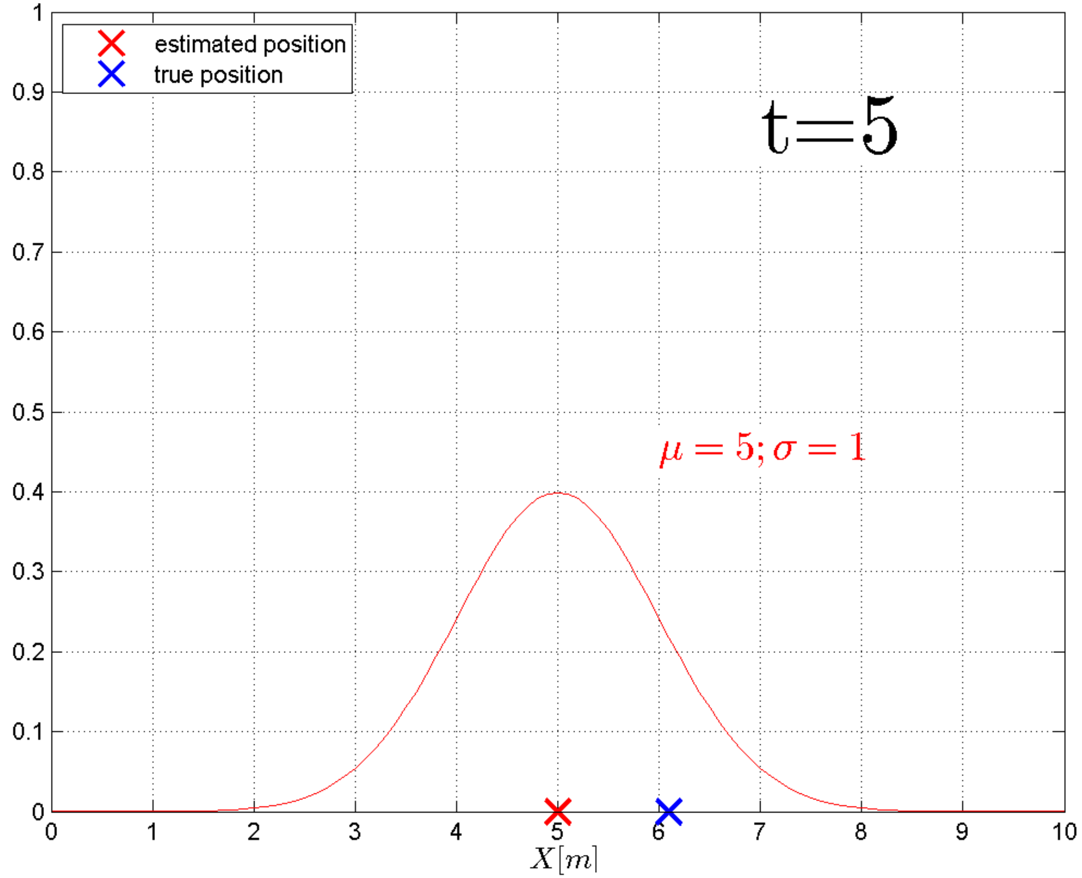




Feature-Based Localization



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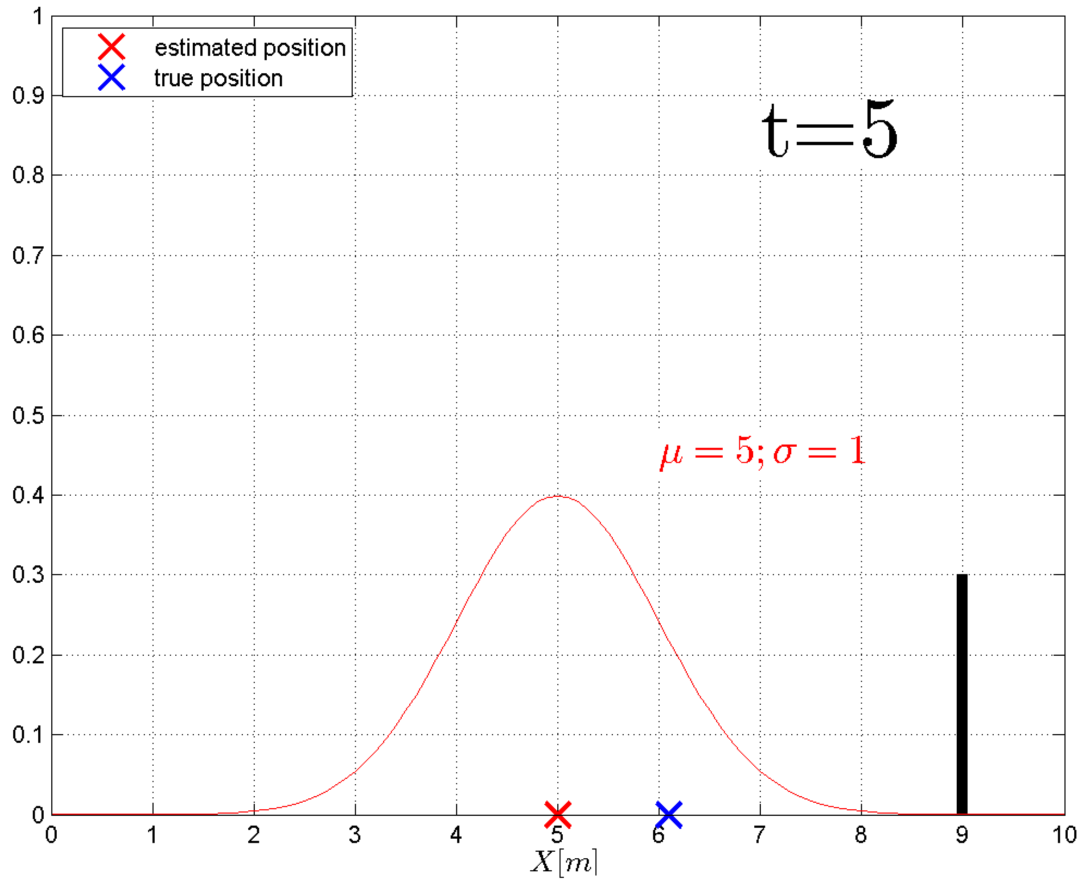

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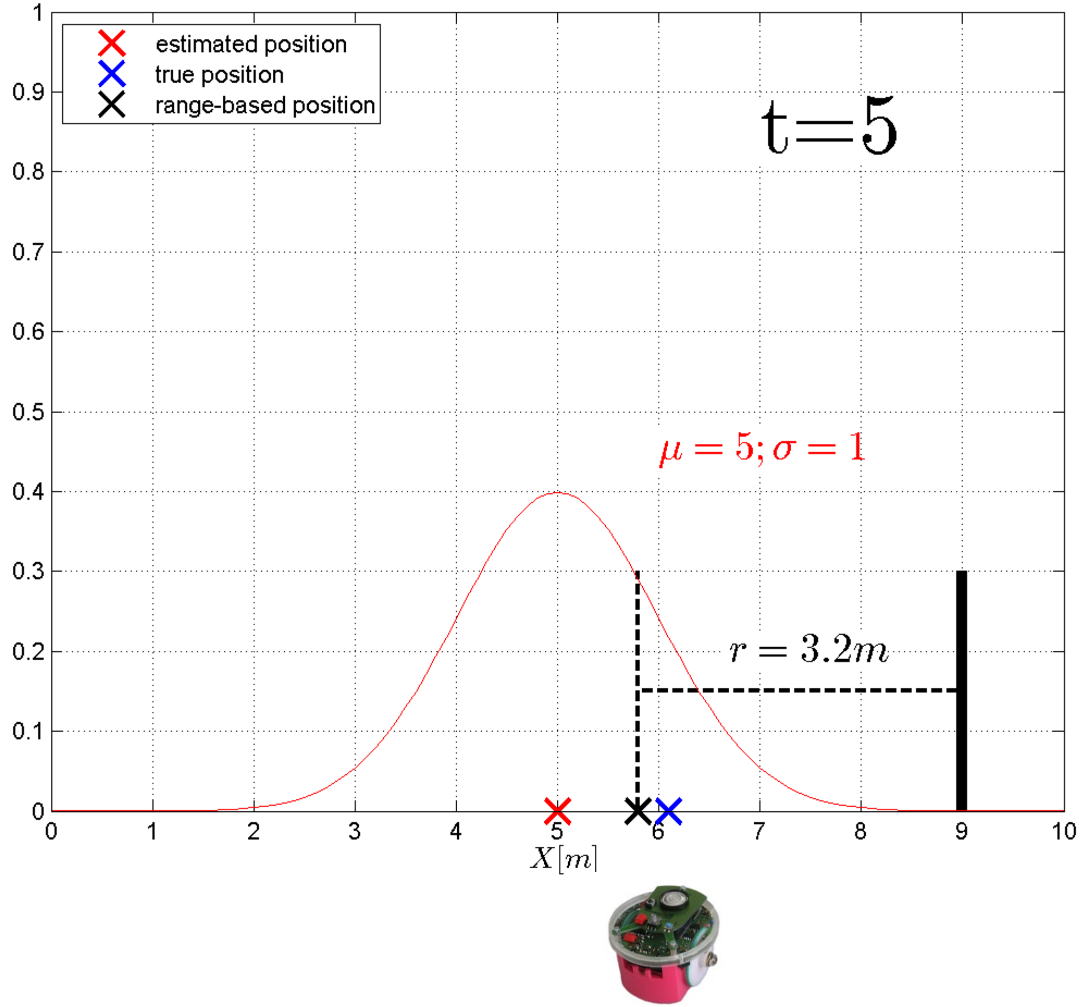

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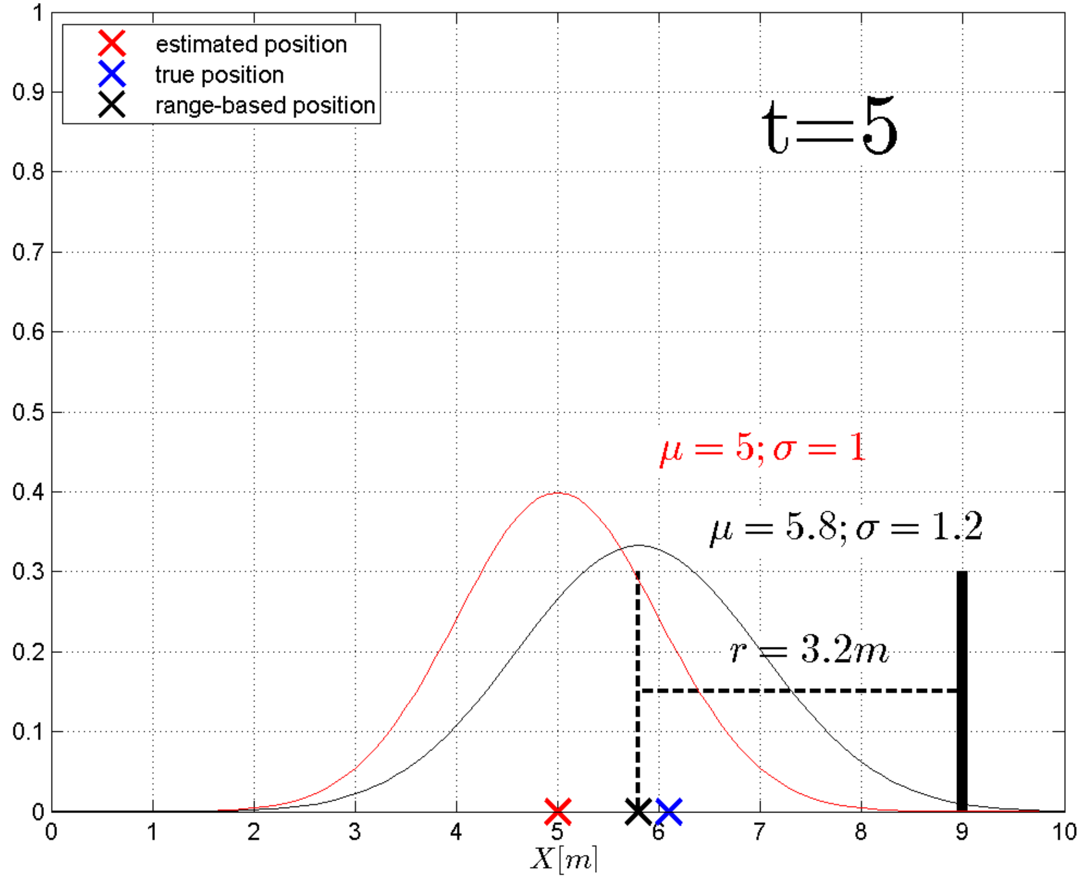
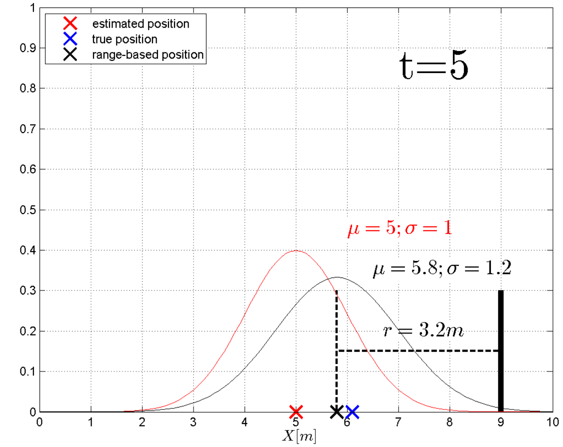
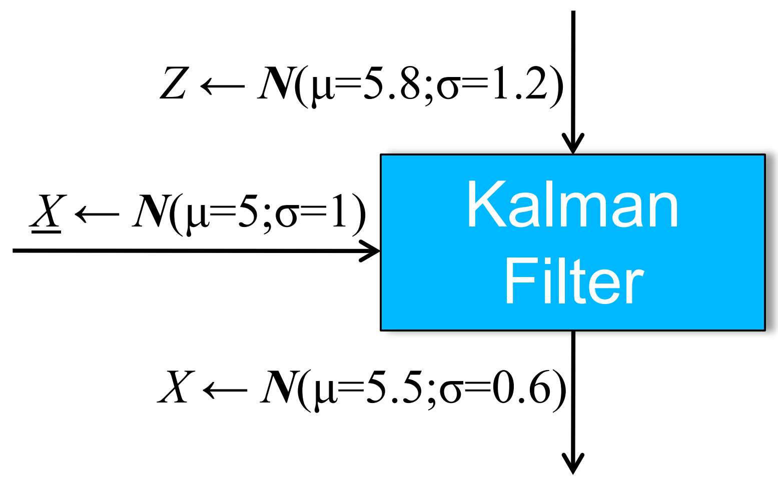


Sensor Fusion

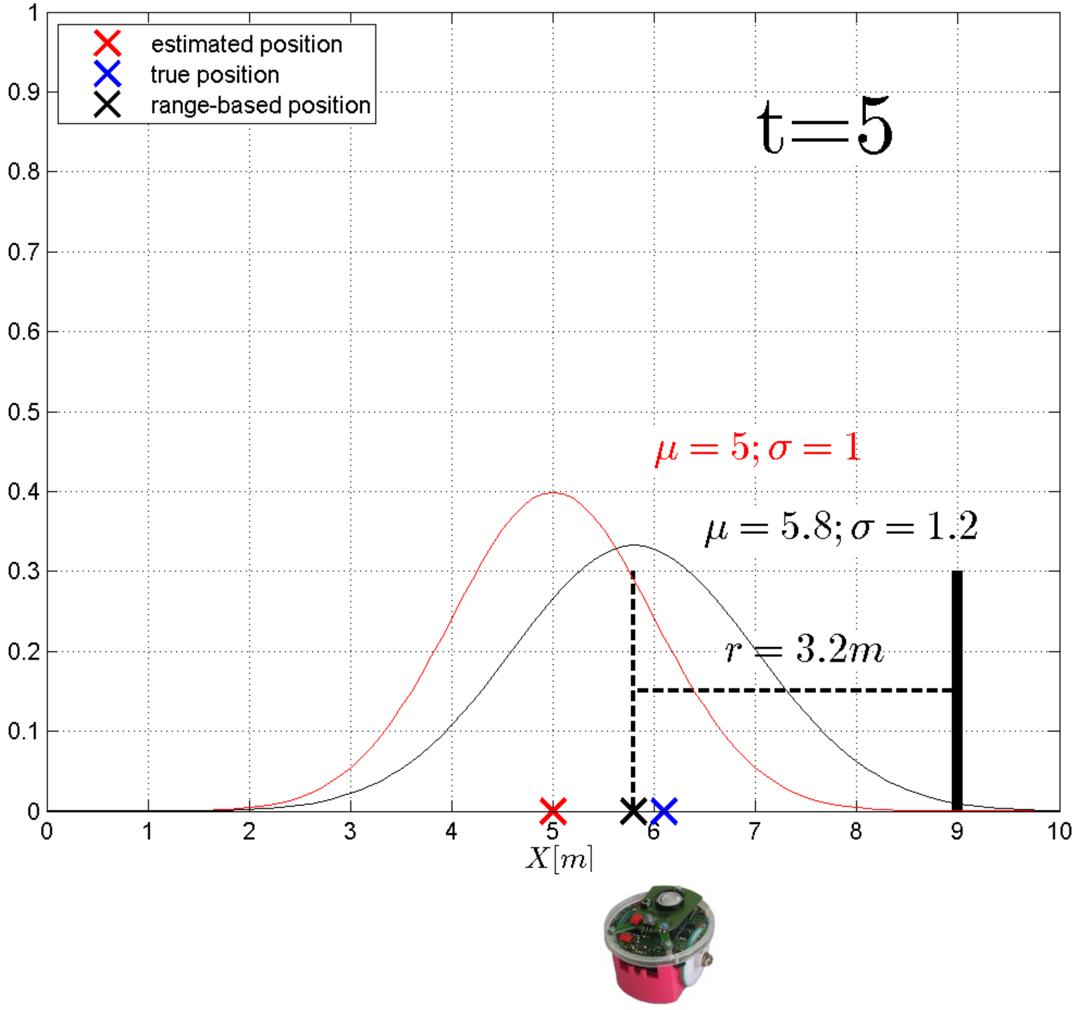
- Given:
  - Position estimate $\underline{X} \leftarrow \boldsymbol{N}(\mu=5;\sigma=1)$
  - Range estimate $R \leftarrow \boldsymbol{N}(\mu=3.2;\sigma=1.2)$
  - Known location of feature (9 m)
- Can be transformed in
  - Motion-model-based estimate $\underline{X} \leftarrow \boldsymbol{N}(\mu=5;\sigma=1)$
  - Observation-based estimate $\underline{Z} \leftarrow \boldsymbol{N}(\mu=5.8;\sigma=1)$
- What is the best estimate AFTER incorporating the observation?

  $\rightarrow$ ***Kalman Filter***
- Requires:
  - White Gaussian noise distribution for all measurements
  - Linear motion and measurement model

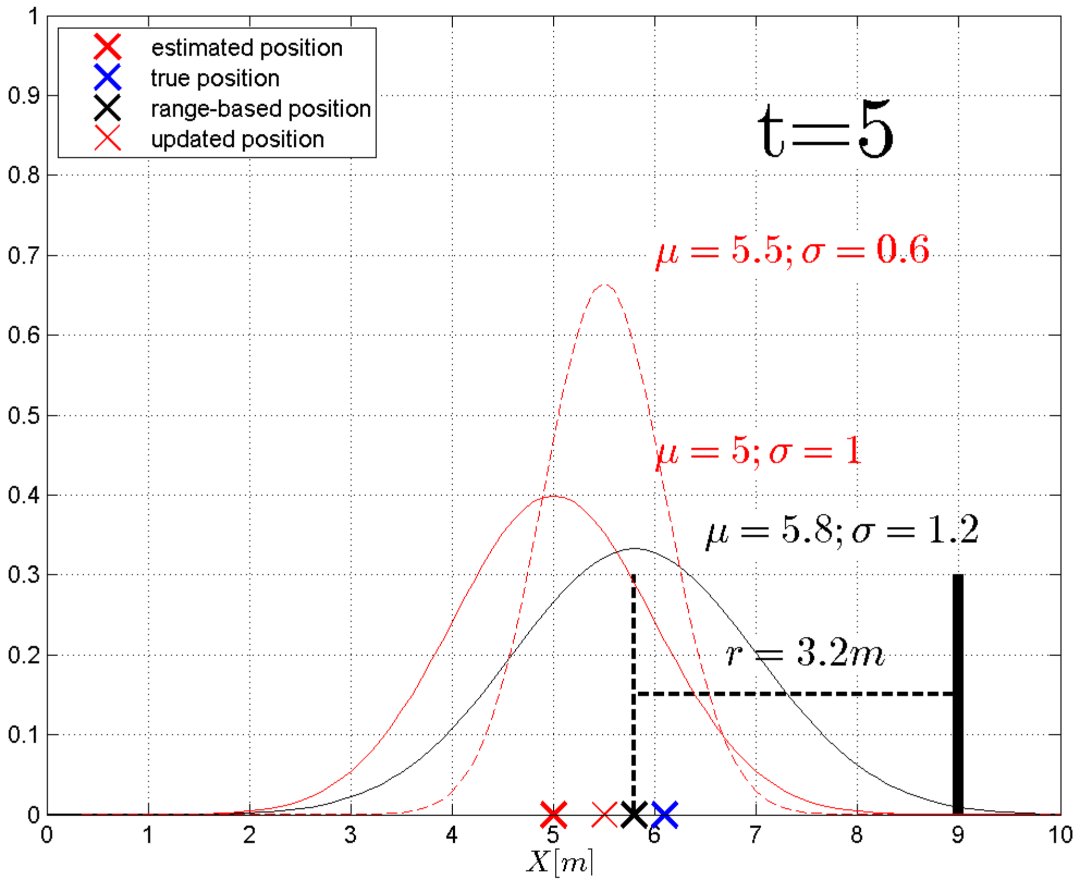




Feature-Based Localization



Feature-Based Localization



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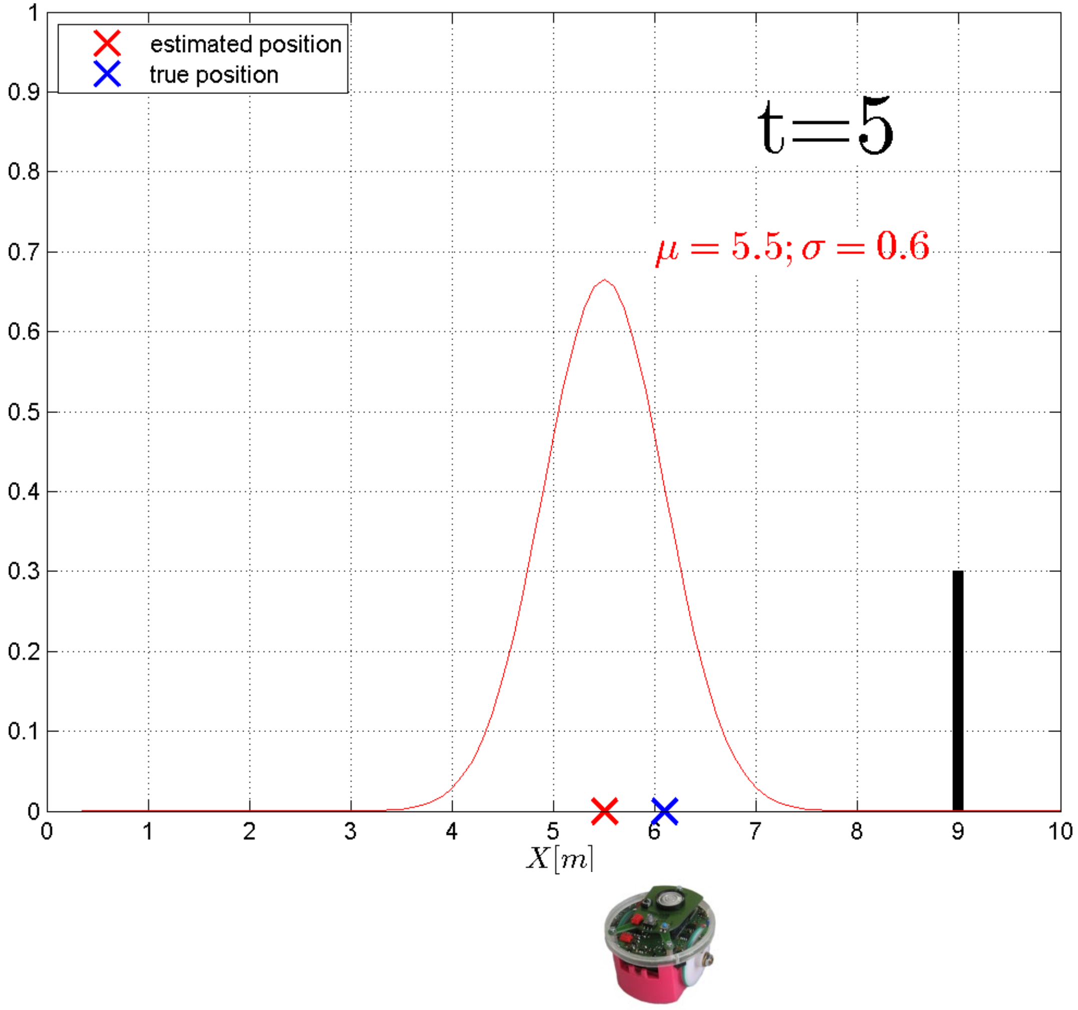
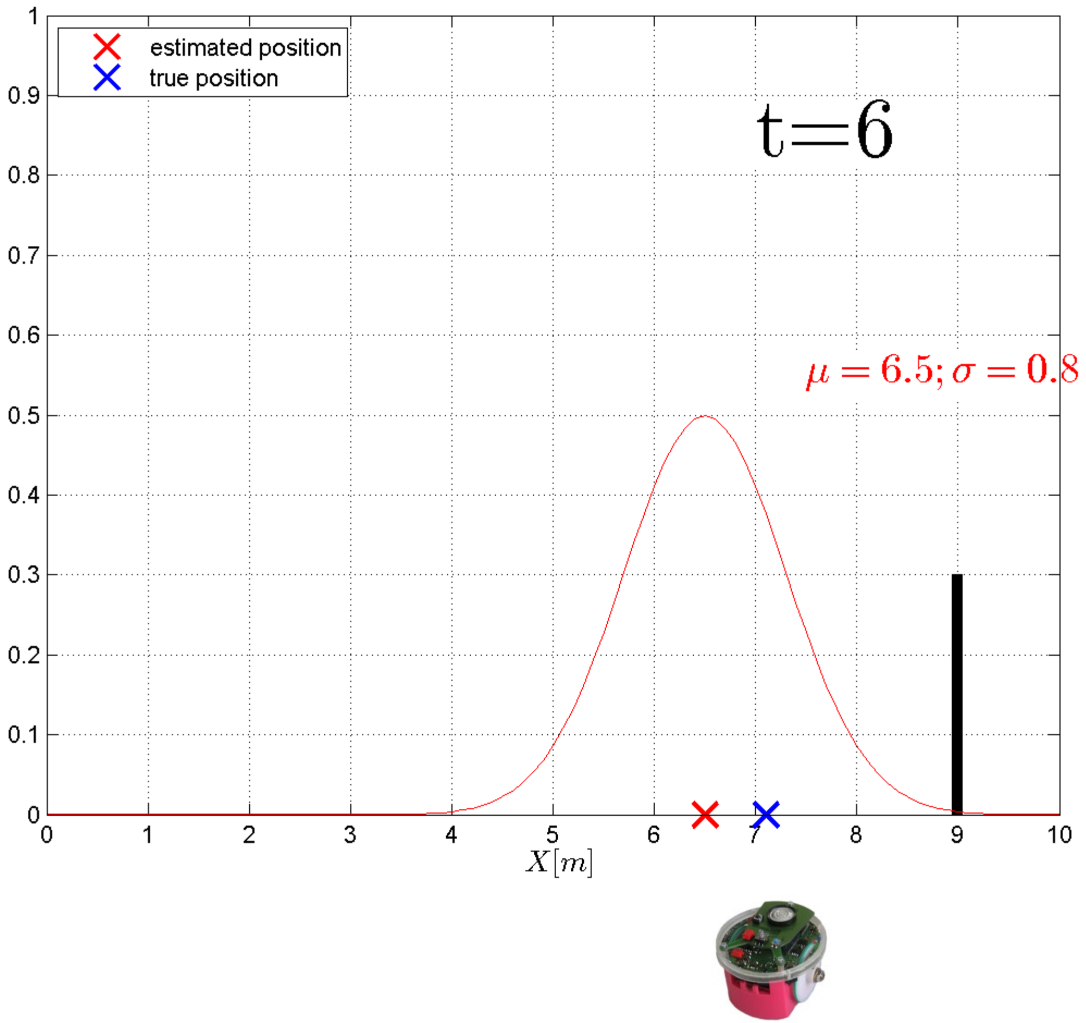


Feature-Based Localization



Conclusion

Take Home Messages

- There are several localization techniques for indoor and outdoor systems
- Each of the localization methods/positioning system has advantage and drawbacks
- Odometry is an absolute localization method using only proprioceptive sensors but affected by a cumulative error
- Localization errors in odometry can be both deterministic and non-deterministic
- Deterministic errors can be mitigated by calibration, non-deterministic error can be probabilistically modeled and taken into account
- Odometry cumulative errors can be reset by leveraging environmental features
- Information coming from proprioceptive and exteroceptive sensors can be fused through Kalman filtering

Additional Literature – Week 4

Books

- Weston J. and Titterton D, “Strapdown Inertial Navigation”, IET, 2005
- Siegwart R., Nourbakhsh I., and Scaramuzza D., “Introduction to Autonomous Mobile Robots, second Edition”, MIT Press, 2011.
- Borenstein J., Everett H. R., and Feng L. “Navigating Mobile Robots: Systems and Techniques”, A. K. Peters, Ltd., 1996.