ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

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 and odometry

- Robot localization using proprioceptive sensors with uncertainties
  - Error sources
  - Methods for handling uncertainties

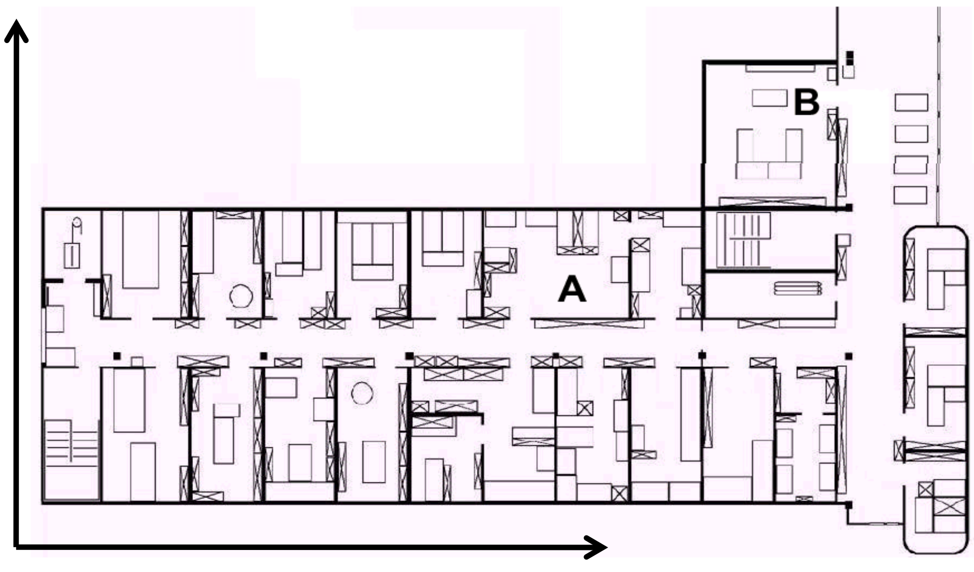
- Robot localization using proprioceptive and exteroceptive sensors
  - Odometry-based and feature-based methods

Robot Localization

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

N 46° 31’ 13’’
E 6 ° 34’ 04’’

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



Positioning Systems

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

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

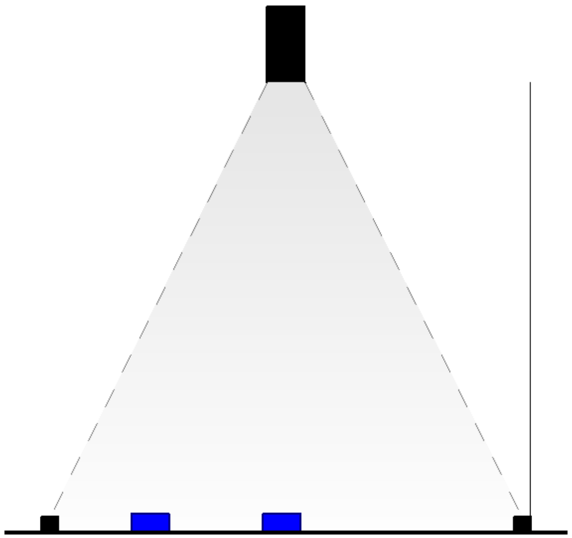
ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Selected Indoor Positioning Systems

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

Overhead (Multi-)Camera Systems

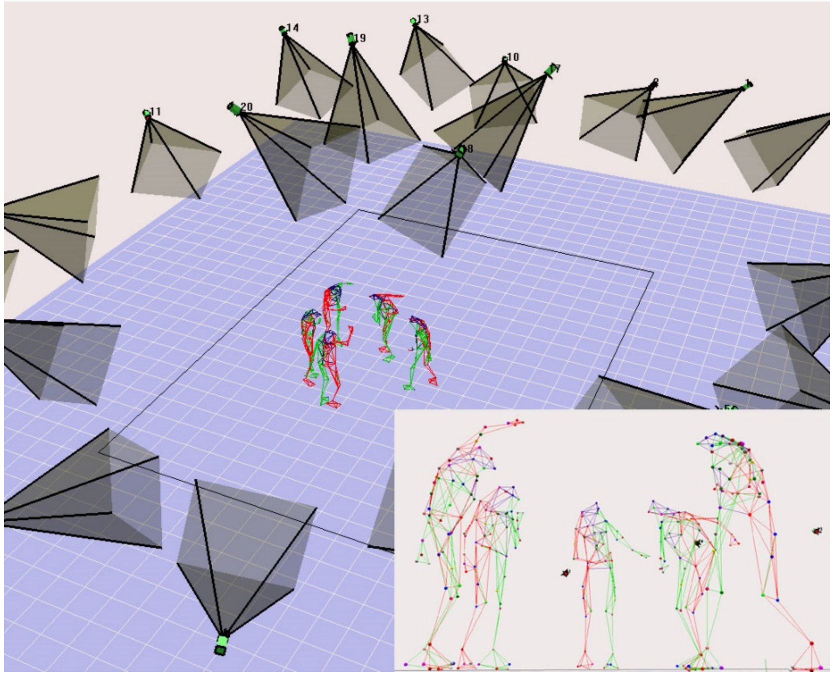
- Tracking objects with one (or more) overhead cameras
- Absolute positions, available outside the robot/sensor
- Active, passive, or no markers
- Open-source software available (e.g., SwisTrack, developed at DISAL)
- Major issues: light, calibration
- Essentially 2D



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

6D Multi-Camera System

- Called also Motion Capture System (MCS)
- 10-50 cameras
- mm accuracy
- 100-500 Hz update
- 2 ms latency
- 6D pose estimation
- 4-5 passive markers per object to be tracked needed
- 200 m^3 arena



ETHZ coordinated ball: throwing
http://www.youtube.com/watch?v=hyGJBV1xnJI
UPenn GRASP: lab
http://www.youtube.com/watch?v=geqip_0Vjec

IR-UWB System - Principles

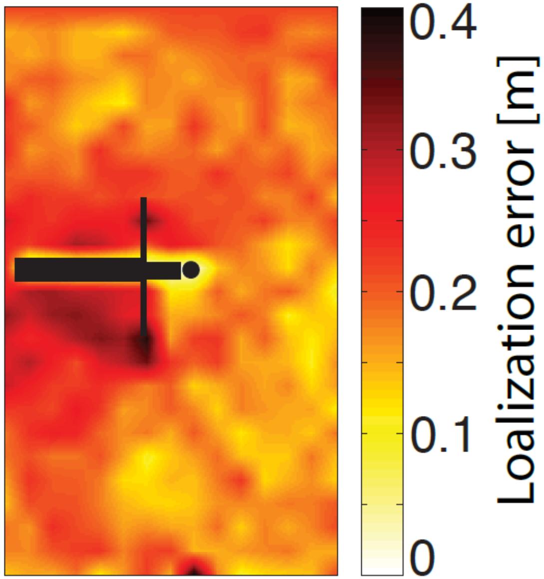
- Impulse Radio Ultra-Wide Band
- Based on time-of-flight (TDOA, Time Difference of Arrival)
- UWB tags (emitters, a few cm, low-power) and multiple synchronized receivers
- Emitters can be unsynchronized but then dealing with interferences not trivial (e.g., Ubisense system synchronized)
- Absolute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

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



ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Infrared + Radio Technology

- Principle:
  - 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]

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Infrared + Radio Technology

Performance summary:

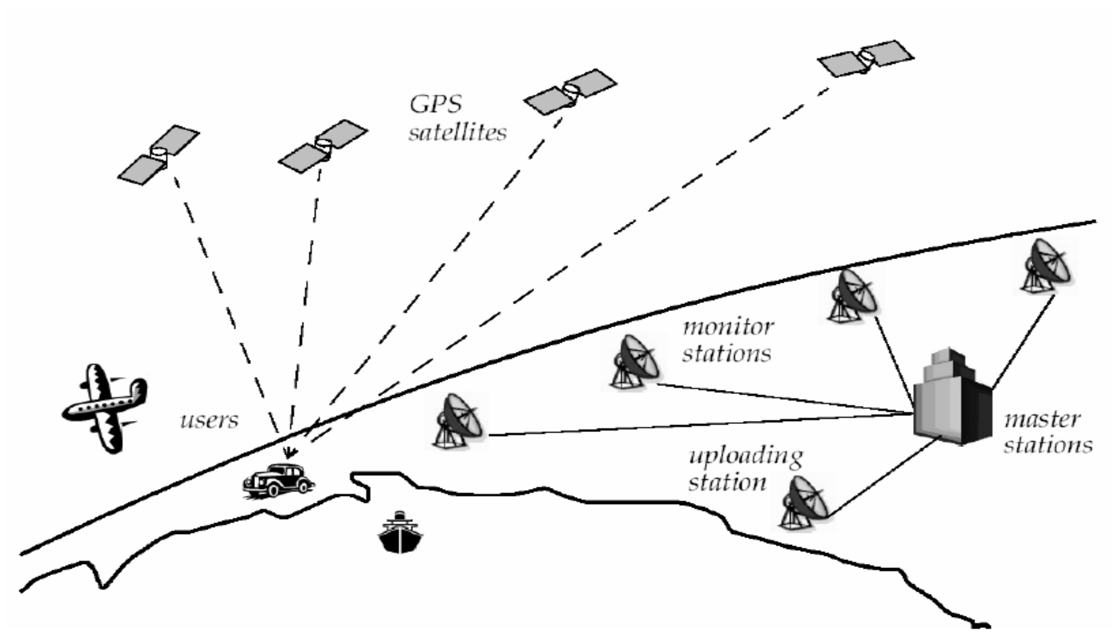
- Range: 3.5 m
- Update frequency 25 Hz with 10 neighboring robots (or 250 Hz with 2)
- Accuracy range: <7% (MAX), generally decrease 1/d
- Accuracy bearing: < 9º (RMS)
- LOS method
- Possible extension in 3D, larger range (but more power) and better bearing accuracy with more photodiodes (e.g. Bergbreiter, PhD UCB 2008, dedicated ASIC, up to 15 m, 256 photodiodes, single emitter with conic lense)

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

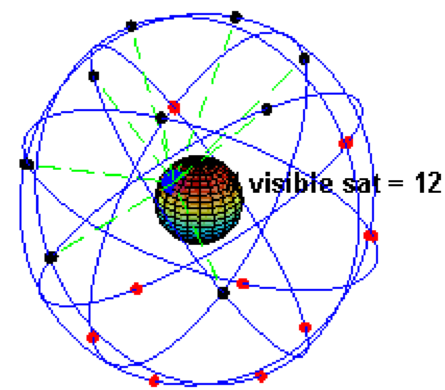
Selected Outdoor Positioning Techniques

- GPS
- Differential GPS (dGPS)

Global Positioning System



© R. Siegwart, ETH Zurich - ASL



(image from Wikipedia)

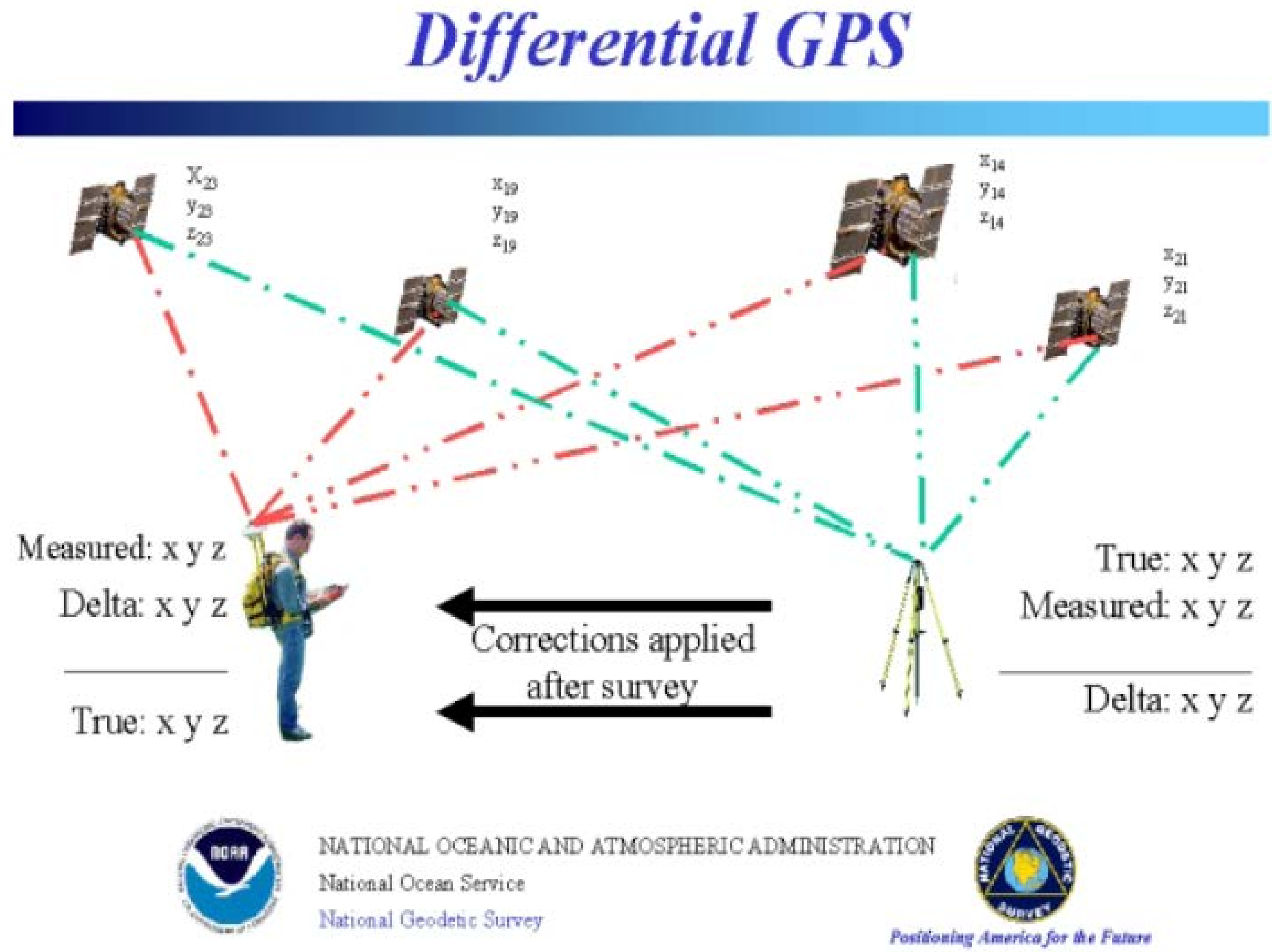
Note: the first and still most prominent example of GNSS systems (Global Navigation Satellite Systems)

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)
- Location of any GPS receiver is determined through a time of flight measurement (*ns* accuracy!)
- 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
- 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

Position accuracy: typically from a few to a few tens of cm



Robot Localization using On-Board Sensors

Sensors for localization

- Proprioceptive sensors:
  - Epuck:
    - 3D accelerometer
    - Motor step counter
  - Others:
    - Wheel encoder
    - Odometer
    - IMU (inertial measurement unit)
- Exteroceptive sensors:
  - Epuck:
    - IR range proximity sensor
    - Camera
  - Others:
    - Laser range finder
    - Ultrasonic range finder

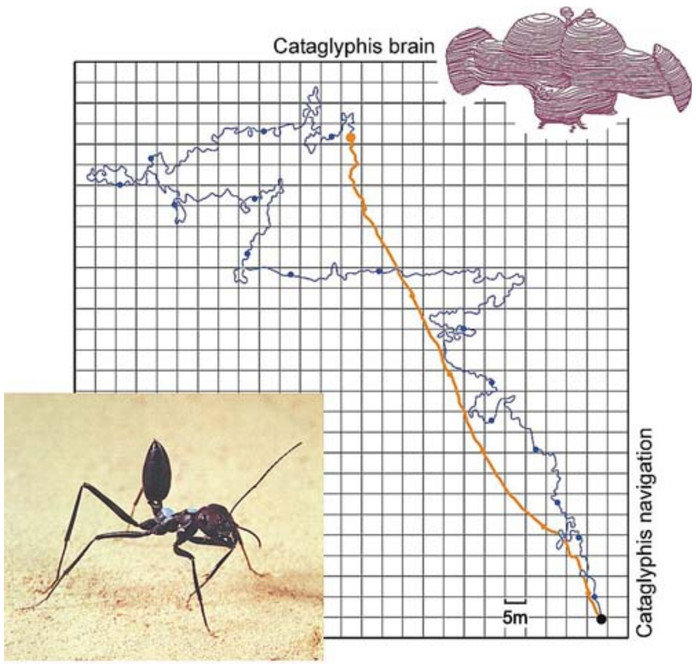
Odometry Definition & Idea

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

- 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
- Idea: navigating a room with the light turned off

Example from Week 1

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

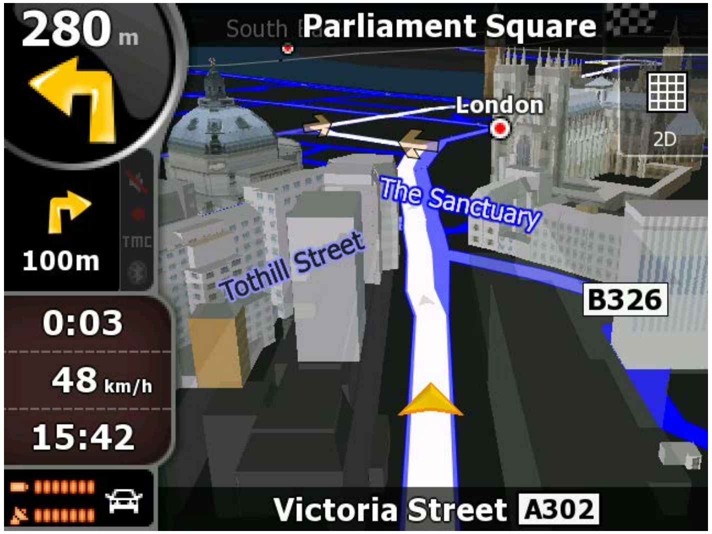


Cataglyphis desert ant

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

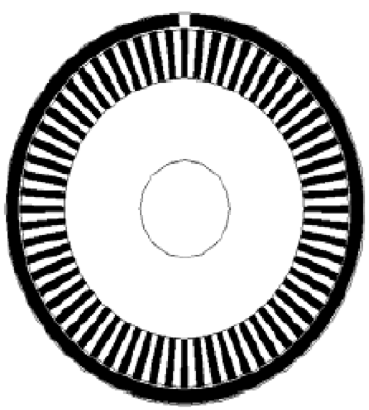


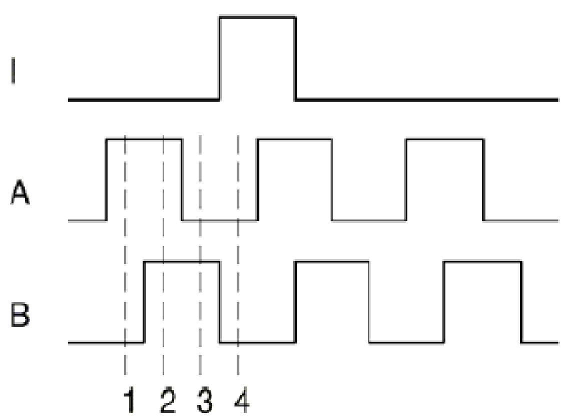
Picture: Courtesy of NavNGo

Odometry using Wheel Encoders

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 - 2048 increments per revolution.

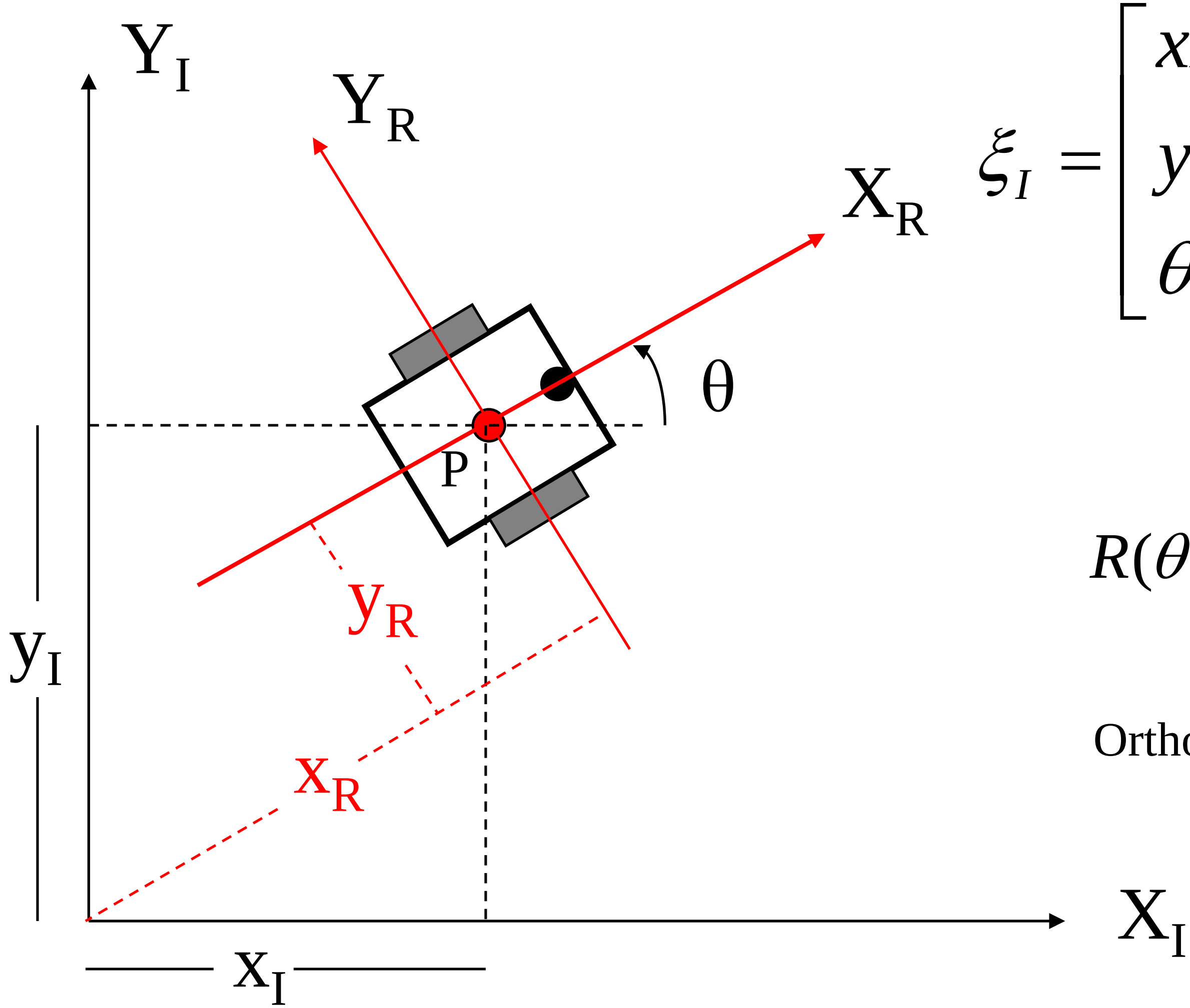




State	Ch A	Ch B
S_1	High	Low
S_2	High	High
S_3	Low	High
S_4	Low	Low

© R. Siegwart, ETH Zurich - ASL

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



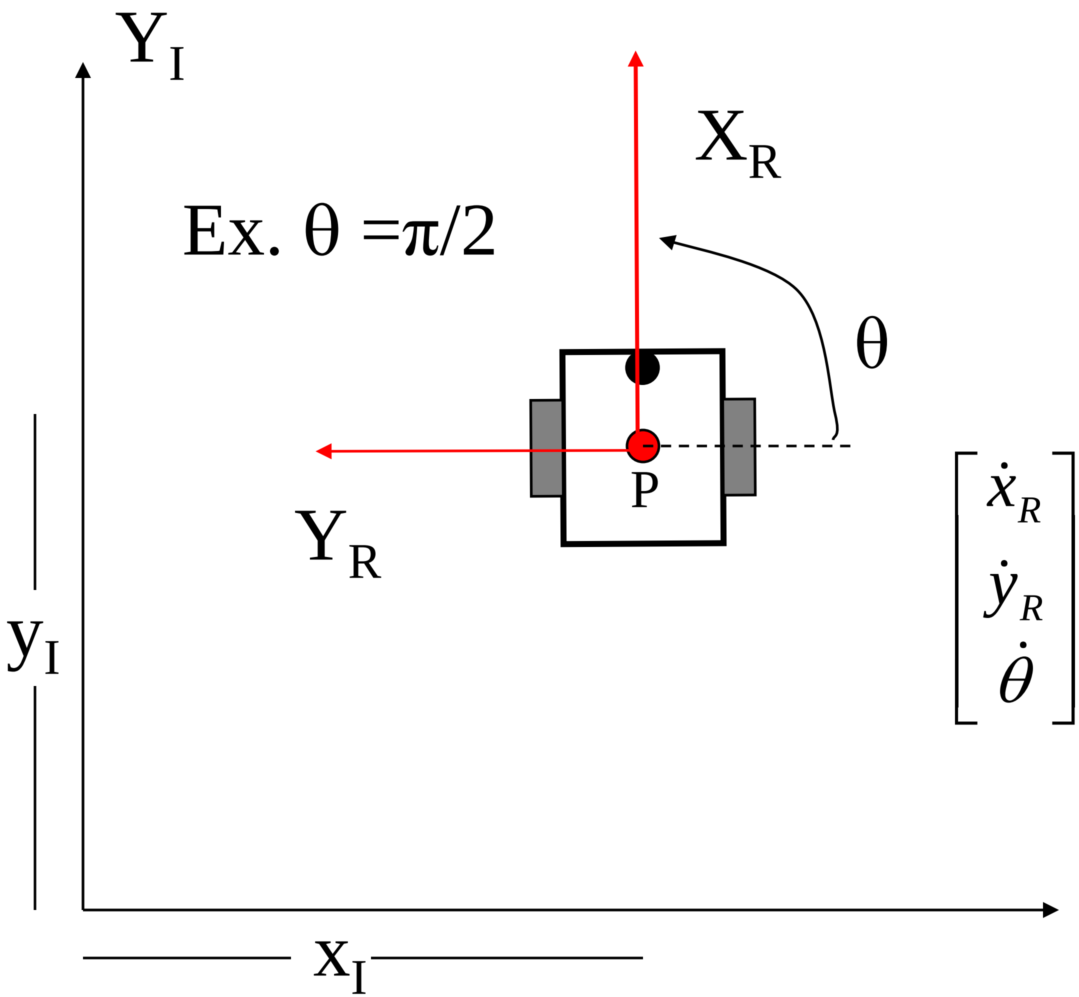
$$\xi_I = \begin{bmatrix} x_I \\ y_I \\ \theta \end{bmatrix} \qquad \xi_R = \begin{bmatrix} x_R \\ y_R \\ \theta \end{bmatrix} = R(\theta)\xi_I$$

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

Orthogonal Rotation Matrix

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

Absolute and Relative Motion of a Differential-Drive Robot



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

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

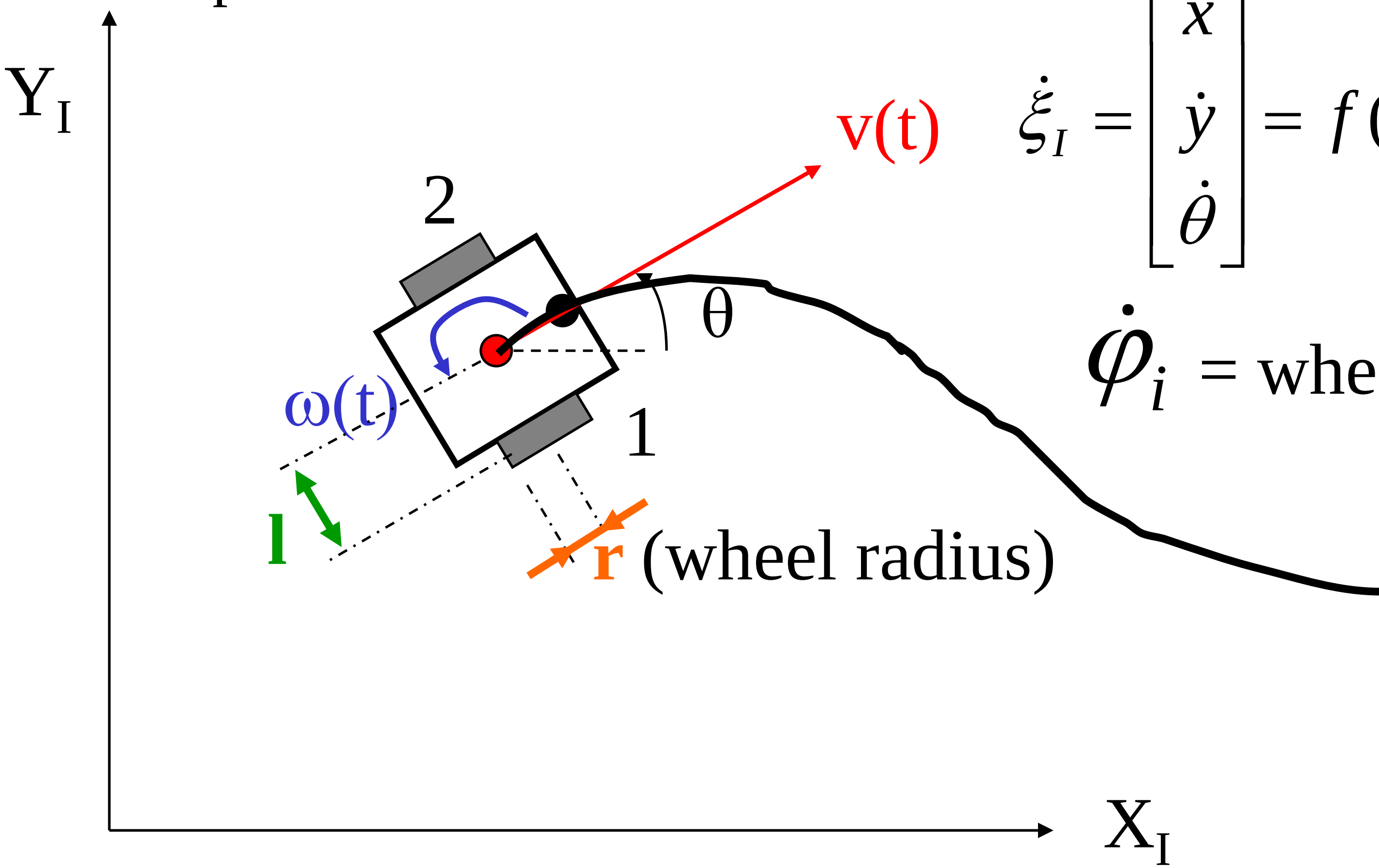
Forward Kinematic Model

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

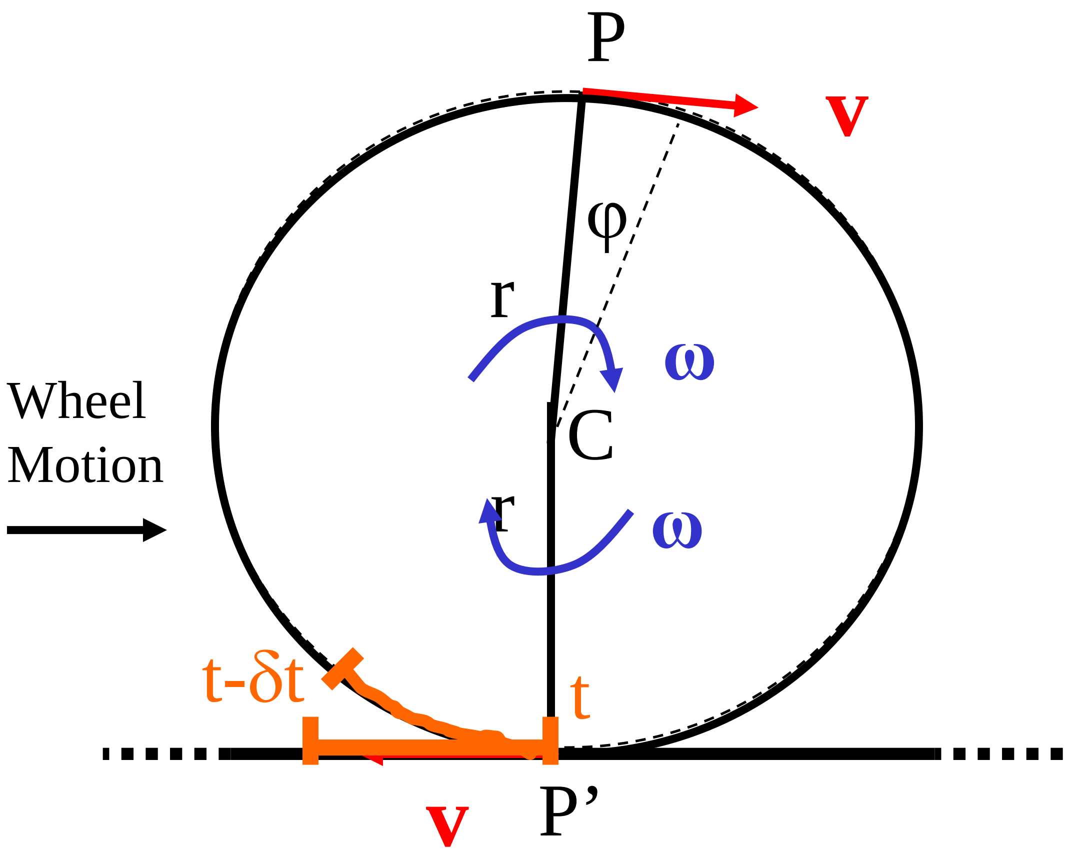
- Assumption: no wheel slip (rolling mode only)!
- In miniature robots no major dynamic effects due to low mass-to-power ratio

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

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



Recap ME/PHY Fundamentals



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

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!

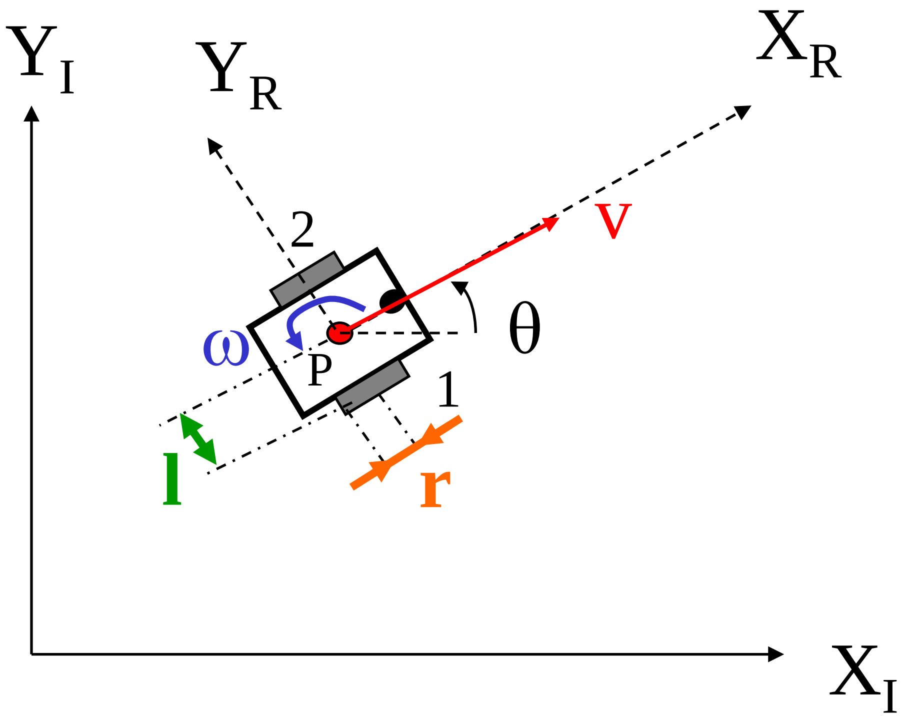
Forward Kinematic Model

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

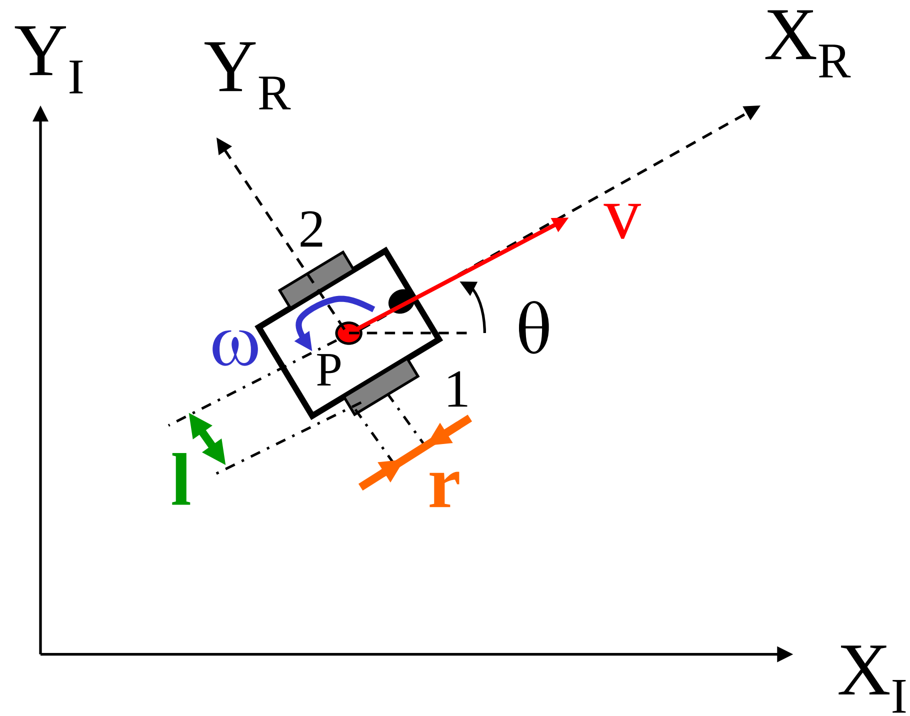
Forward Kinematic Model

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

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

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

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

$$\xi_I(T) = \xi_{I0} + \int_0^T \dot{\xi}_I dt = \xi_{I0} + \int_0^T R^{-1}(\theta)\dot{\xi}_R dt$$

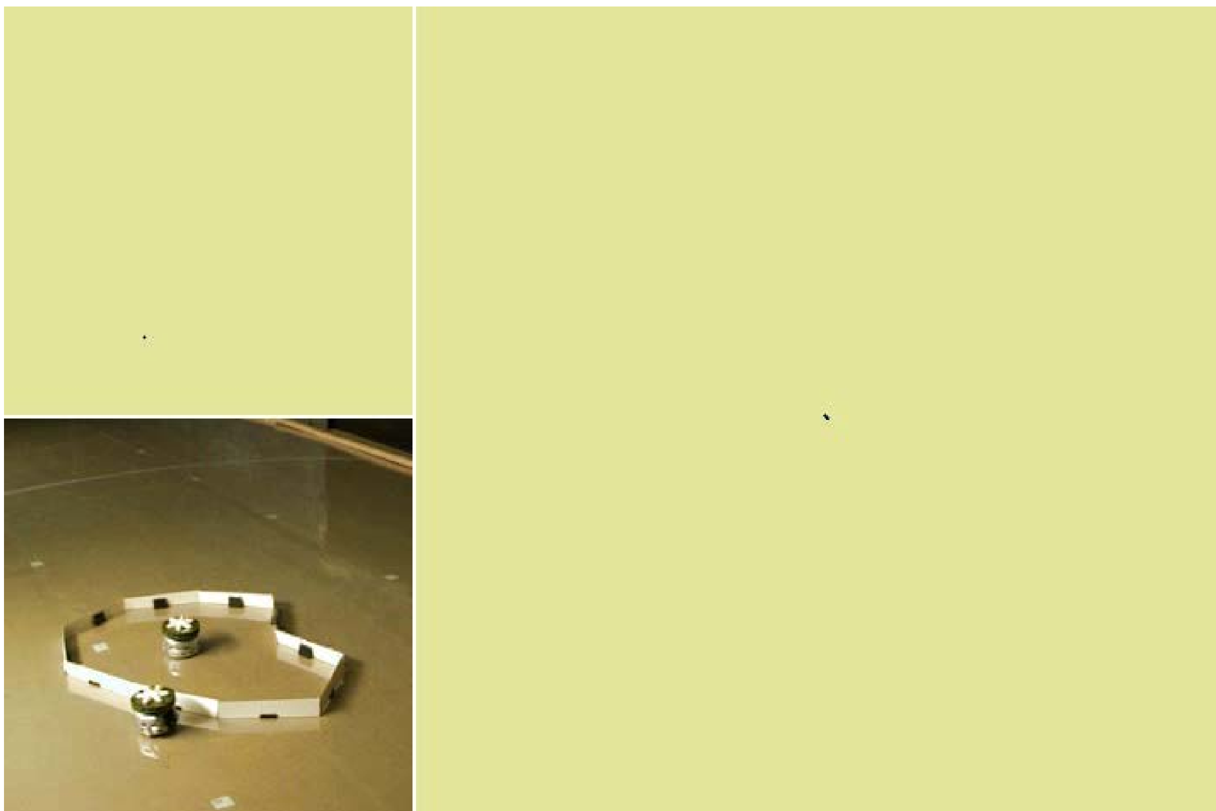
- Given an initial pose ξ_{I0}, after time *T*, the pose of the vehicle will be $\xi_I(T)$
- $\xi_I(T)$ computable with wheel speed 1, wheel speed 2, and parameters *r* and *l*

Localization Uncertainities in Odometry

Deterministic Error Sources

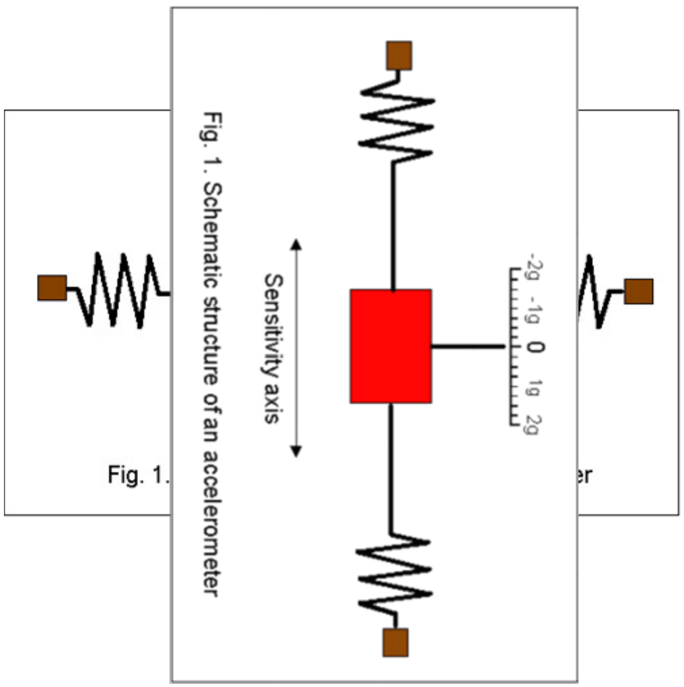
- Limited encoder resolution
- Wheel misalignment and small differences in wheel diameter

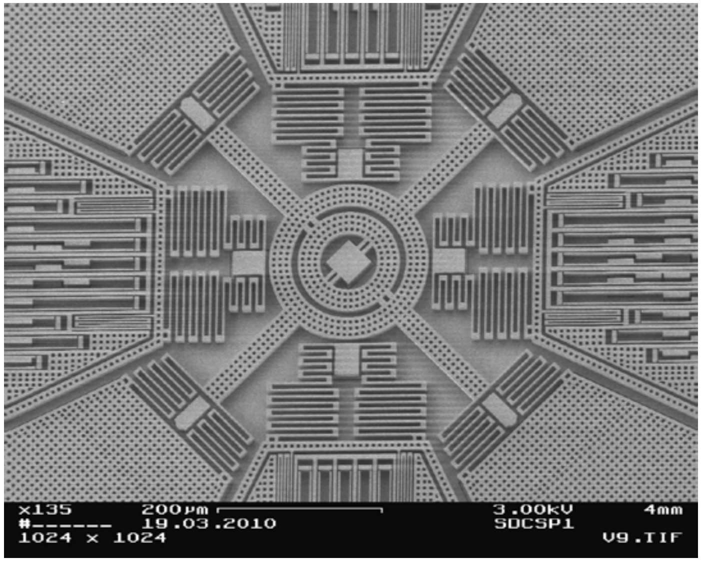
➢ Can be fixed by calibration



Non-Deterministic Error Sources

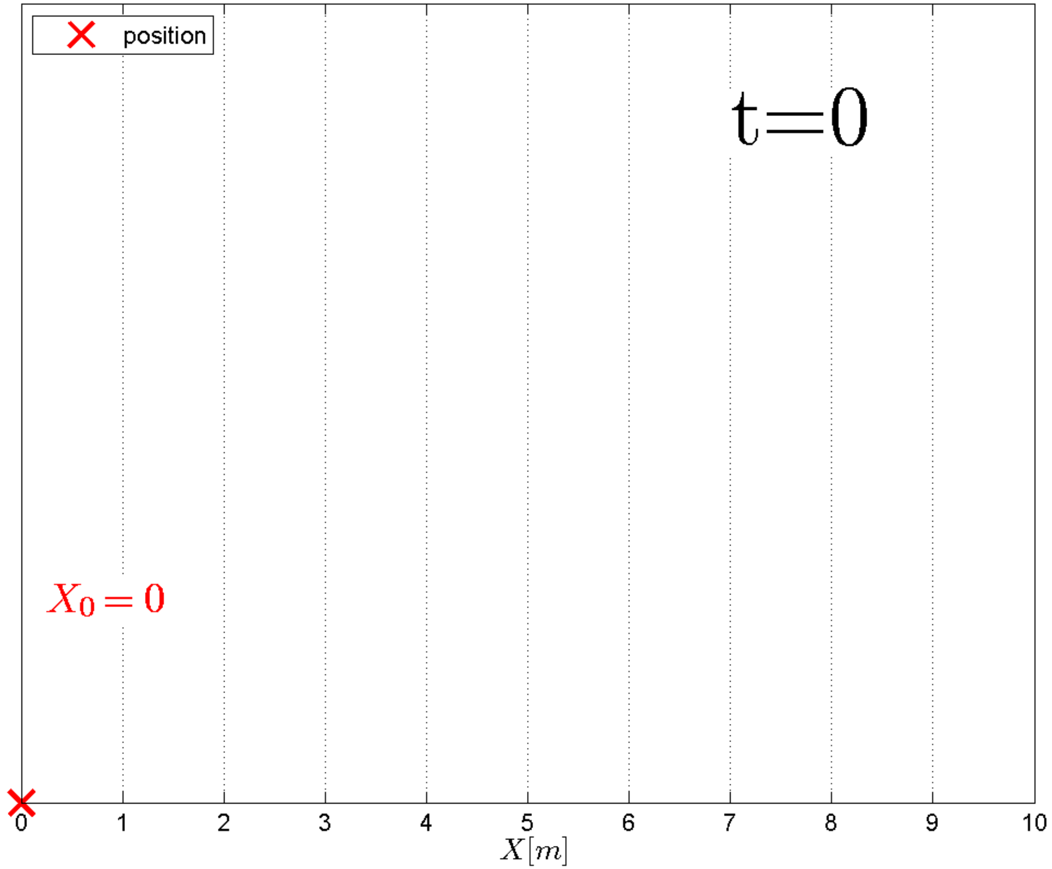
- From Week 3: no deterministic prediction possible → we have to describe them probabilistically
- Example: accelerometer-based odometry

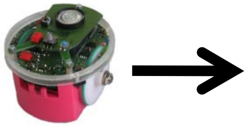




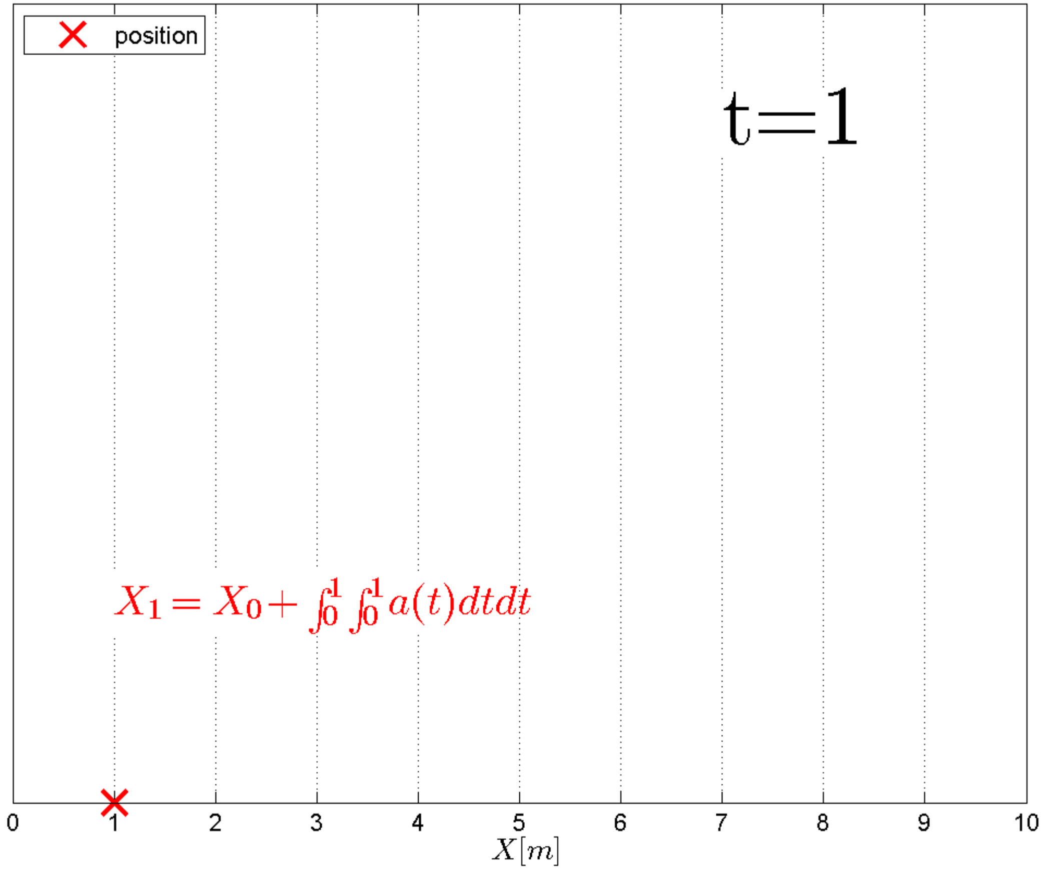
MEMS-Based accelerometer (e.g., on e-puck)

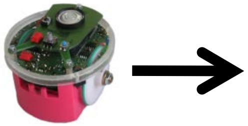
Odometry in 1D



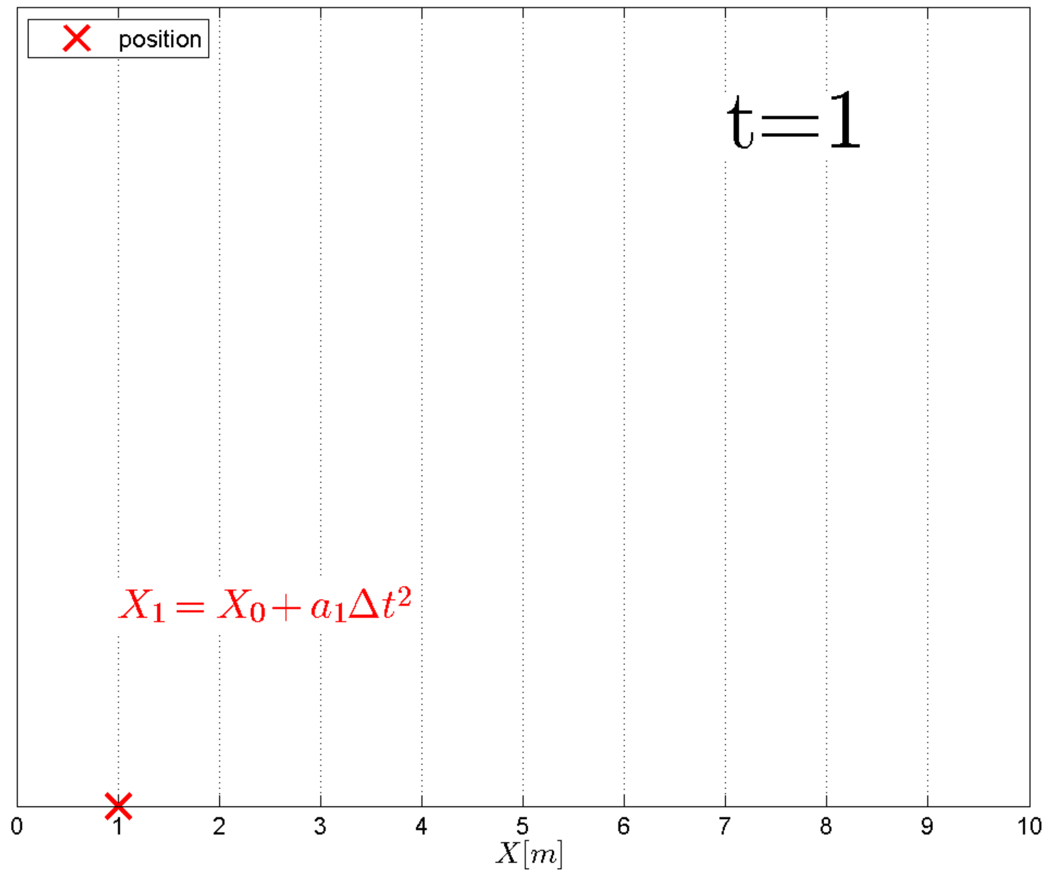


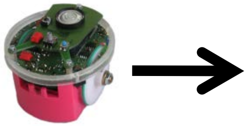
Odometry in 1D



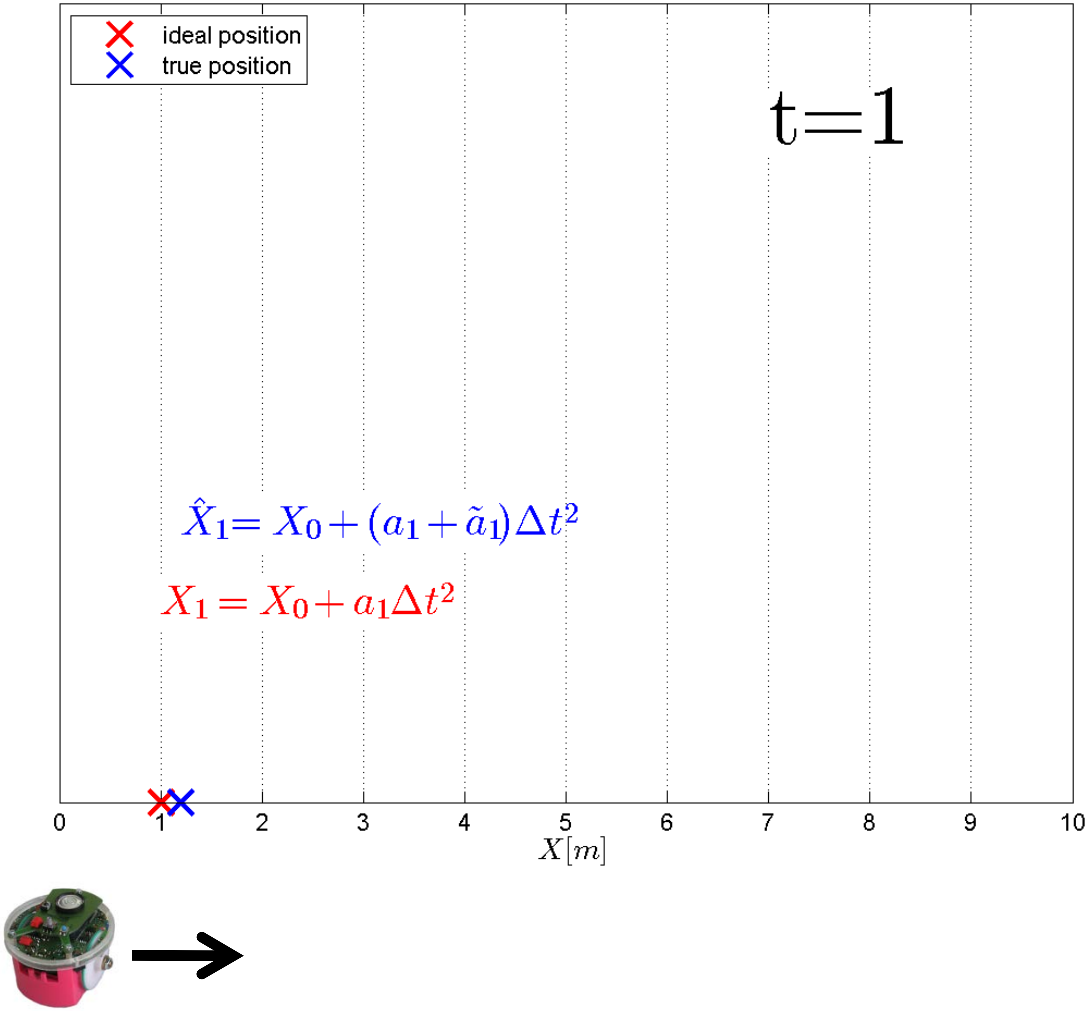


Odometry in 1D

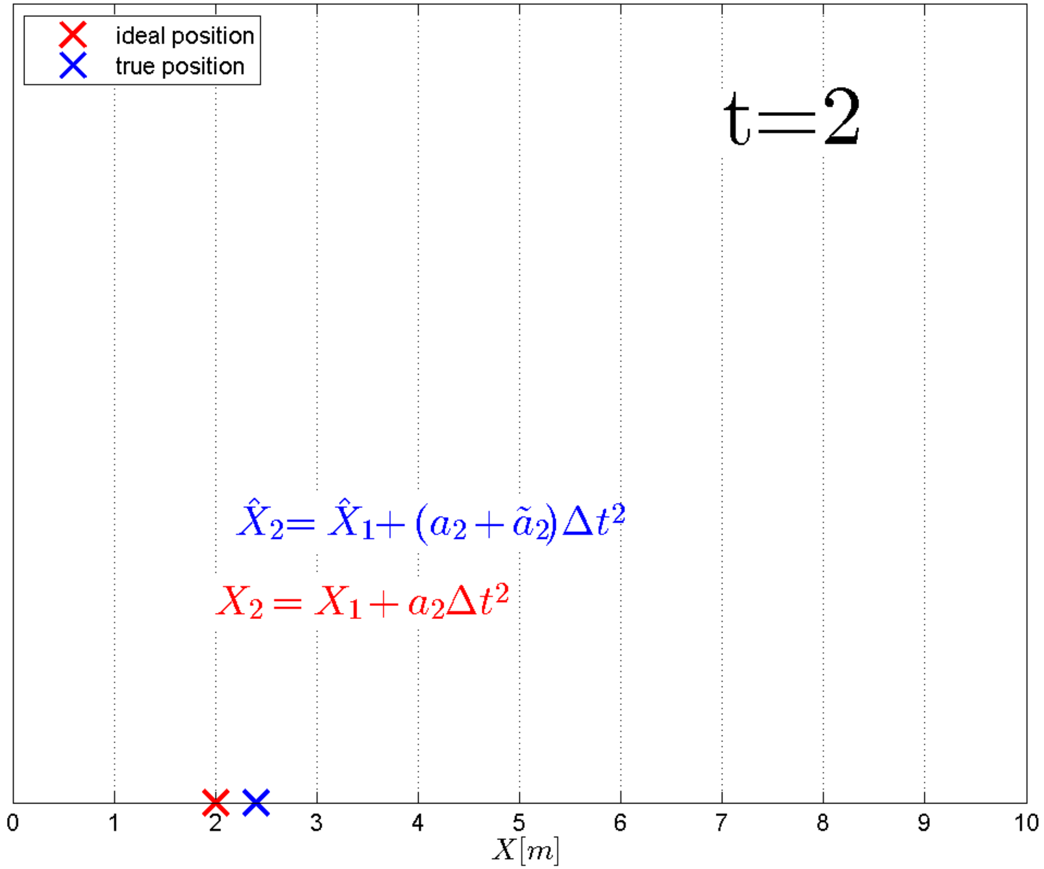


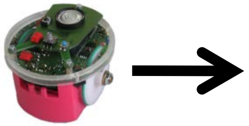


Odometry in 1D

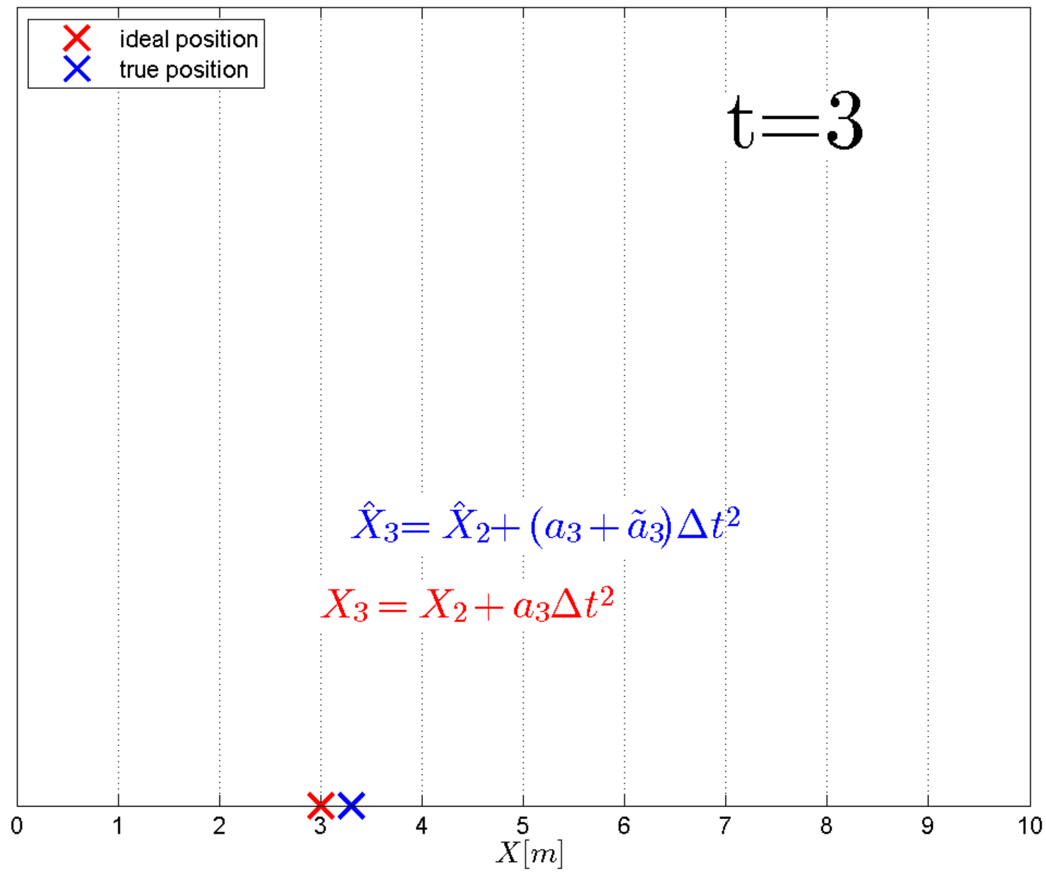


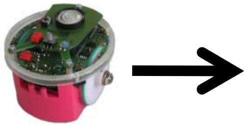
Odometry in 1D



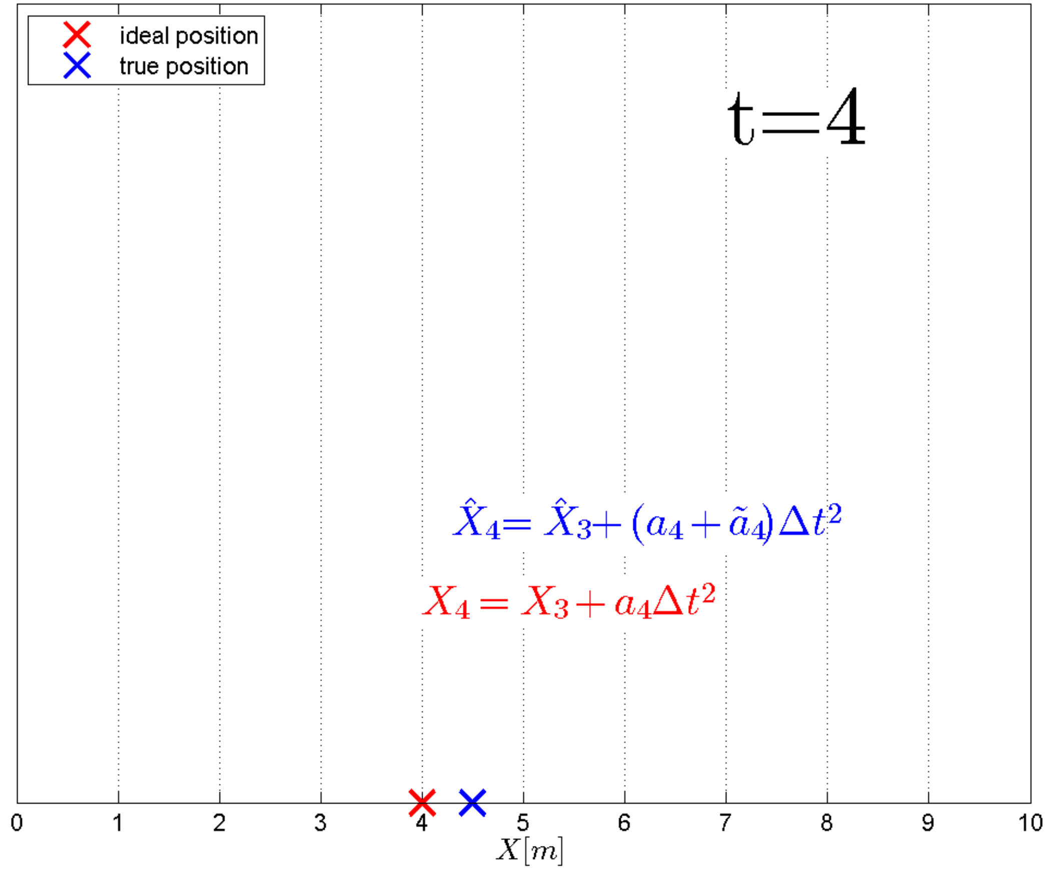


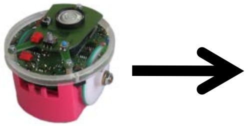
Odometry in 1D



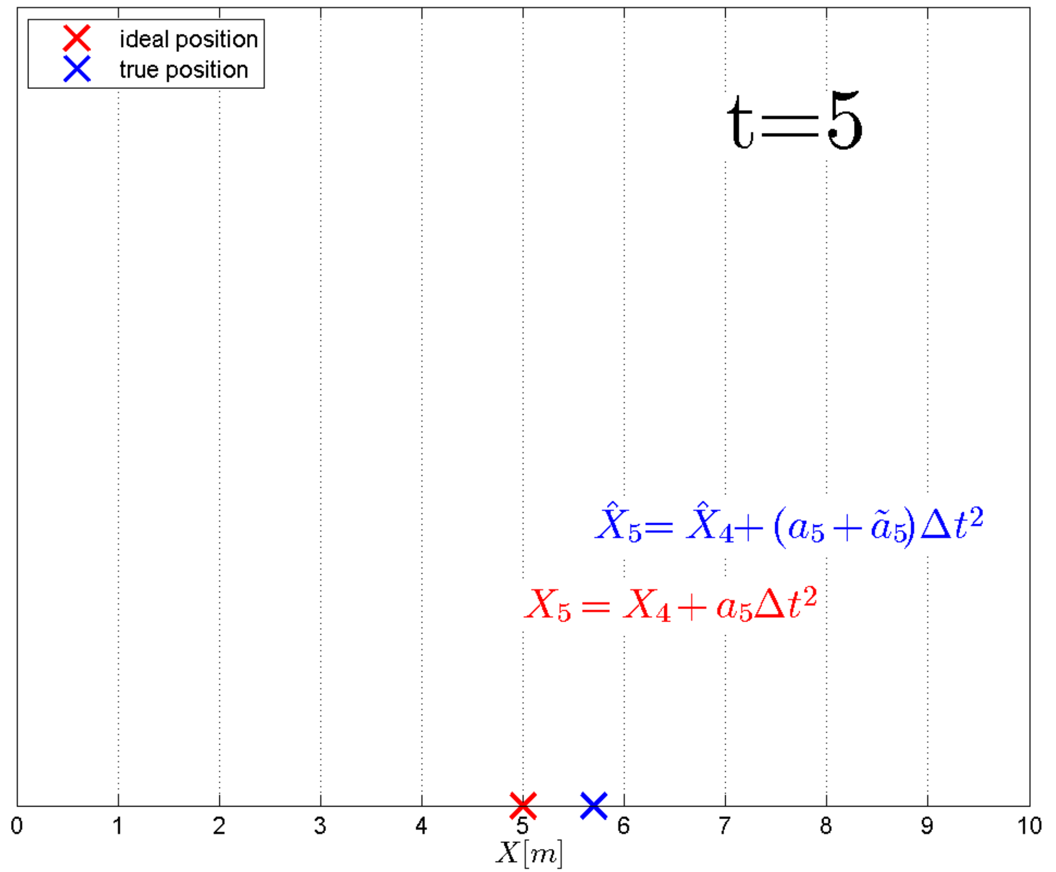


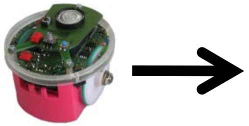
Odometry in 1D





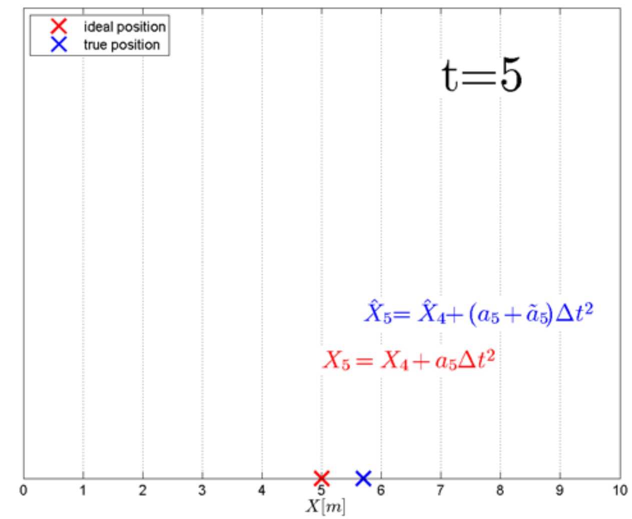
Odometry in 1D

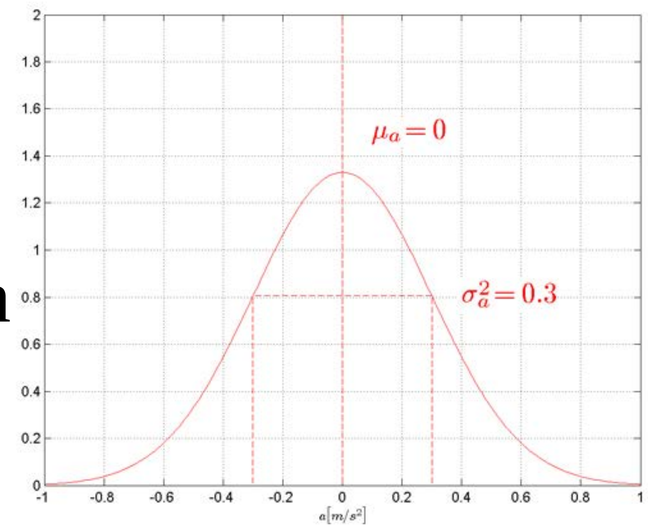




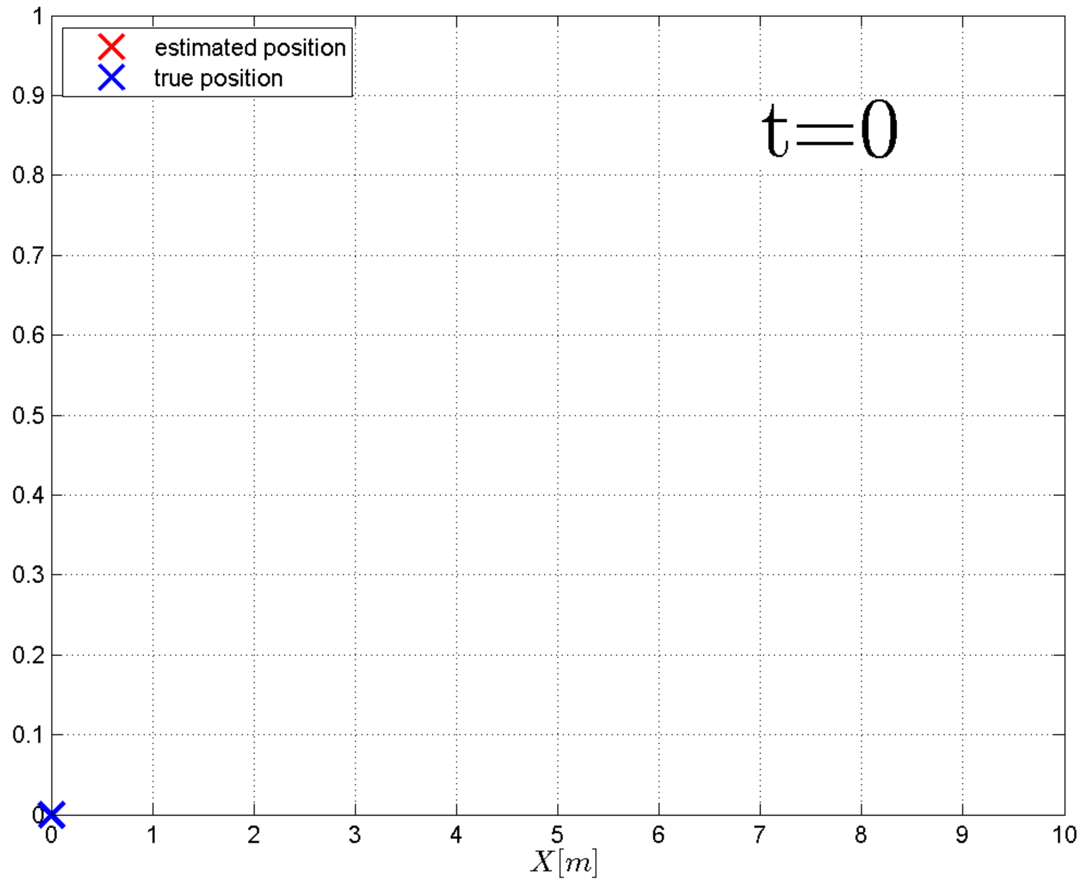
1D Odometry: Error Modeling

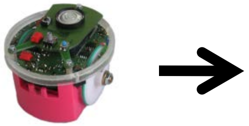
- Error happens!
- Odometry error is cumulative.
  → grows without bound
- We need to be aware of it.
  → We need to model odometry error.
  → We need to model sensor error.
- Acceleration is random variable *A* drawn from "mean-free" Gaussian ("Normal") distribution.
  → Position *X* is random variable with Gaussian distribution.



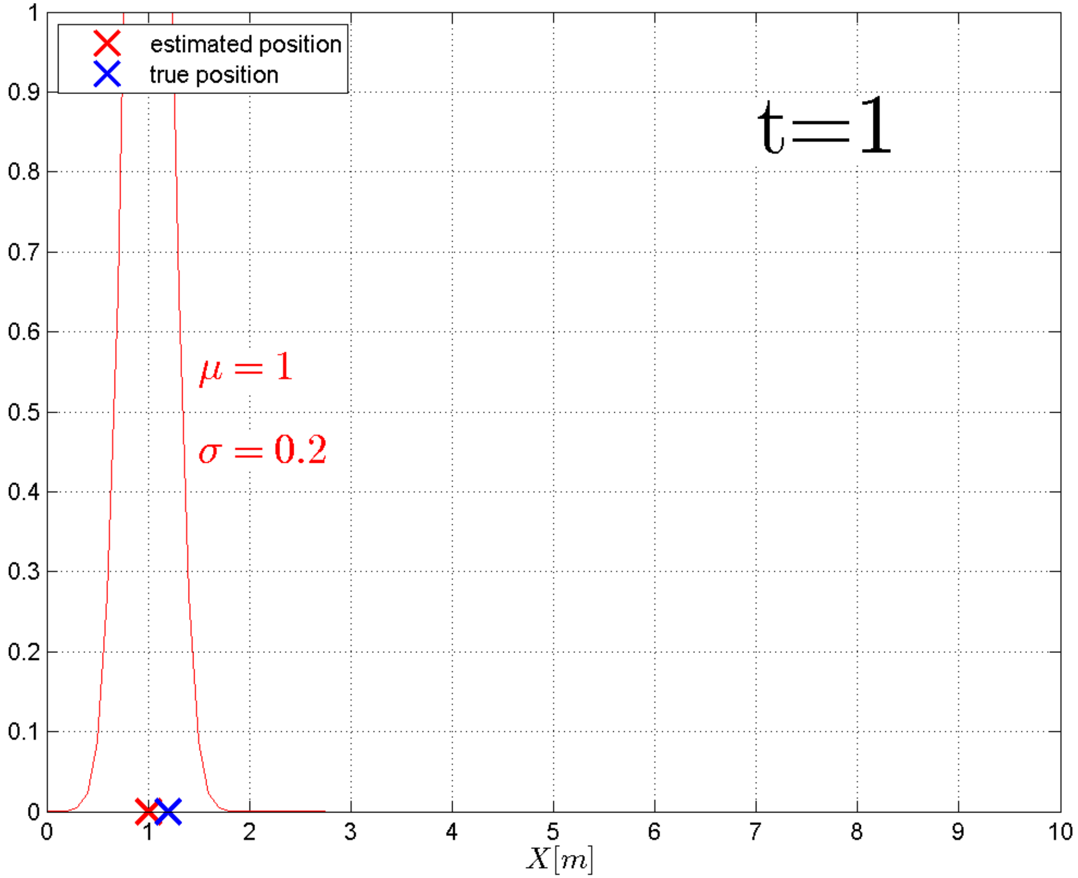


1D Odometry with Gaussian Uncertainty

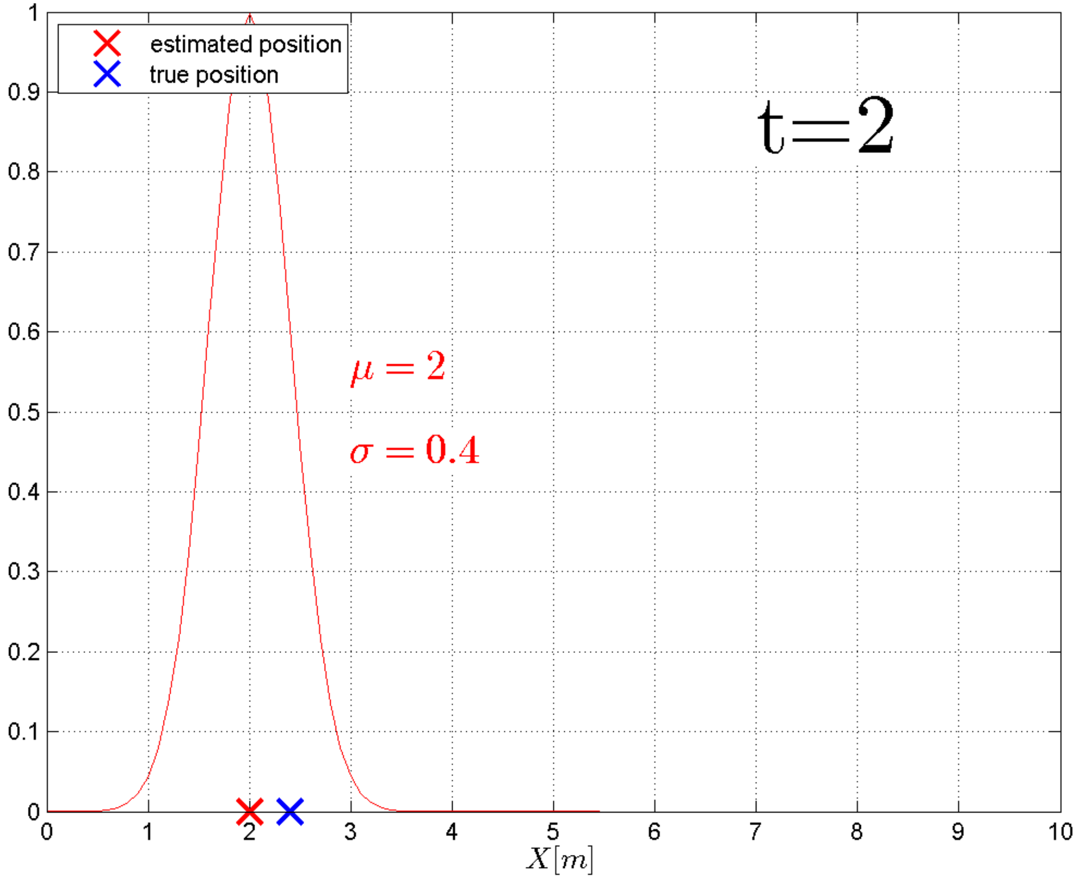


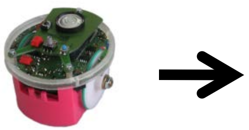


1D Odometry with Gaussian Uncertainty

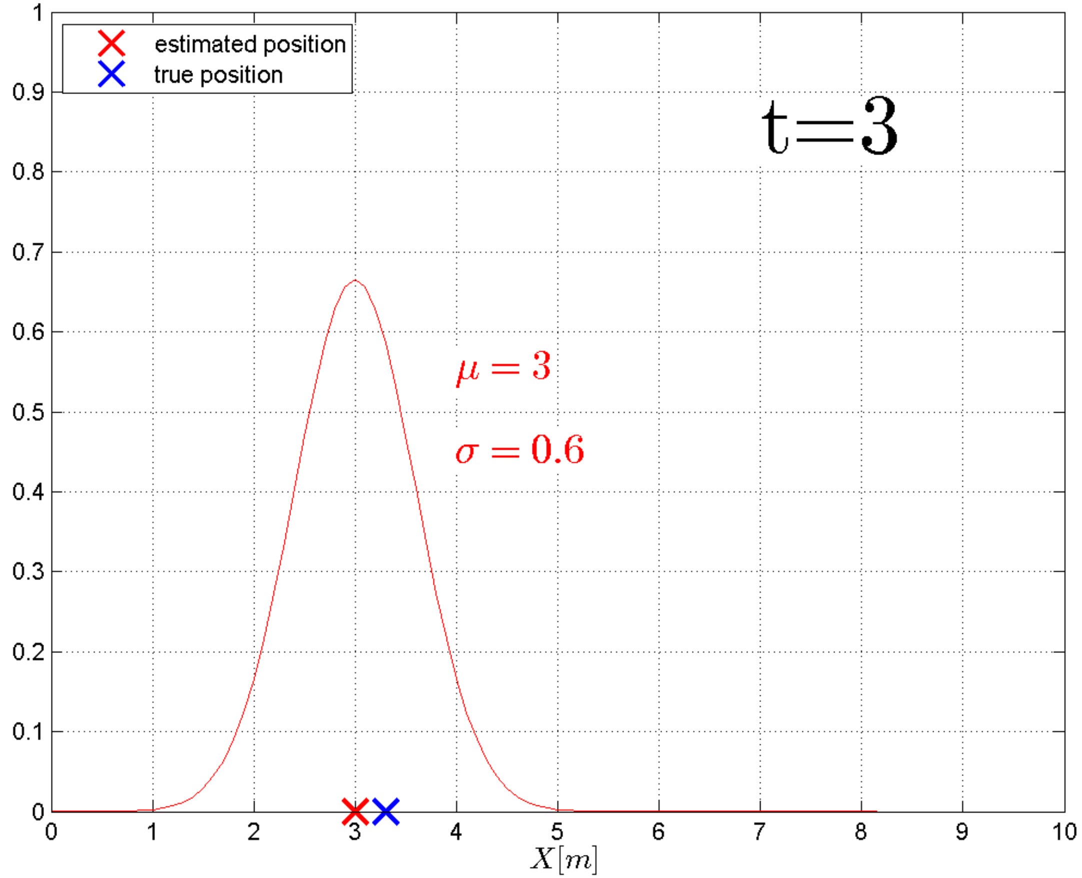


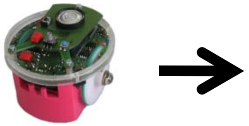
1D Odometry with Gaussian Uncertainty



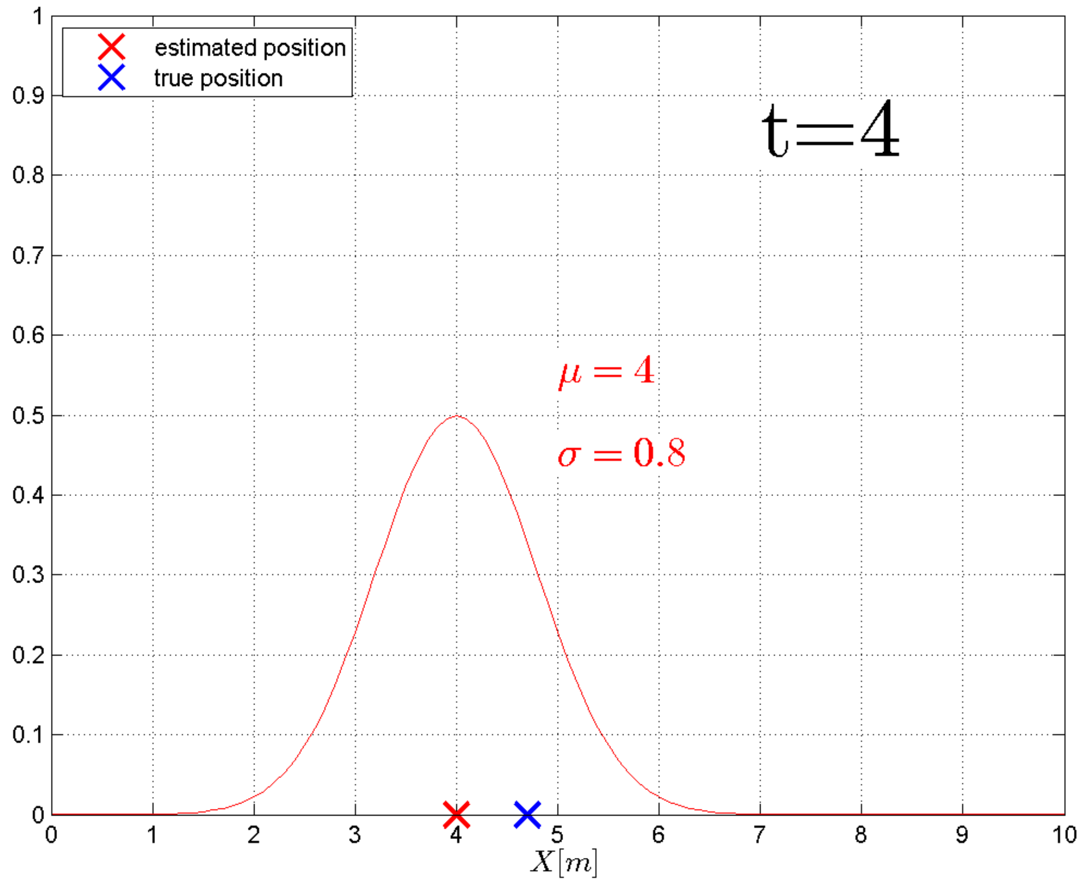


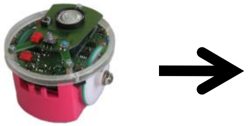
1D Odometry with Gaussian Uncertainty



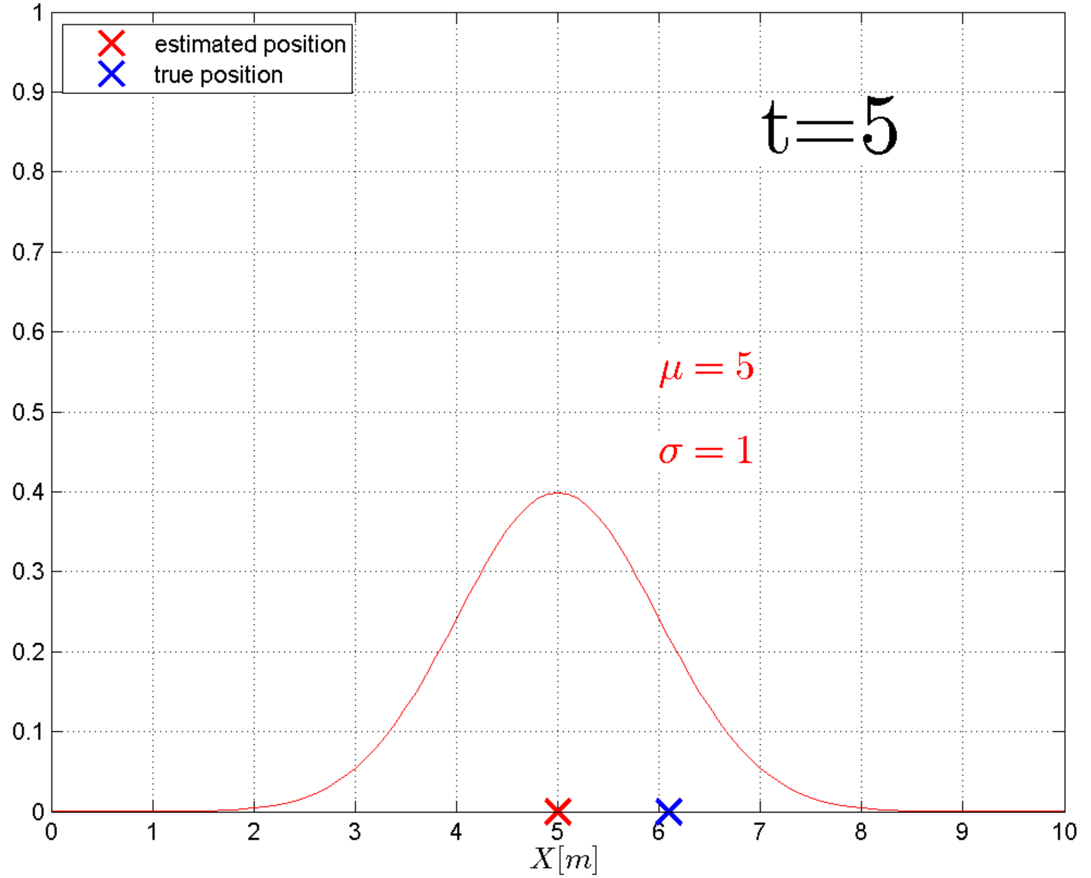


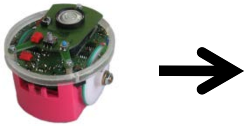
1D Odometry with Gaussian Uncertainty





1D Odometry with Gaussian Uncertainty





Non-Deterministic Uncertainities in Odometry based on Wheel Encoders

Nondeterministic Error Sources

- Variation of the contact point of the wheel
- Unequal floor contact (e.g., wheel slip, nonplanar surface)

- ➢ Wheels cannot be assumed to roll perfectly
- ➢ Measured encoder values do not perfectly reflect the actual motion
- ➢ Pose error is cumulative and incrementally increases
- ➢ Probabilistic modeling for assessing quantitatively the error

Odometric Error Types

- Range error: sum of the wheel movements
- Turn error: difference of wheel motion
- Drift error: difference between wheel errors lead to heading error

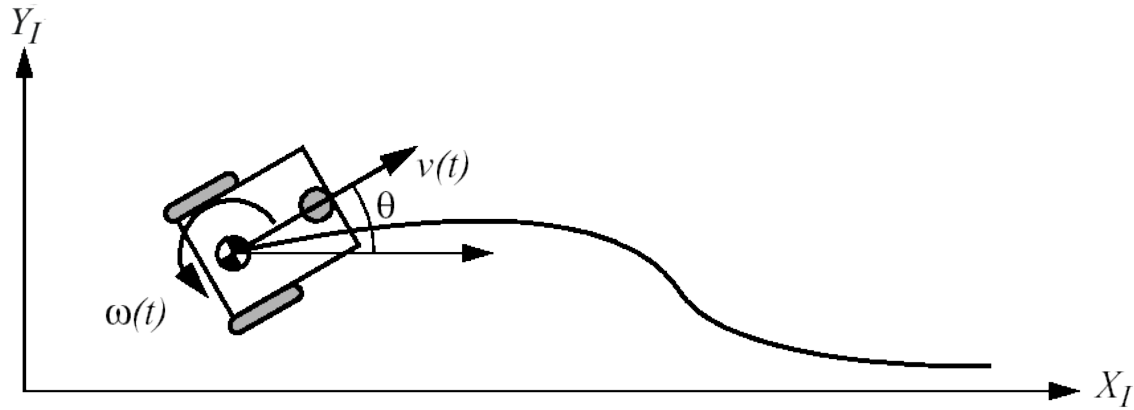
Pose Variation During Δt

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

$$\Delta x = \Delta s \cos(\theta + \frac{\Delta\theta}{2})$$

$$\Delta y = \Delta s \sin(\theta + \frac{\Delta\theta}{2})$$

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



$b = 2l$ = inter-wheel distance

Δs_r = traveled distance right wheel

Δs_l = traveled distance left wheel

$\Delta\theta$ = orientation change of the vehicle

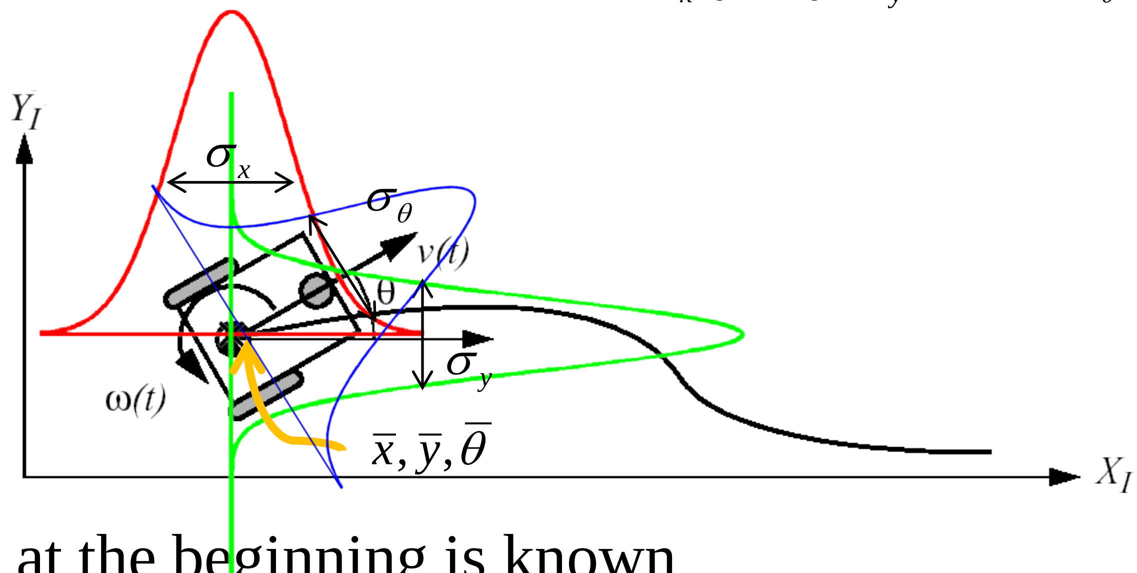
$$p = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \xrightarrow{t'=t+\Delta t} p' = \begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix}$$

$$p' = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta s \cos(\theta + \Delta\theta/2) \\ \Delta s \sin(\theta + \Delta\theta/2) \\ \Delta\theta \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{\Delta s_r + \Delta s_l}{2}\cos(\theta + \frac{\Delta s_r - \Delta s_l}{2b}) \\ \frac{\Delta s_r + \Delta s_l}{2}\sin(\theta + \frac{\Delta s_r - \Delta s_l}{2b}) \\ \frac{\Delta s_r - \Delta s_l}{b} \end{bmatrix}$$

Noise modeling

Model error in each dimension with a Gaussian $x \rightarrow \bar{x}, \sigma_x; y \rightarrow \bar{y}, \sigma_y; \theta \rightarrow \bar{\theta}, \sigma_\theta$

$$\Sigma_p = \begin{bmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 & \sigma_{x\theta}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 & \sigma_{y\theta}^2 \\ \sigma_{\theta x}^2 & \sigma_{\theta y}^2 & \sigma_{\theta\theta}^2 \end{bmatrix}$$



Assumptions:

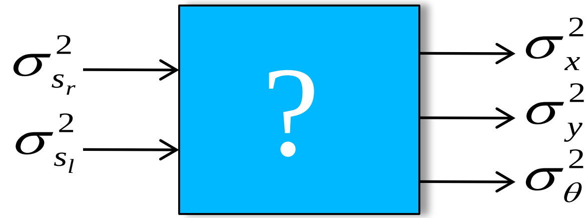
- Covariance matrix Σ_p at the beginning is known
- Errors of the two individual wheels are independent
- Errors are independent of direction of motion
- Errors are proportional to the distance traveled (k_r, k_l model parameters)

$$\sum_\Delta = \mathrm{cov}(\Delta s_r, \Delta s_l) = \begin{bmatrix} k_r|\Delta s_r| & 0 \\ 0 & k_l|\Delta s_l| \end{bmatrix} = \begin{bmatrix} \sigma_{s_r}^2 & 0 \\ 0 & \sigma_{s_l}^2 \end{bmatrix}$$

Actuator Noise → Pose Noise

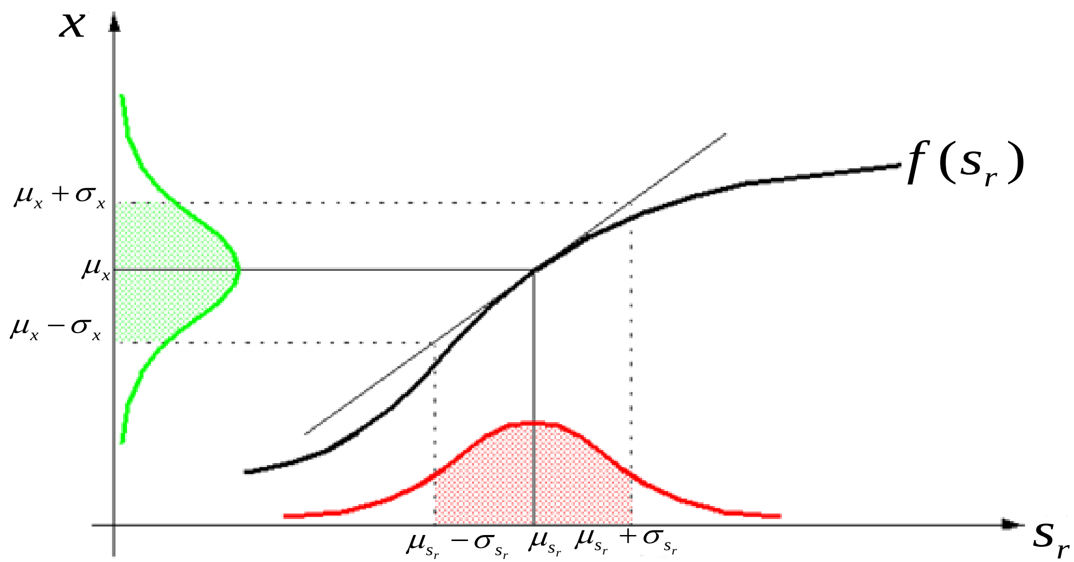
- How is the actuator noise (2D) propagated to the pose (3D)?

$$\Sigma_\Delta = \begin{bmatrix} \sigma_{s_r}^2 & 0 \\ 0 & \sigma_{s_l}^2 \end{bmatrix}$$



$$\begin{bmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 & \sigma_{x\theta}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 & \sigma_{y\theta}^2 \\ \sigma_{\theta x}^2 & \sigma_{\theta y}^2 & \sigma_{\theta\theta}^2 \end{bmatrix} = \Sigma_p$$

- 1D to 1D example $N(\mu_{s_r}, \sigma_{s_r}) \to N(\mu_x, \sigma_x)$



- We need to linearize → Taylor Series

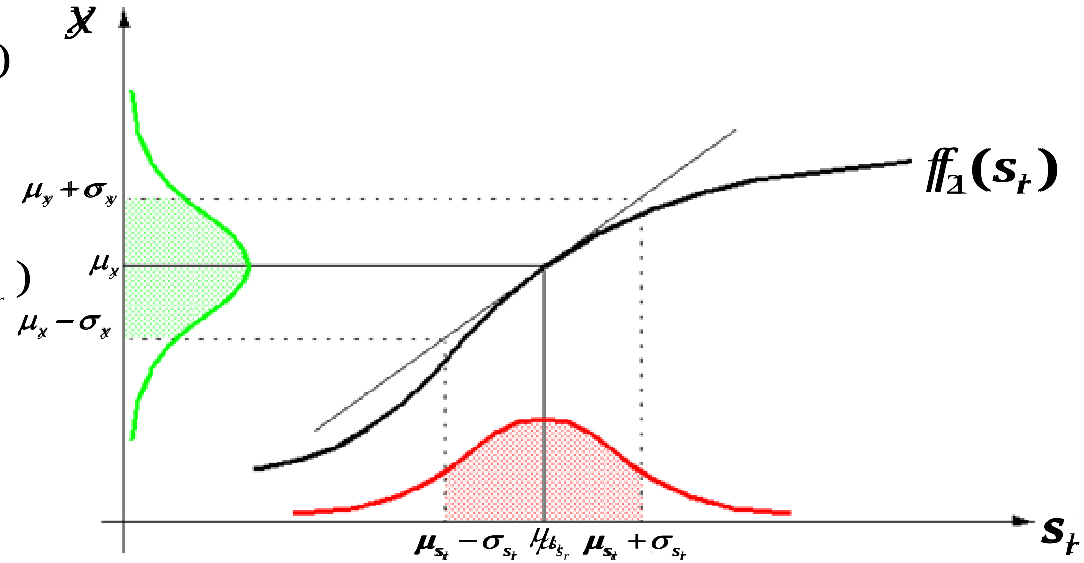
$$x \approx f(s_r)\big|_{s_r=\mu_{s_r}} \approx f(s_r) + \frac{1}{1!}\frac{\partial f}{\partial s_r}(s_r - \mu_{s_r}) + \frac{1}{2!}\frac{\partial^2 f}{\partial s_r^2}(s_r - \mu_{s_r})^2 + \ldots$$

Actuator Noise → Pose Noise

$$x \approx f_1(s_r)\big|_{s_r=\mu_{s_r}} \approx f_1(s_r) + \frac{\partial f_1}{\partial s_r}(s_r - \mu_{s_r})$$

$$x \approx f_1(s_l)\big|_{s_l=\mu_{s_l}} \approx f_1(s_l) + \frac{\partial f_1}{\partial s_l}(s_l - \mu_{s_l})$$

$$y \approx f_2(s_r)\big|_{s_r=\mu_{s_r}} \approx f_2(s_r) + \frac{\partial f_2}{\partial s_r}(s_r - \mu_{s_r})$$



$$F_{\Delta rl} = \begin{bmatrix} \frac{\partial f_1}{\partial \Delta s_r} & \frac{\partial f_1}{\partial \Delta s_l} \\ \frac{\partial f_2}{\partial \Delta s_r} & \frac{\partial f_2}{\partial \Delta s_l} \\ \frac{\partial f_3}{\partial \Delta s_r} & \frac{\partial f_3}{\partial \Delta s_l} \end{bmatrix}$$ Jacobian

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

- General error propagation law

$$\Sigma_{\Delta rl} = F_{\Delta rl} \Sigma_\Delta F_{\Delta rl}^T$$

Actuator Noise → Pose Noise

How does the state covariance Σ_p evolve over time?

- Initial covariance of vehicle at t=0:

$$\Sigma_p^{(t=0)} = \begin{bmatrix} \sigma_{xx}^2 & \sigma_{xy}^2 & \sigma_{x\theta}^2 \\ \sigma_{yx}^2 & \sigma_{yy}^2 & \sigma_{y\theta}^2 \\ \sigma_{\theta x}^2 & \sigma_{\theta y}^2 & \sigma_{\theta\theta}^2 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

- Additional noise at each time step Δt: $\Sigma_{\Delta rl} = F_{\Delta rl} \Sigma_{\Delta} F_{\Delta rl}^T$
- Covariance at t=1Δt: $\Sigma_p^{(t=1\Delta t)} = \Sigma_p^{(t=0)} + \Sigma_{\Delta rl} = \Sigma_{\Delta rl}$
- Covariance at t=2Δt:

$$\Sigma_p^{(t=2\Delta t)} = F_p \Sigma_p^{(t=1\Delta t)} F_p^T + F_{\Delta rl} \Sigma_{\Delta} F_{\Delta rl}^T$$

$$F_p = \begin{bmatrix} \frac{\partial f_1}{\partial_x} & \frac{\partial f_1}{\partial_y} & \frac{\partial f_1}{\partial_\theta} \\ \frac{\partial f_2}{\partial_x} & \frac{\partial f_2}{\partial_y} & \frac{\partial f_2}{\partial_\theta} \\ \frac{\partial f_3}{\partial_x} & \frac{\partial f_3}{\partial_y} & \frac{\partial f_3}{\partial_\theta} \end{bmatrix}$$

Actuator Noise → Pose Noise

Algorithm

Precompute:

- Determine actuator noise Σ_Δ
- Compute mapping actuator-to-pose noise incremental $F_{\Delta rl}$
- Compute mapping actuator-to-pose noise absolute F_p

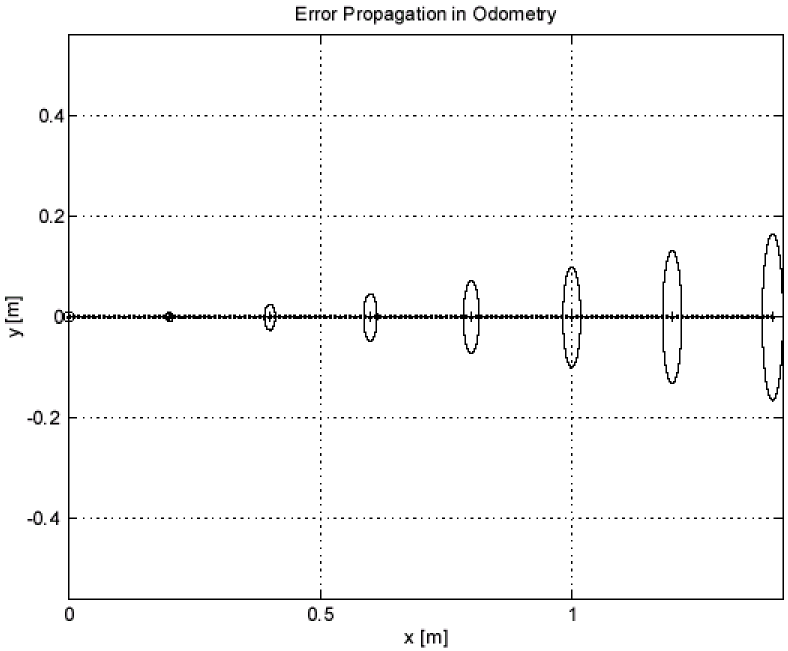
Initialize:

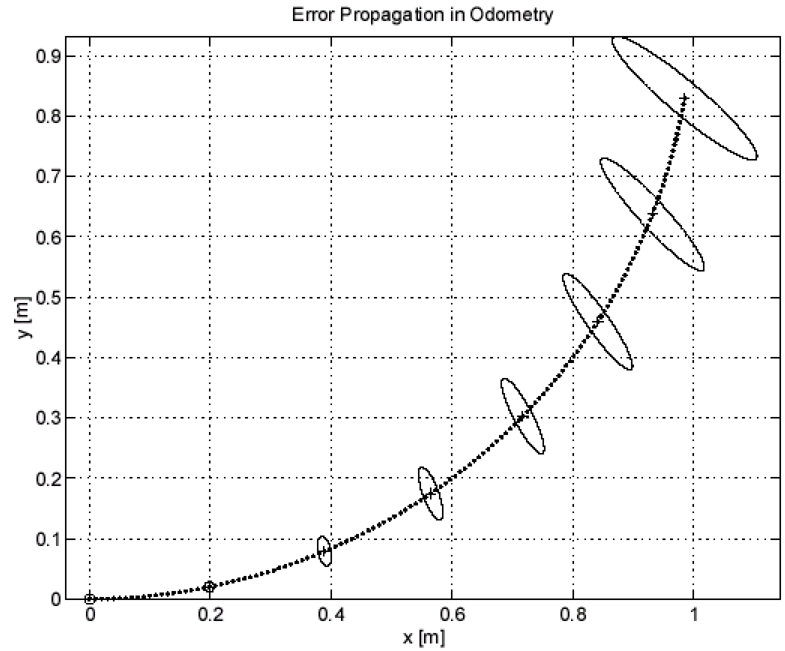
- Initialize $\Sigma_p^{(t=0)} = [0]$

Iterate:

$$\Sigma_p^{(t=(k+1)\Delta t)} = F_p \Sigma_p^{(t=k\Delta t)} F_p^T + F_{\Delta rl} \Sigma_\Delta F_{\Delta rl}^T$$

Classical 2D Representation





Courtesy of R. Siegwart and R. Nourbakhsh

Ellipses: typical 3σ bounds

Robot Localization based on Proprioceptive and Exteroceptive Sensors

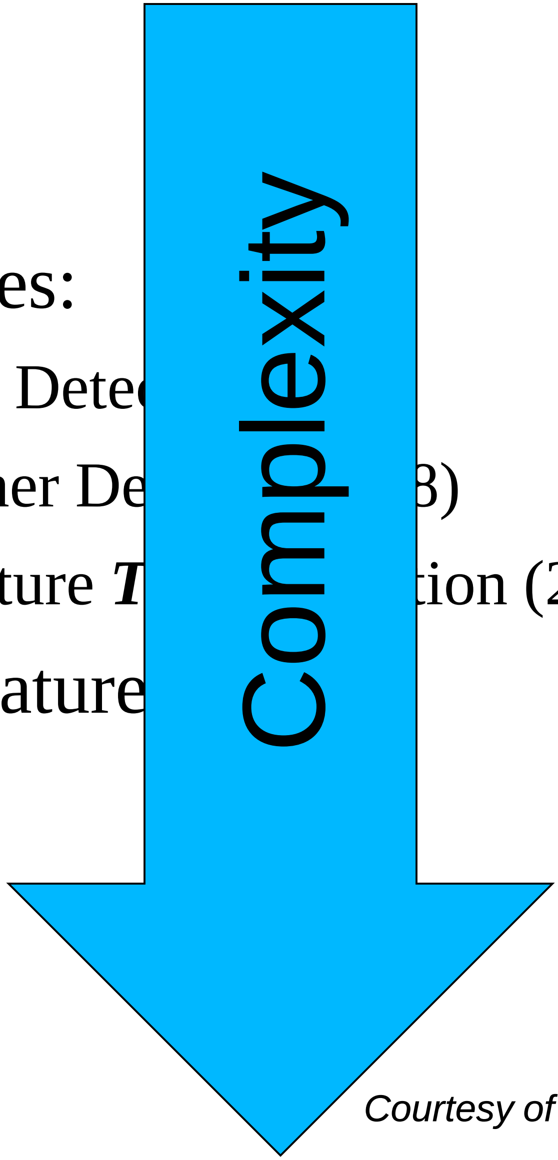
Features

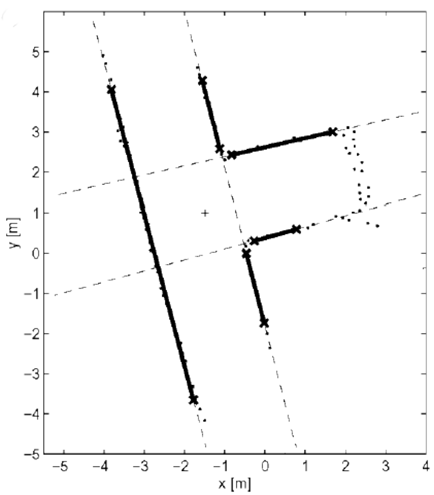
- Odometry based position error grows without bound.
- Use relative measurement to features ("landmarks") to reduce position uncertainty
- ***Feature***:
  - Uniquely identifiable
  - Position is known
  - We can obtain relative measurements between robot and feature (usually angle or range).
- Examples: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

Courtesy of Albert Huang

Automatic Feature Extraction

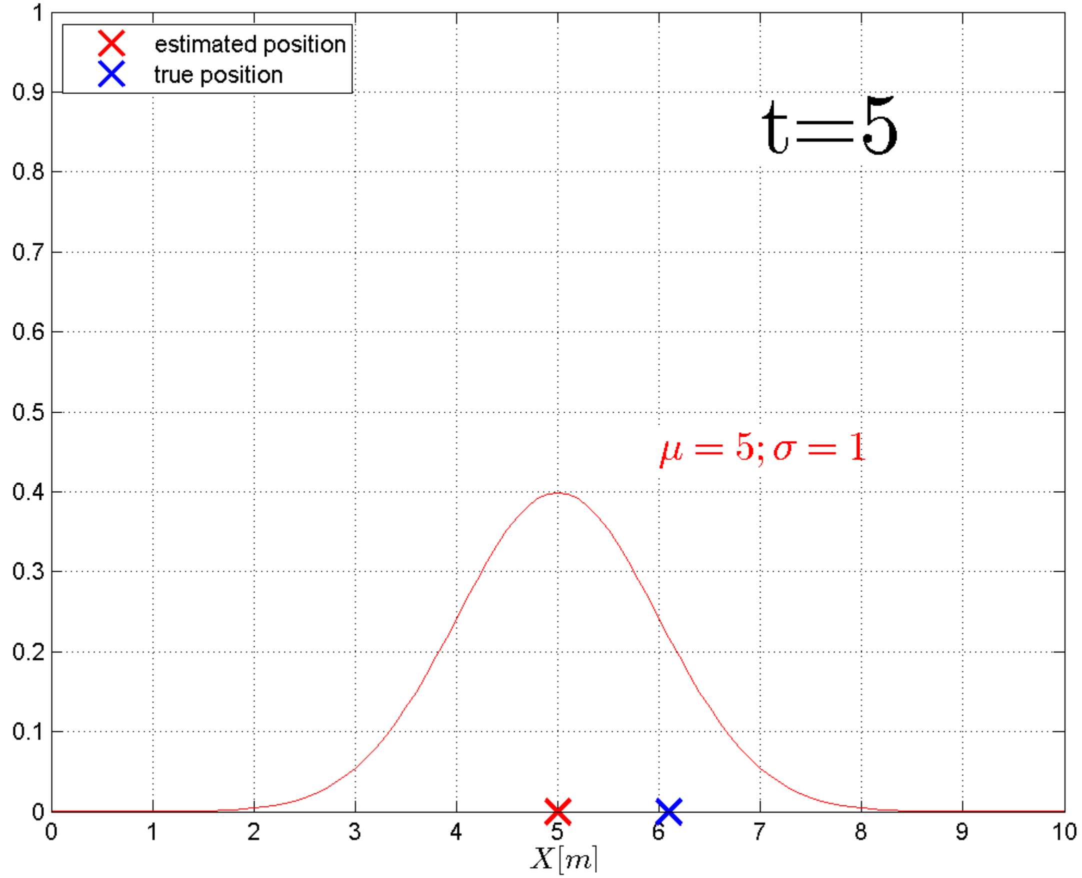
- High level features:
  - Doors, persons
- Simple visual features:
  - Edges (Canny Edge Dete
  - Corner (Harris Corner De 3)
  - ***S***cale ***I***nvariant ***F***eature ***T*** tion (2004)
- Simple geometric feature
  - Lines
  - Corners
- “Binary” feature



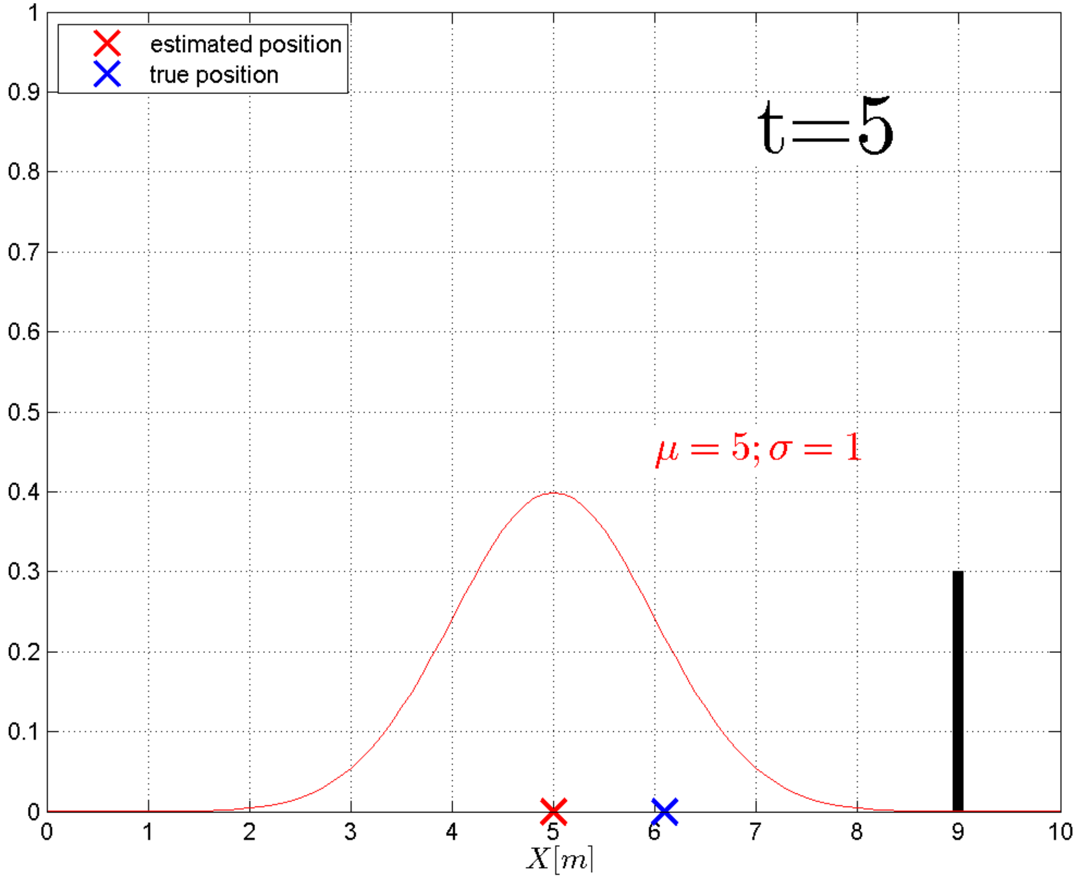


Courtesy of R. Siegwart and R. Nourbakhsh

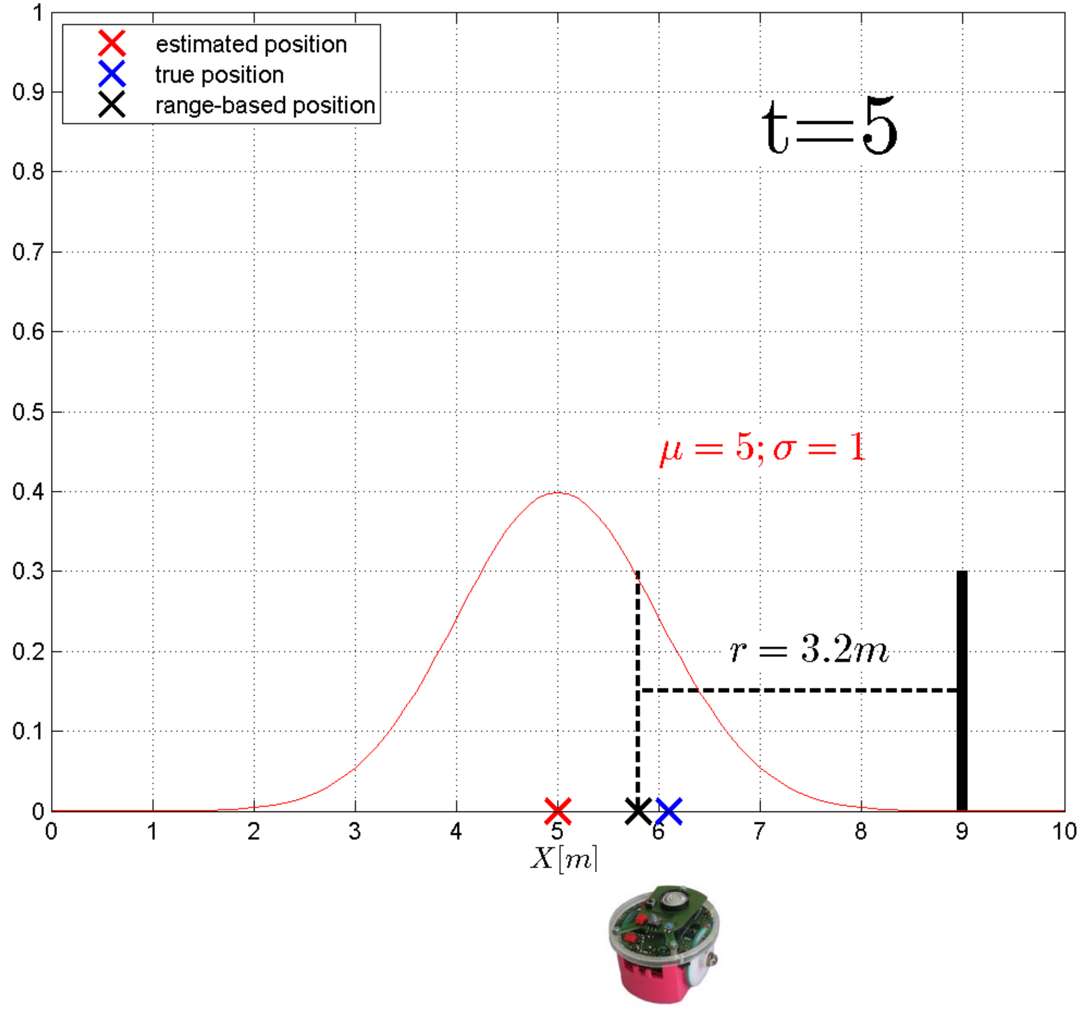
Feature-Based Navigation



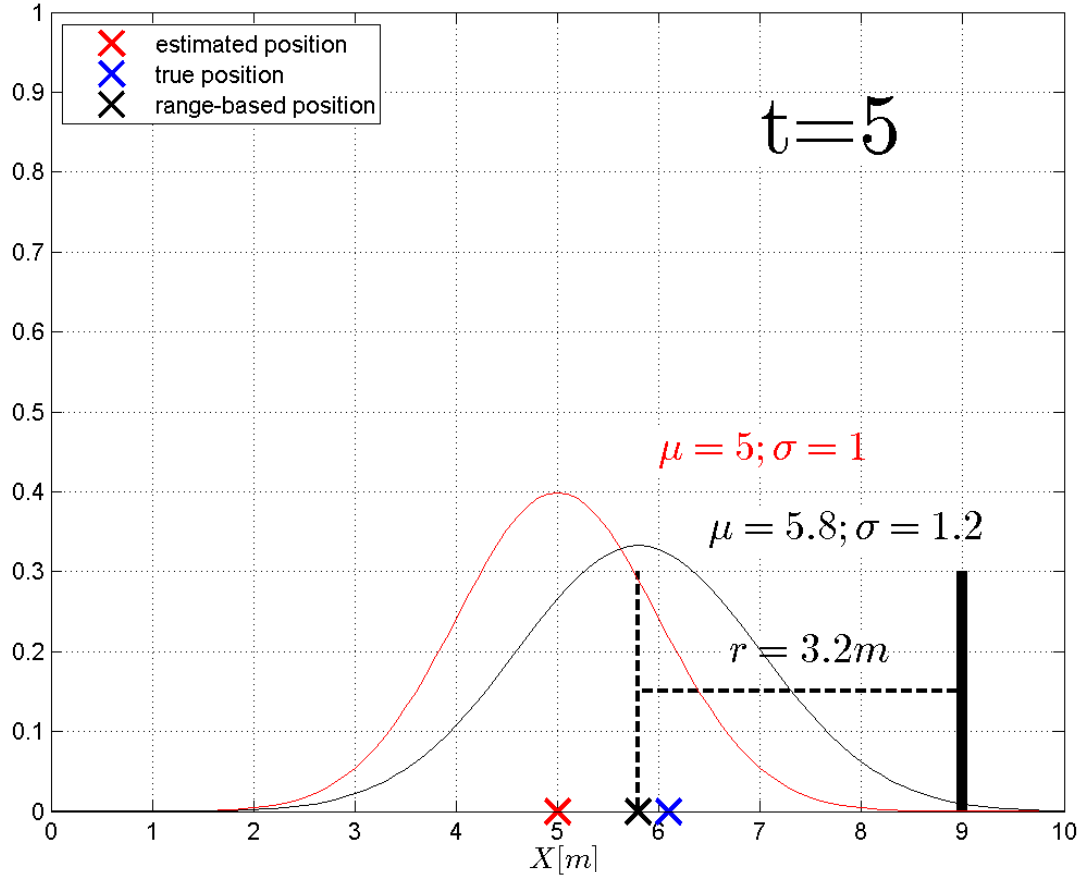
Feature-Based Navigation



Feature-Based Navigation



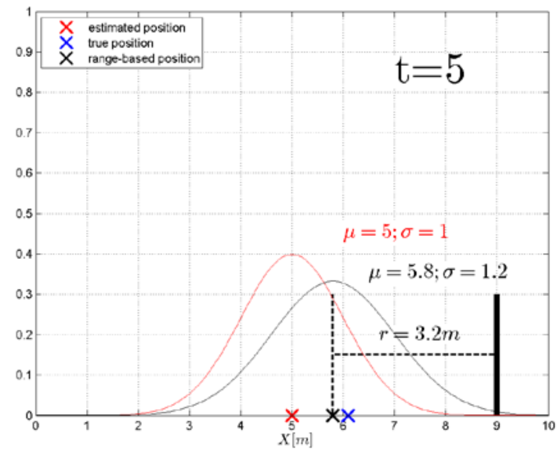
Feature-Based Navigation



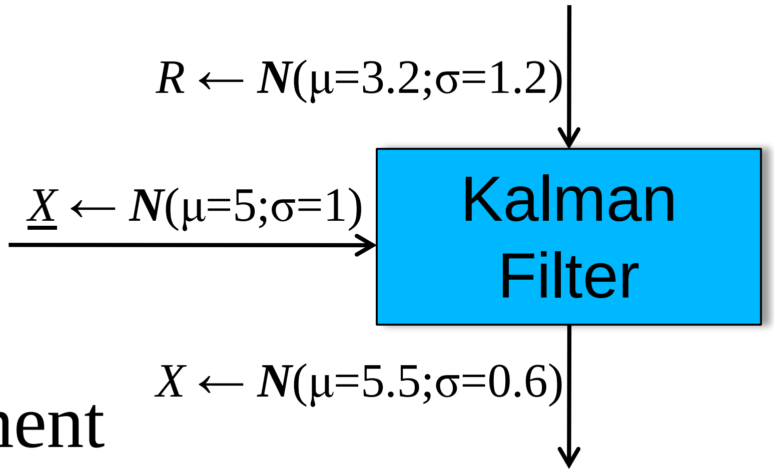
Sensor Fusion

- Given:
  - Position estimate $\underline{X} \leftarrow \boldsymbol{N}(\mu=5;\sigma=1)$
  - Range estimate $R \leftarrow \boldsymbol{N}(\mu=3.2;\sigma=1.2)$

  What is the best estimate AFTER incorporating r ?



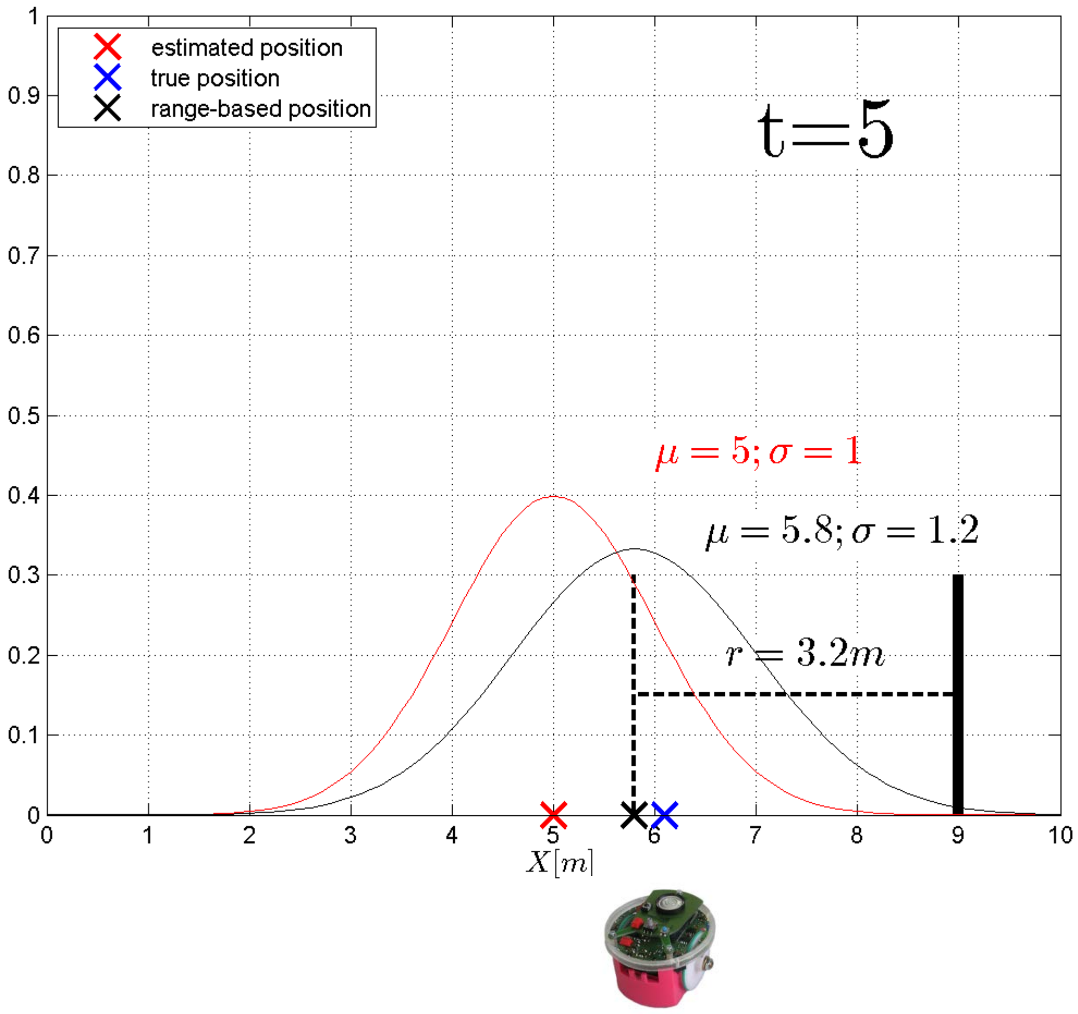
→ ***Kalman Filter***



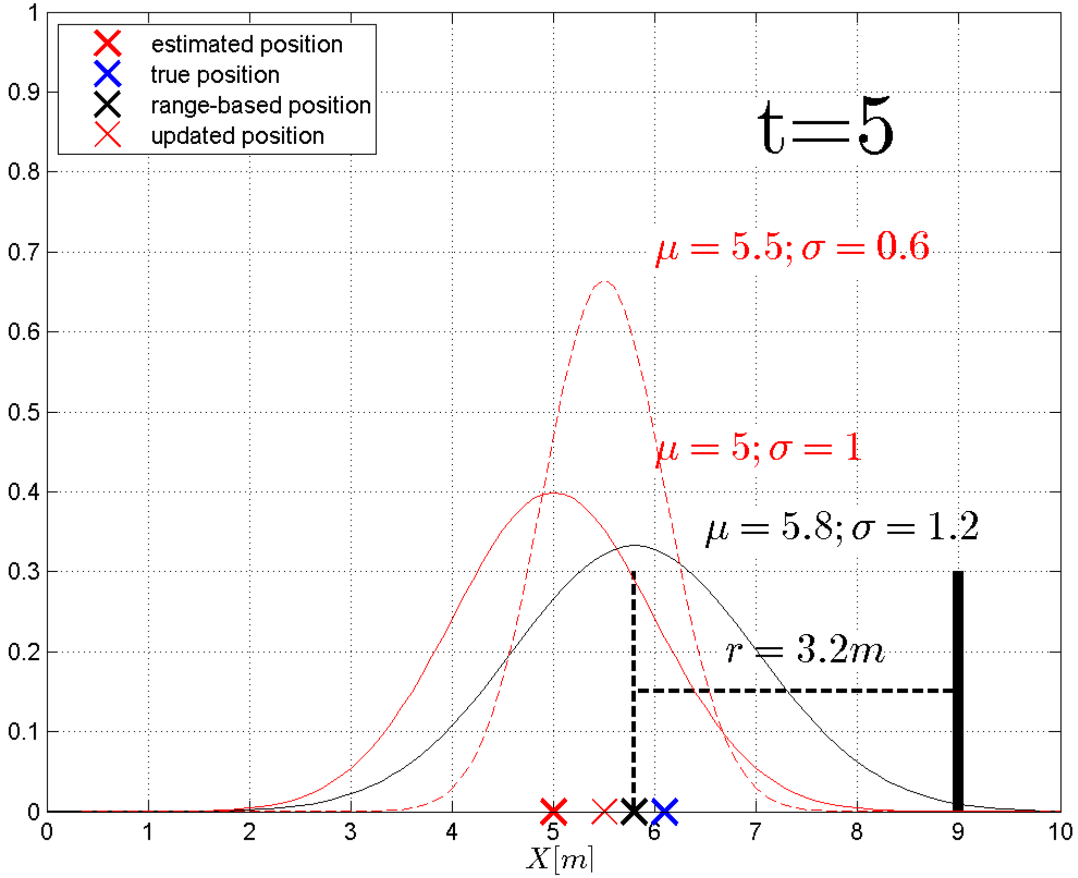
- Requires:
  - Gaussian noise distribution for all measurements
  - Linear motion and measurement model
  - …

http://www.cs.unc.edu/~welch/kalman/media/pdf/maybeck_ch1.pdf

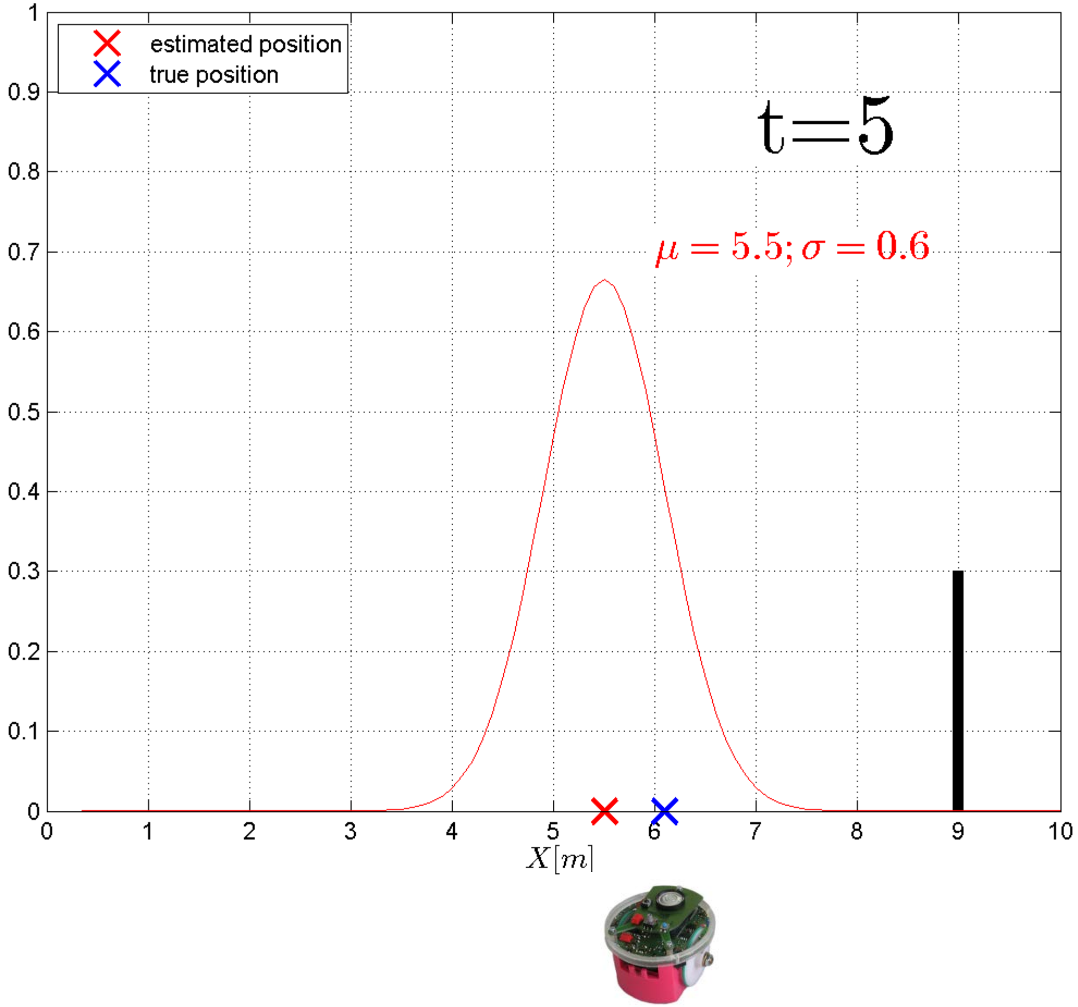
Feature-Based Navigation



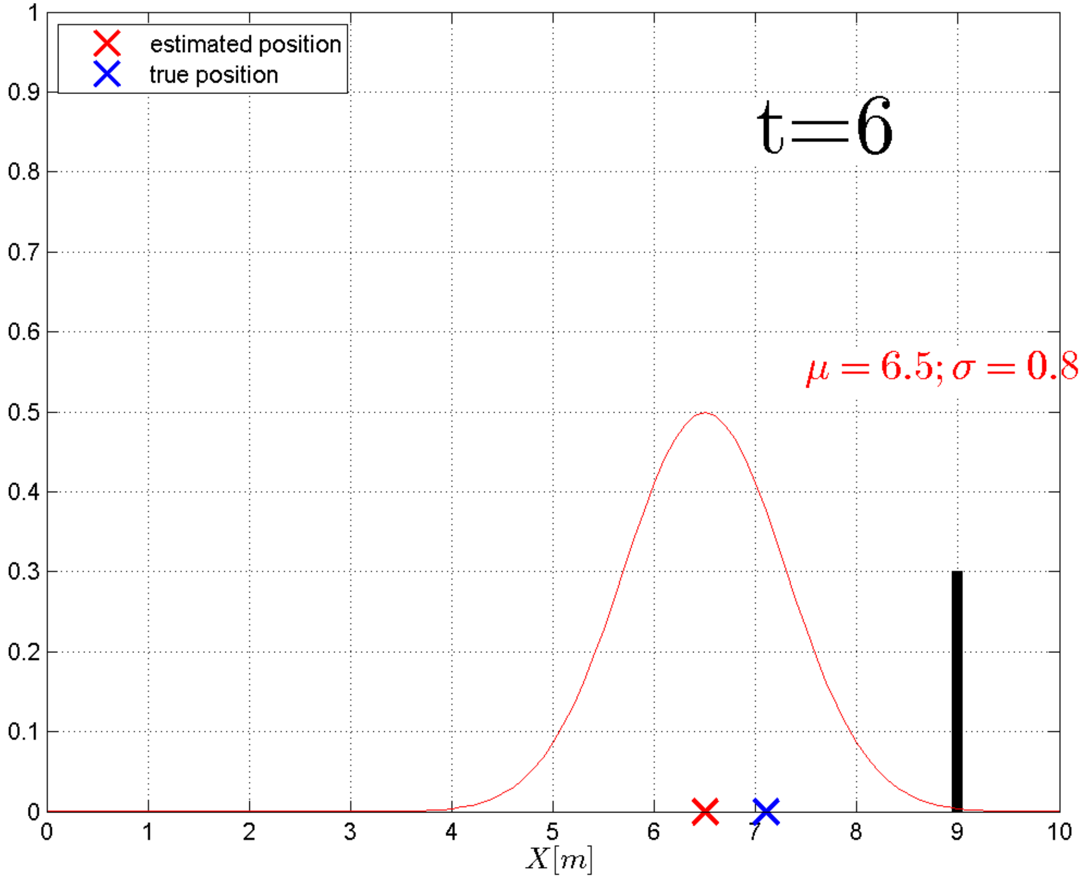
Feature-Based Navigation



Feature-Based Navigation



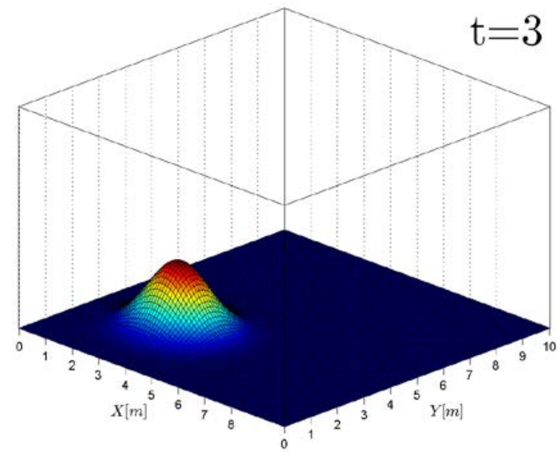
Feature-Based Navigation

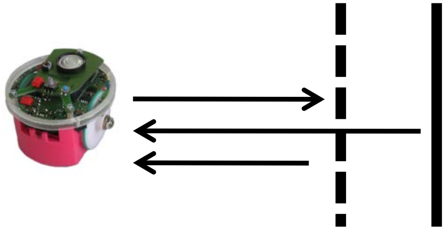


Feature-Based Navigation

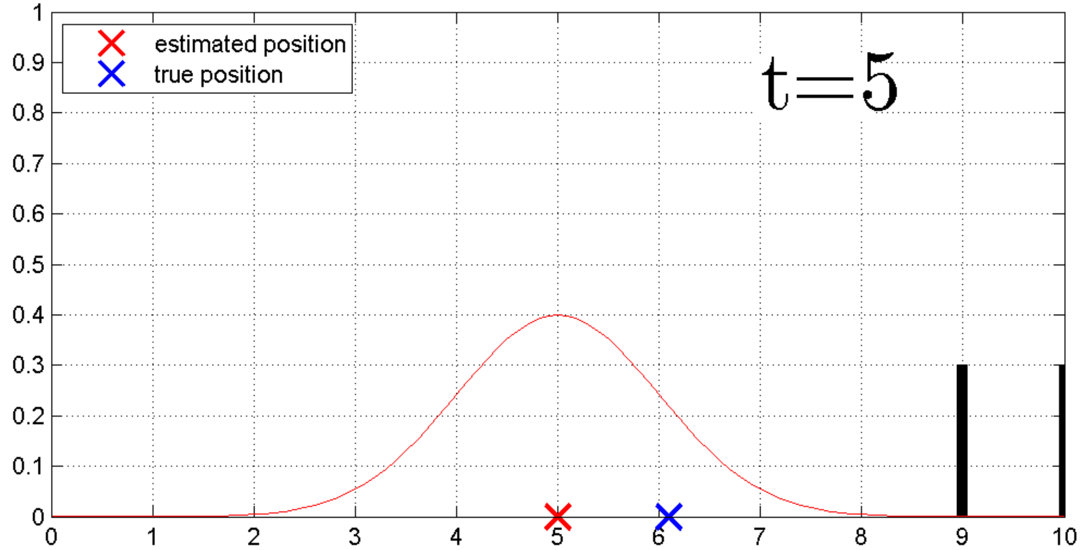
Belief representation through Gaussian distribution

- Advantages:
  - Compact (only mean and variance required)
  - Continuous
  - Powerful tools (Kalman Filter)
- Disadvantages:
  - Requires Gaussian noise assumption
  - Uni-modal
  - Cannot represent ignorance ("kidnapped robot problem")

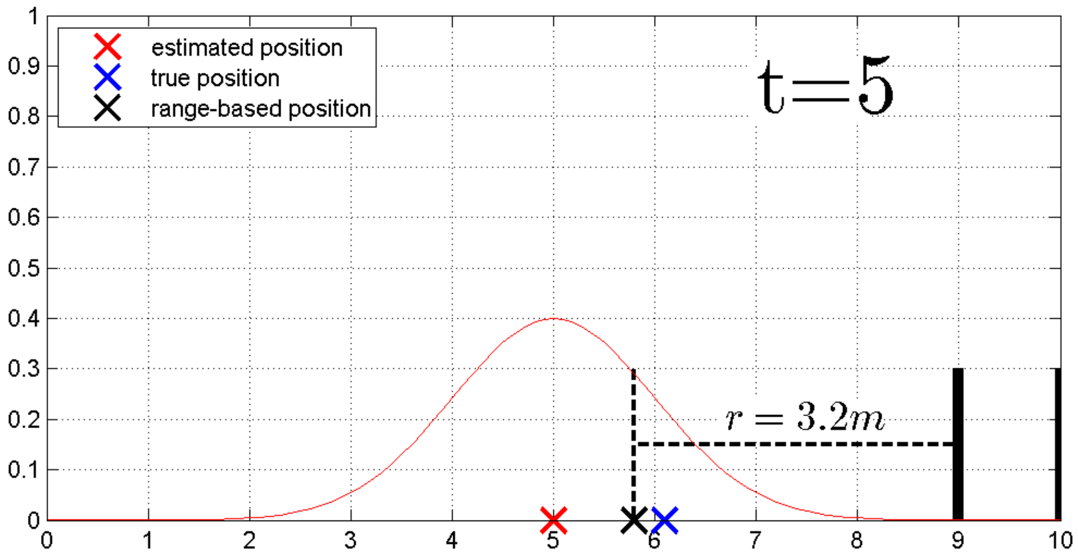




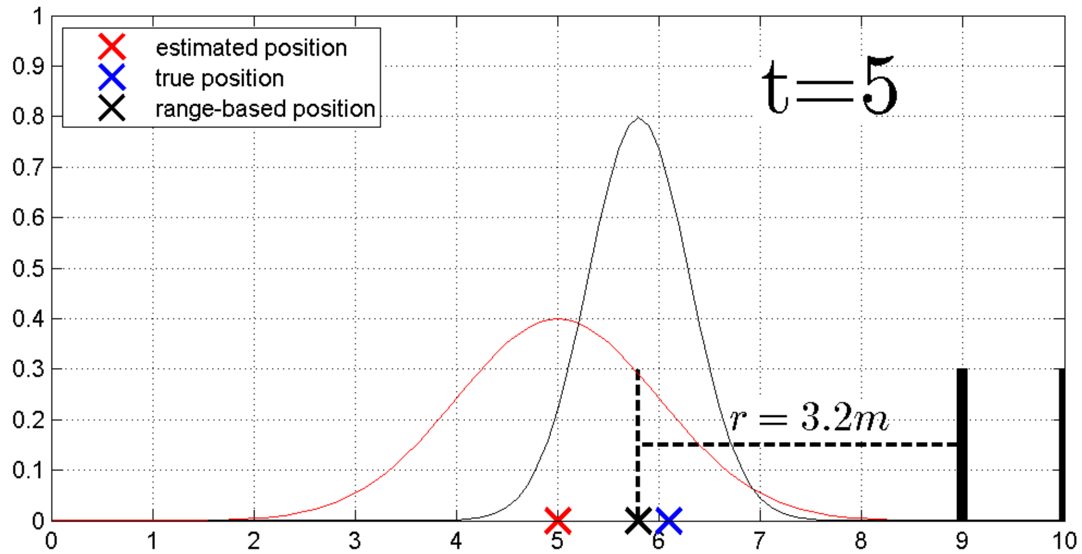
Feature-Based Navigation



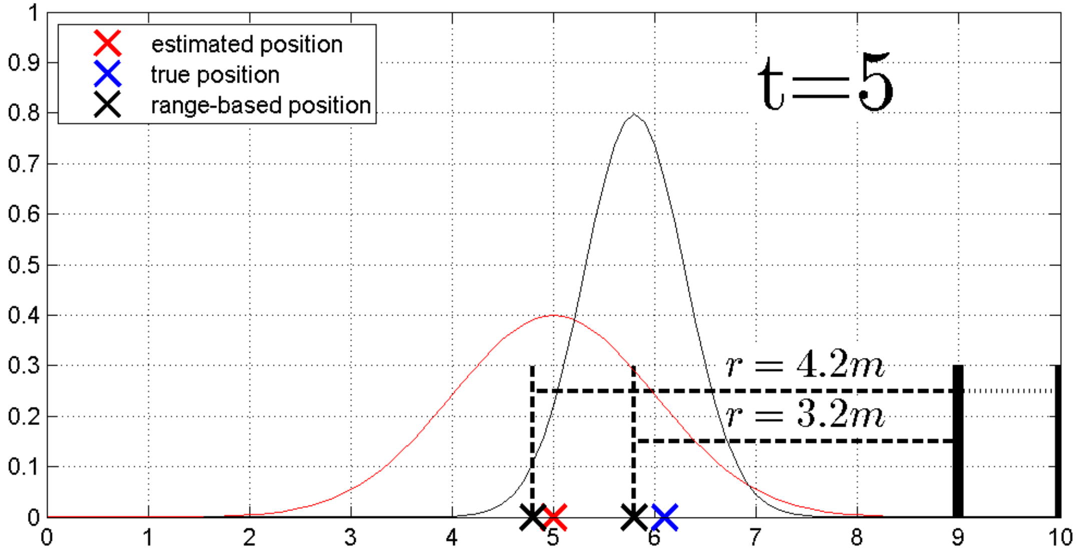
Feature-Based Navigation



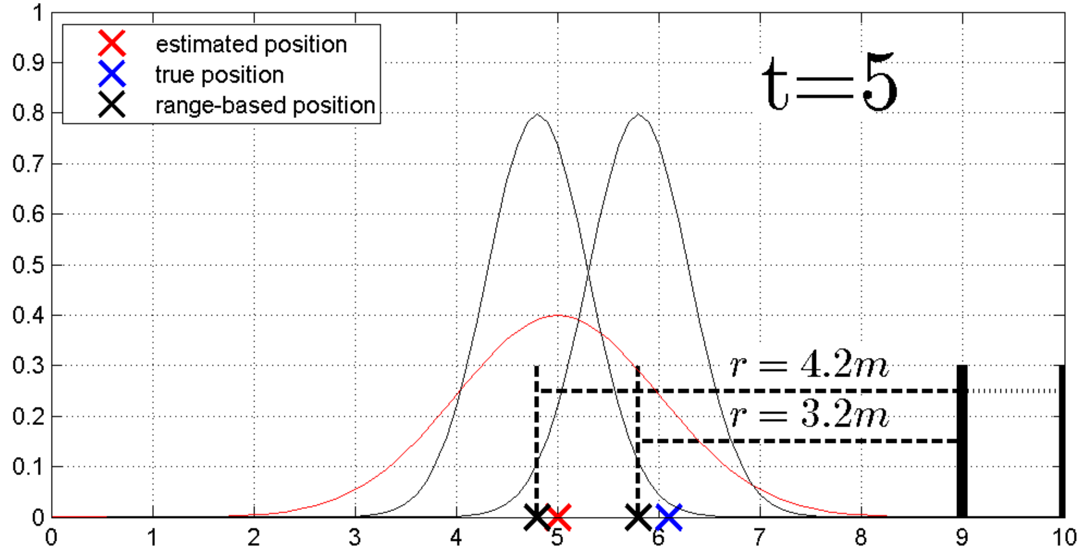
Feature-Based Navigation



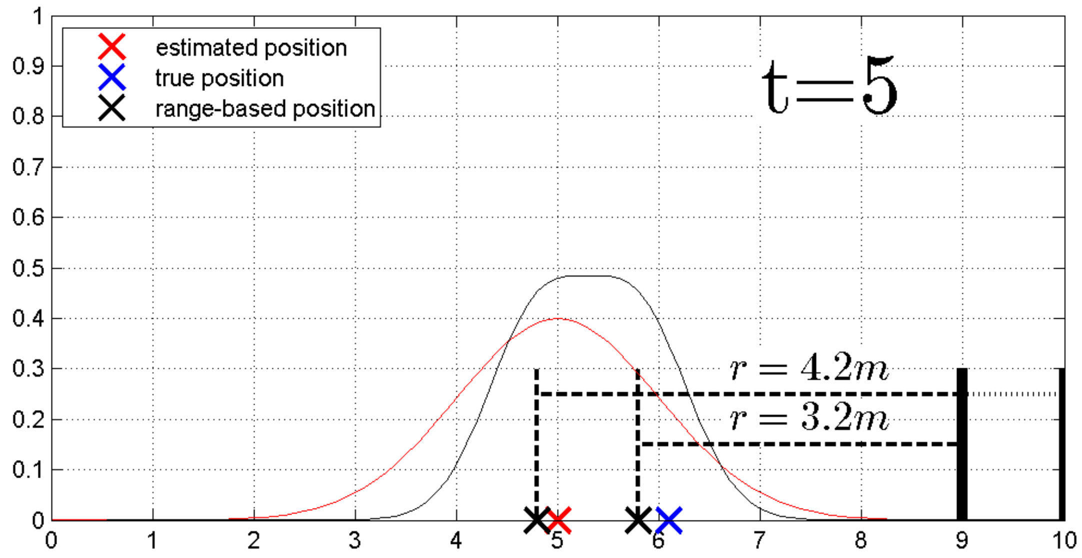
Feature-Based Navigation



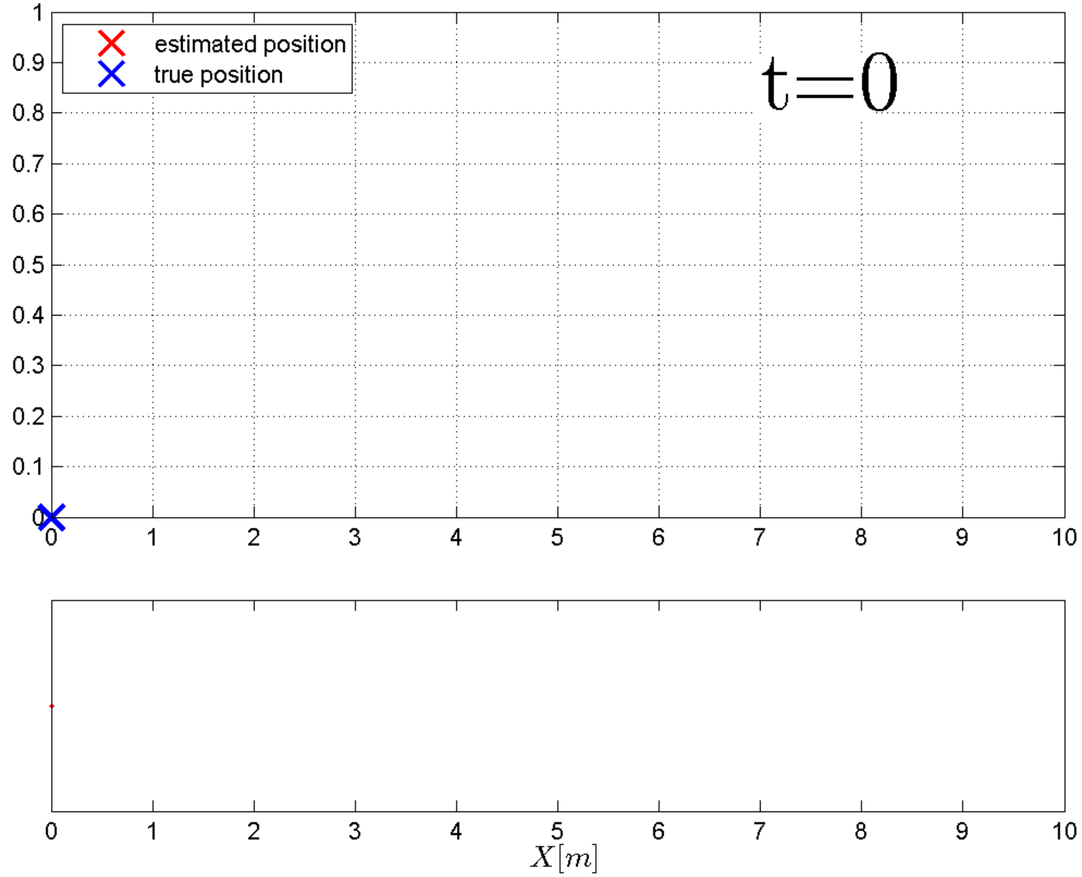
Feature-Based Navigation



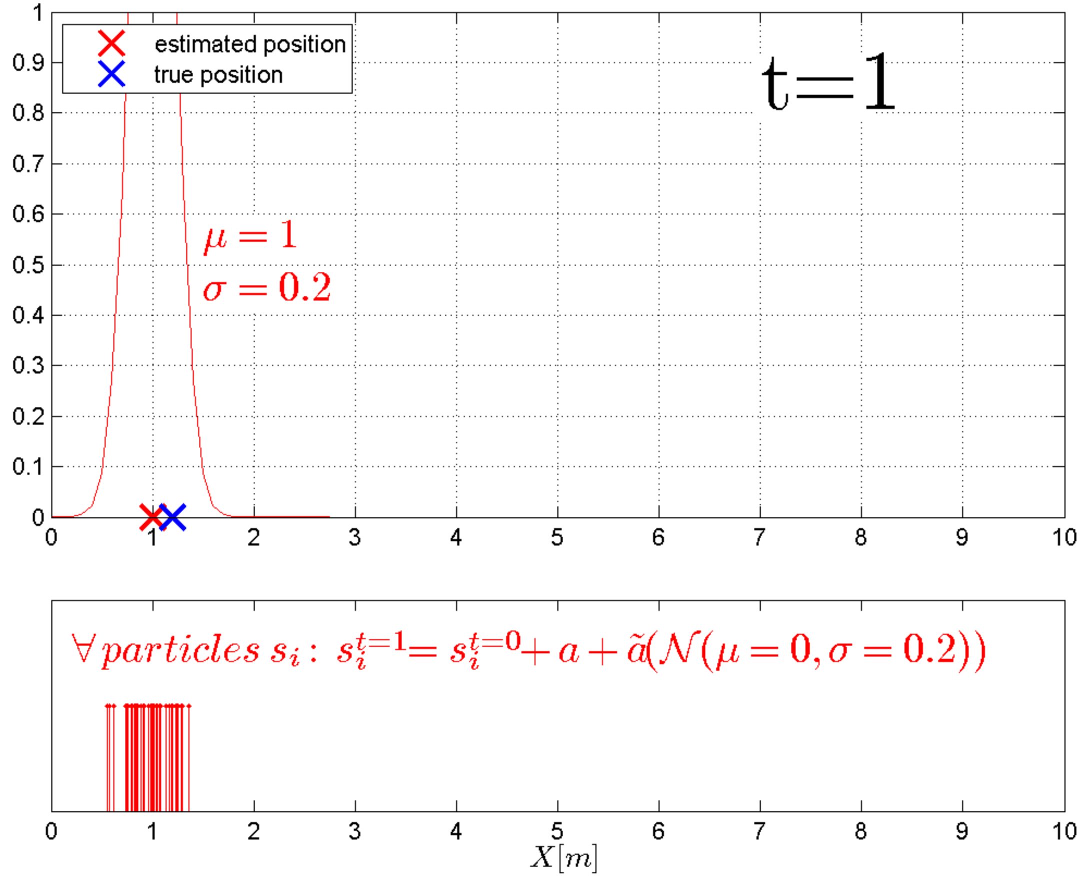
Feature-Based Navigation



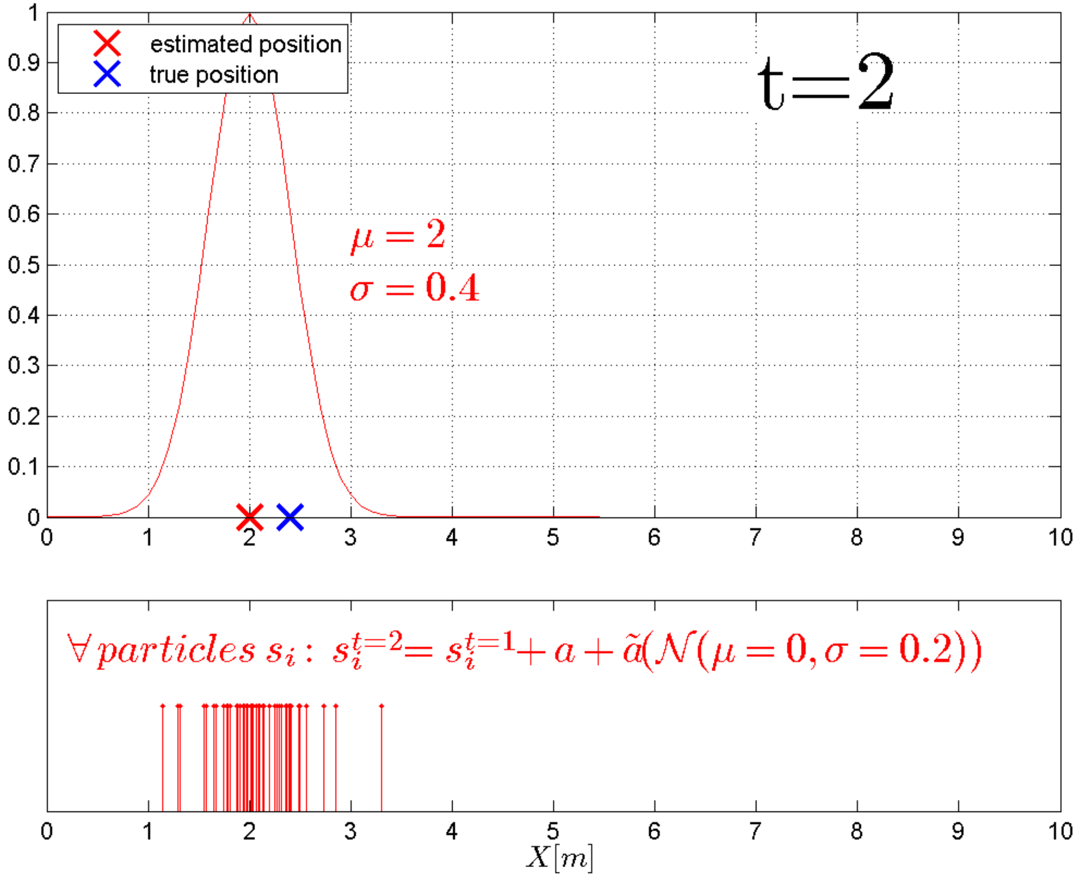
Feature-Based Navigation



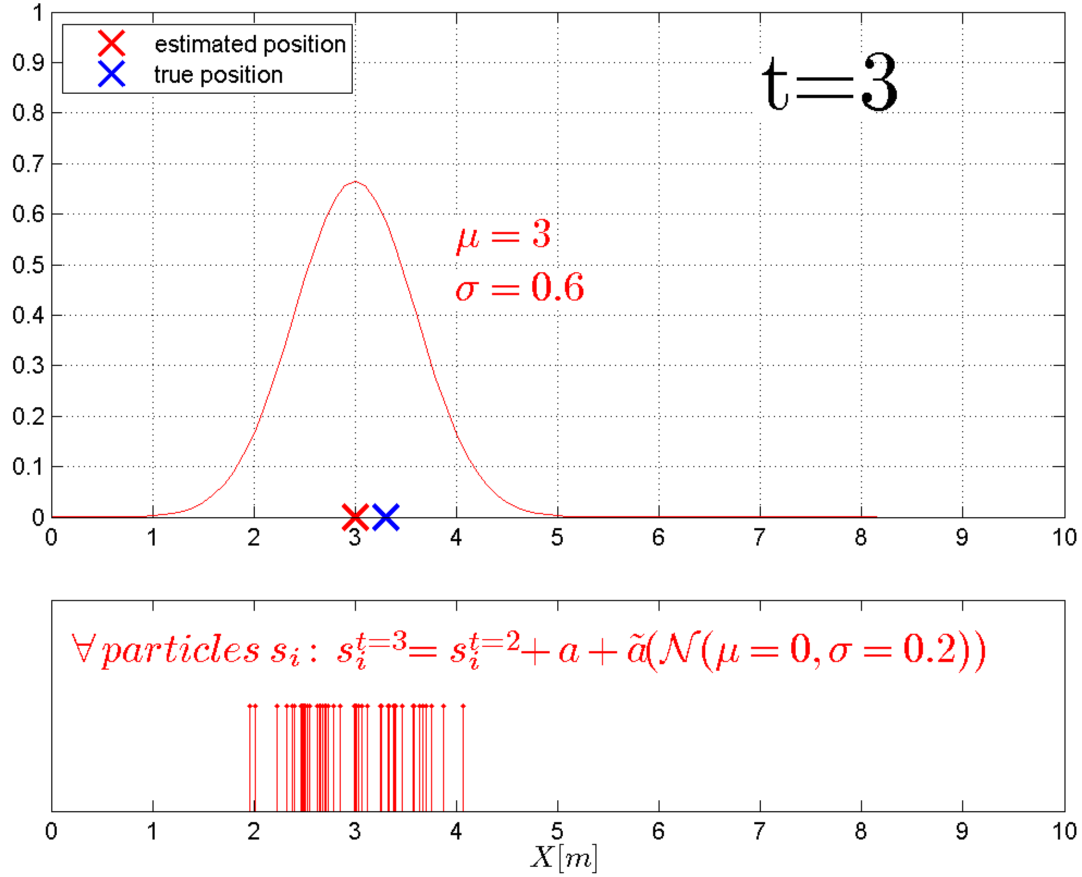
Feature-Based Navigation



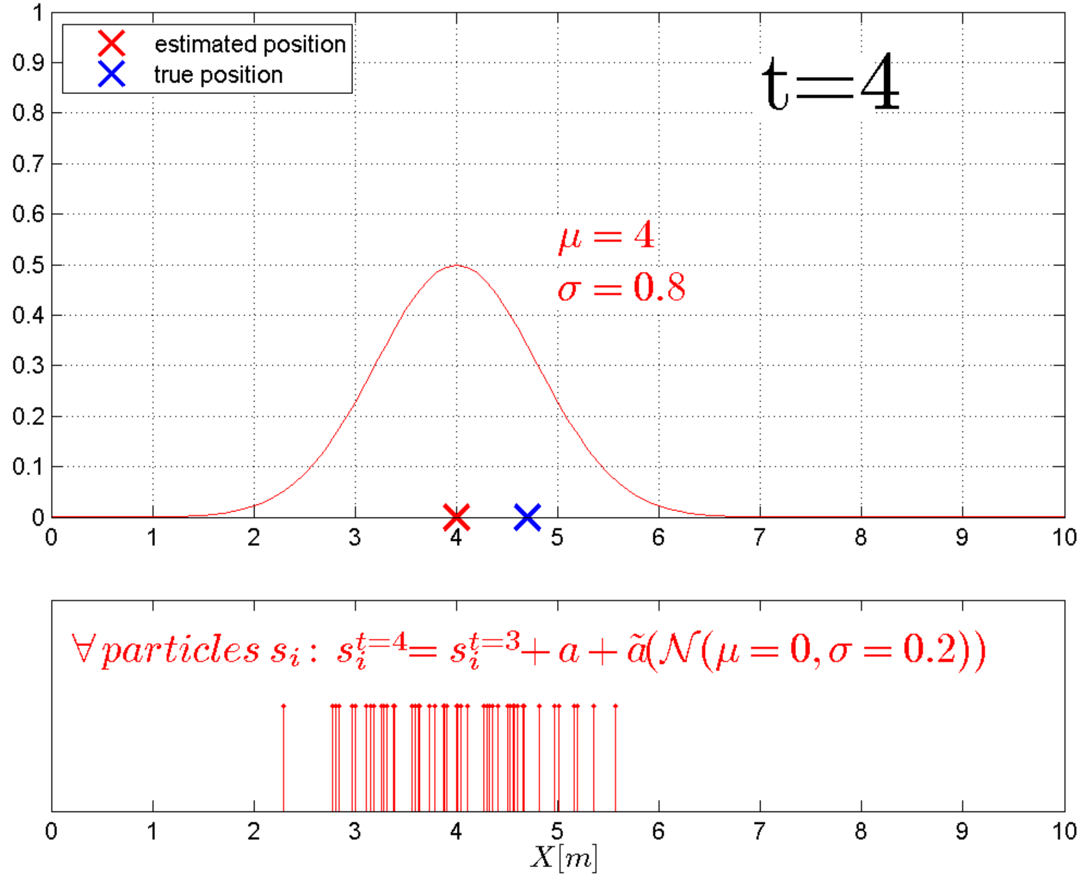
Feature-Based Navigation



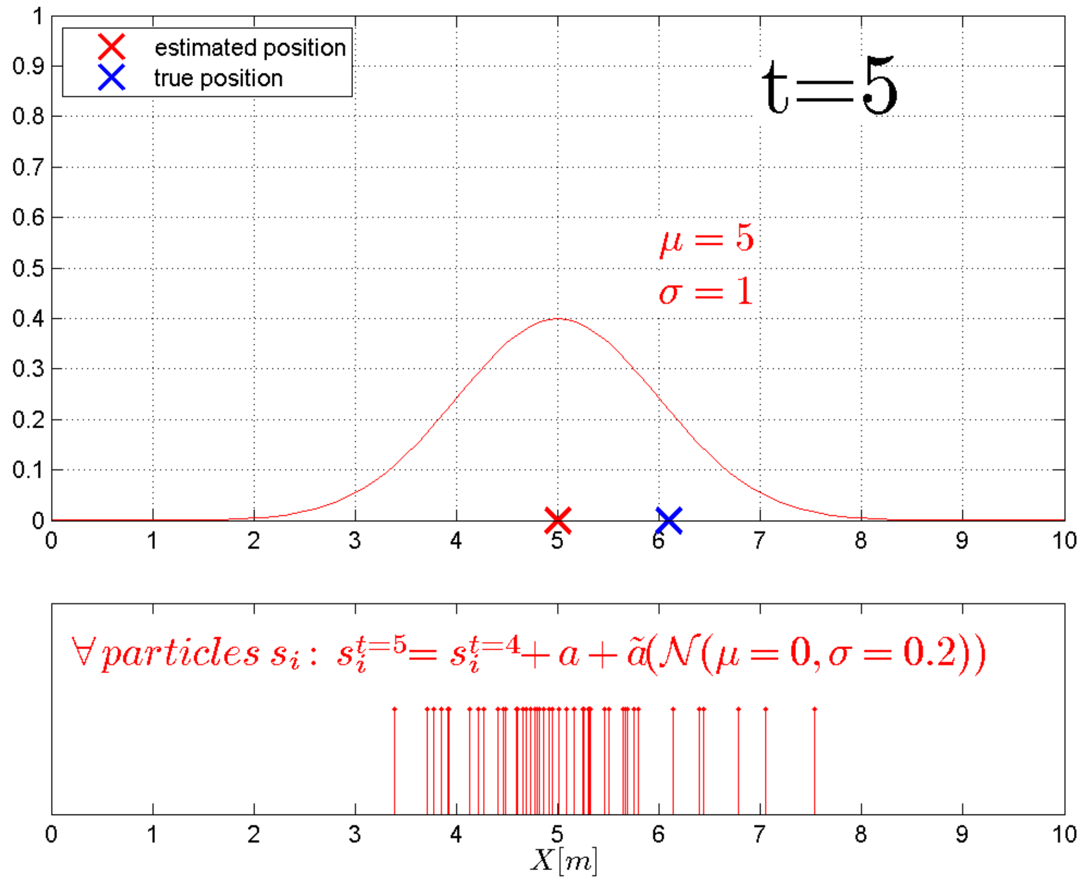
Feature-Based Navigation



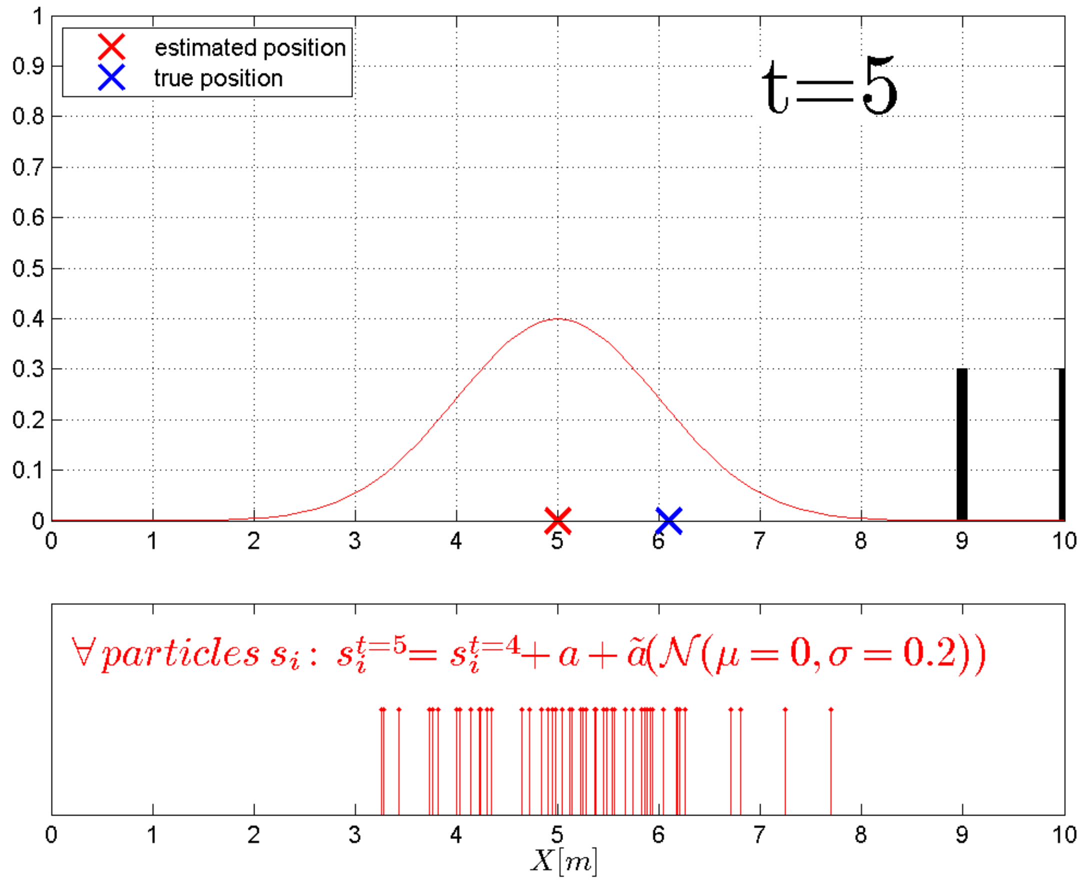
Feature-Based Navigation



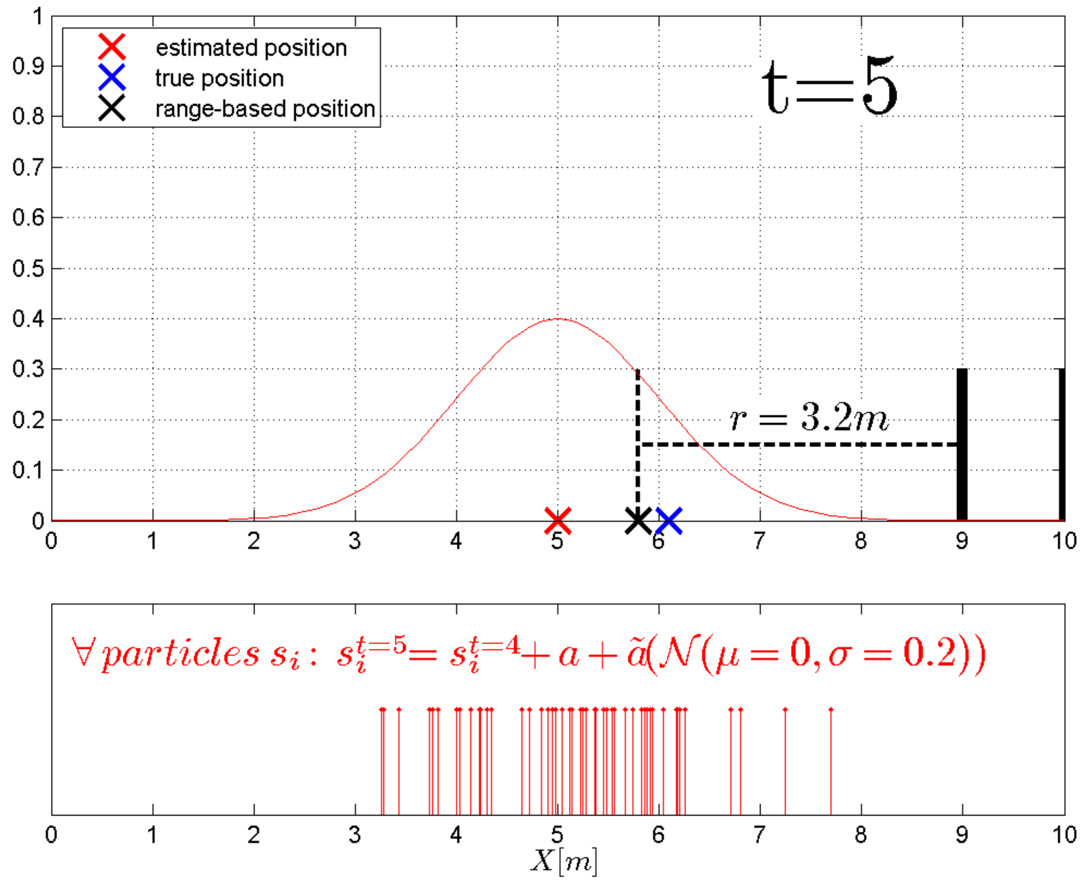
Feature-Based Navigation



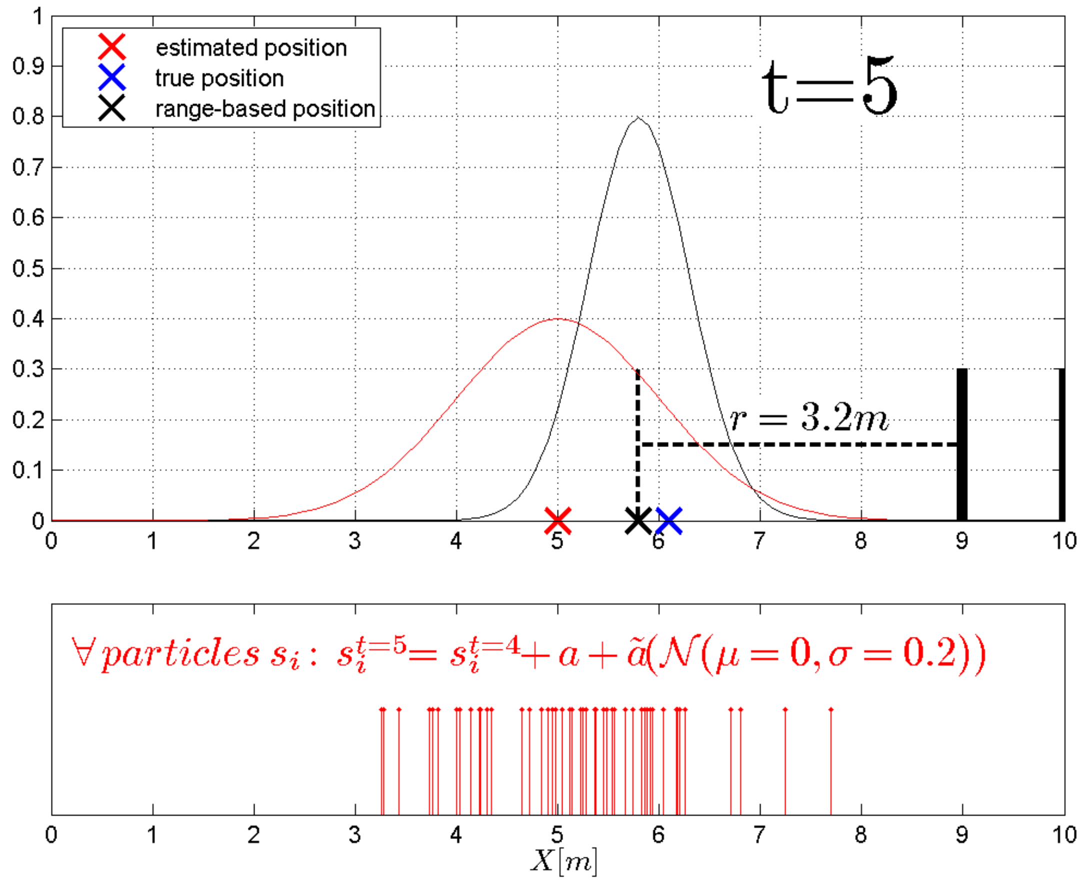
Feature-Based Navigation



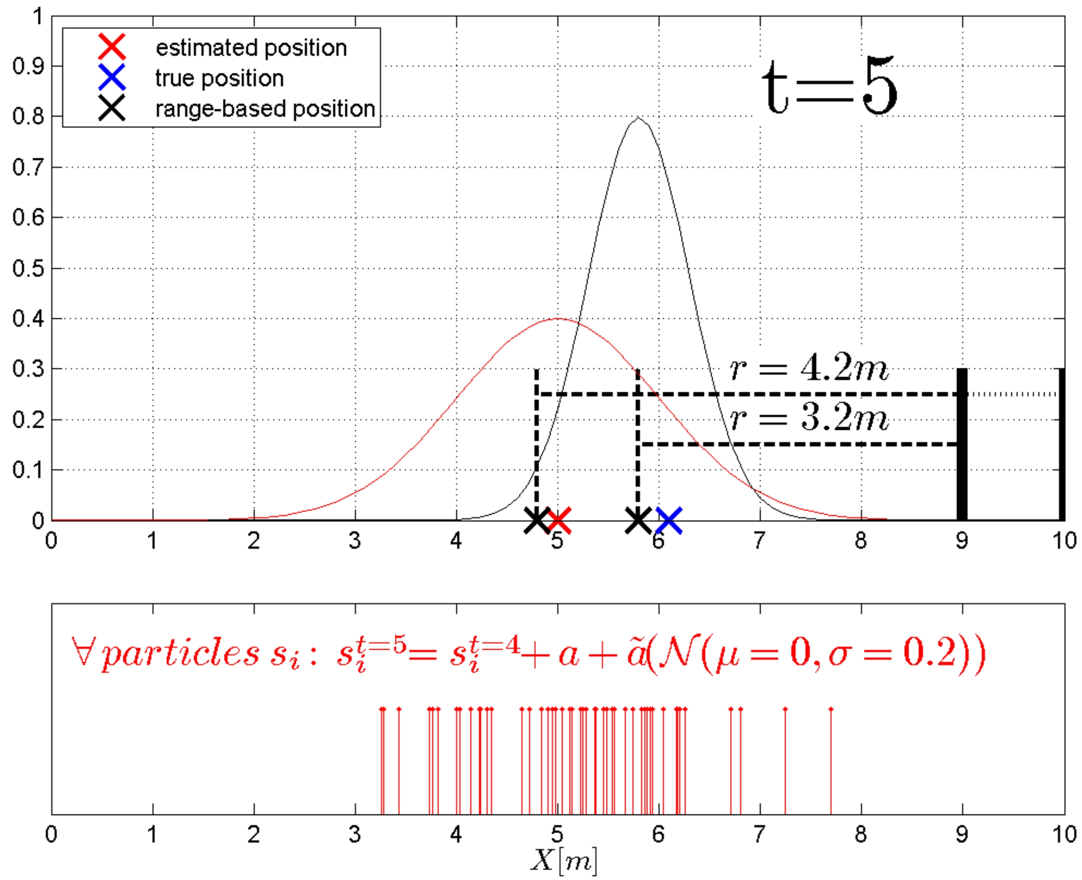
Feature-Based Navigation



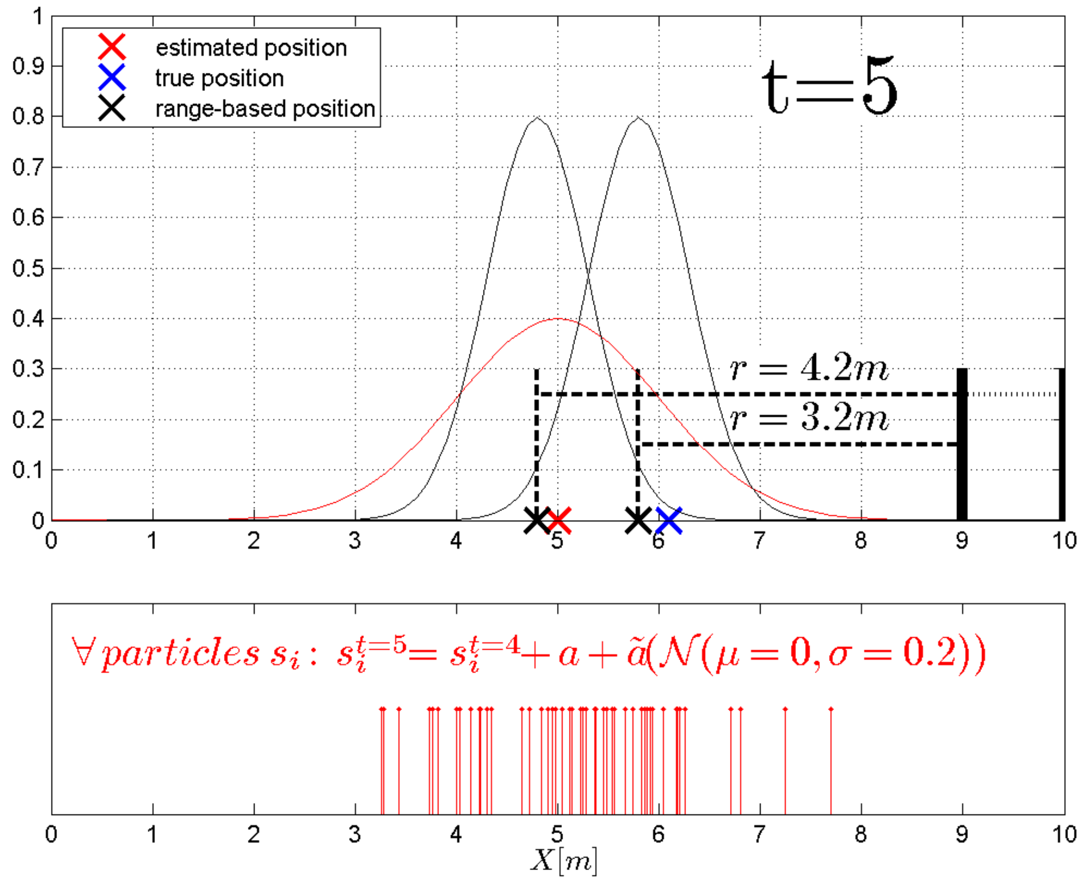
Feature-Based Navigation



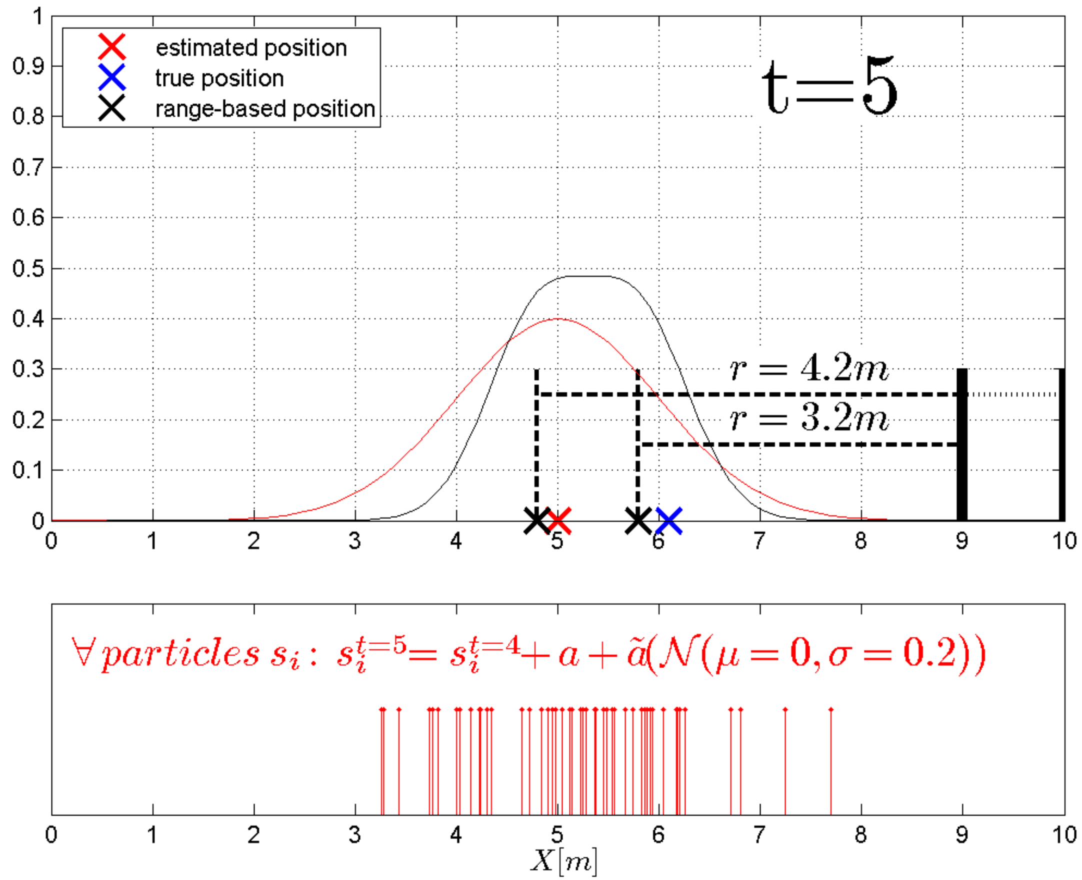
Feature-Based Navigation



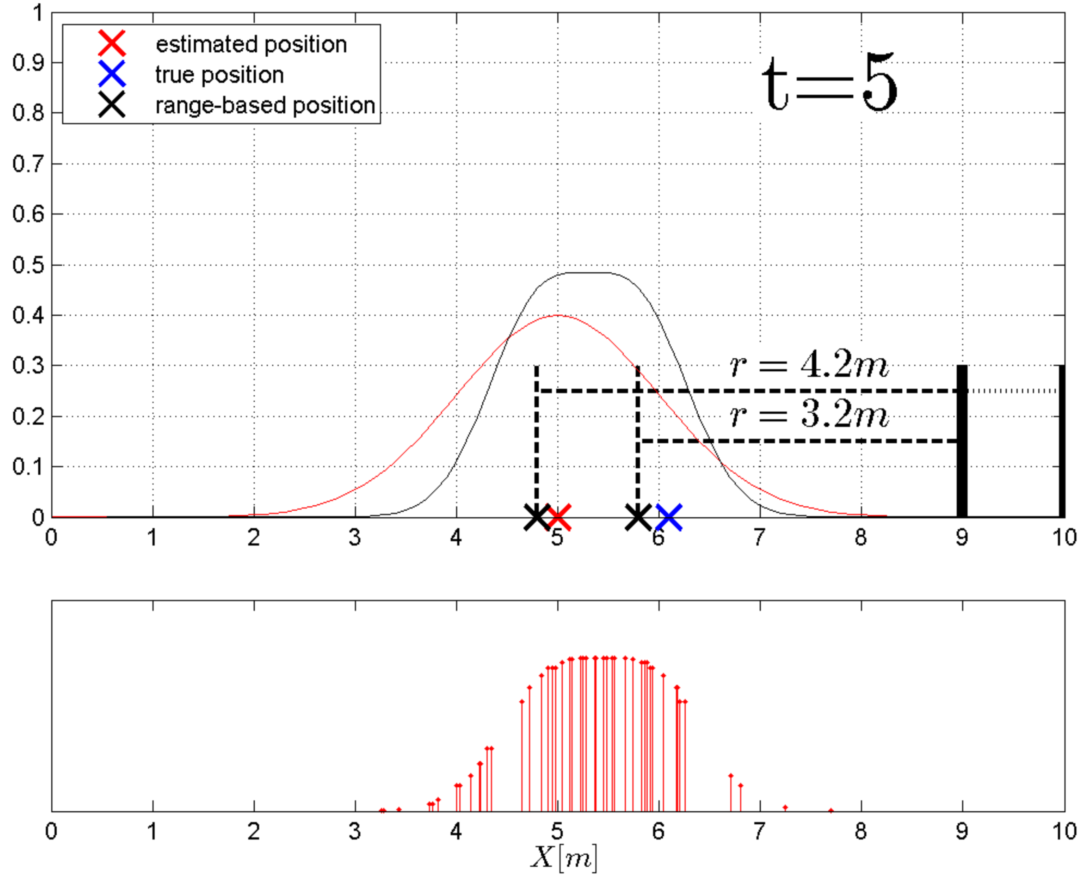
Feature-Based Navigation



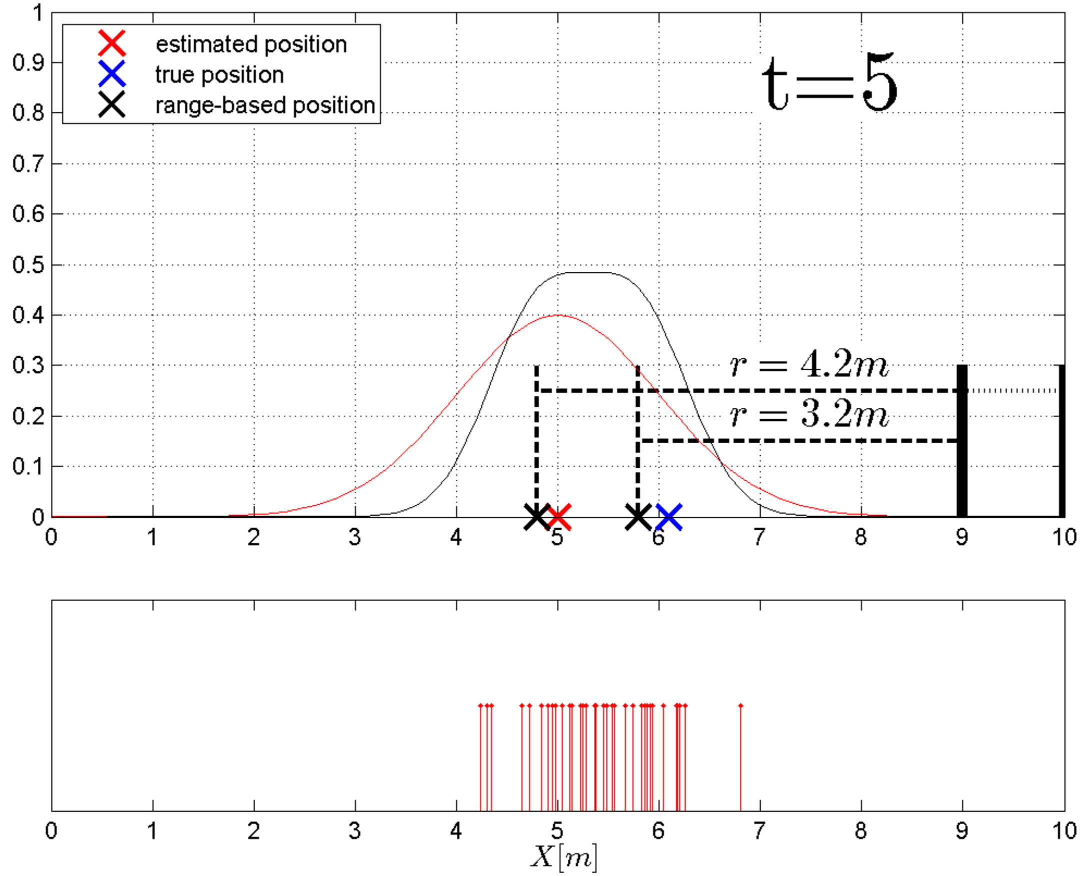
Feature-Based Navigation



Feature-Based Navigation



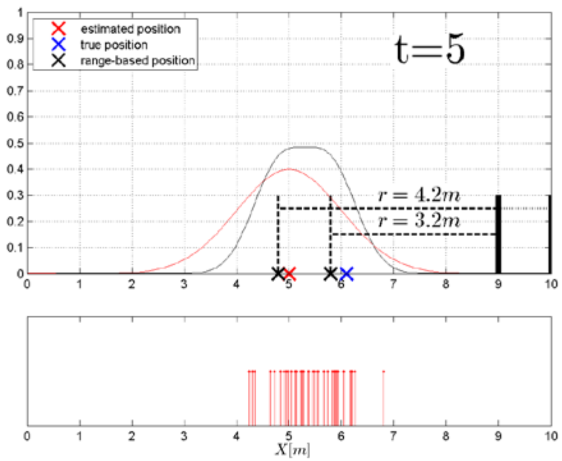
Feature-Based Navigation



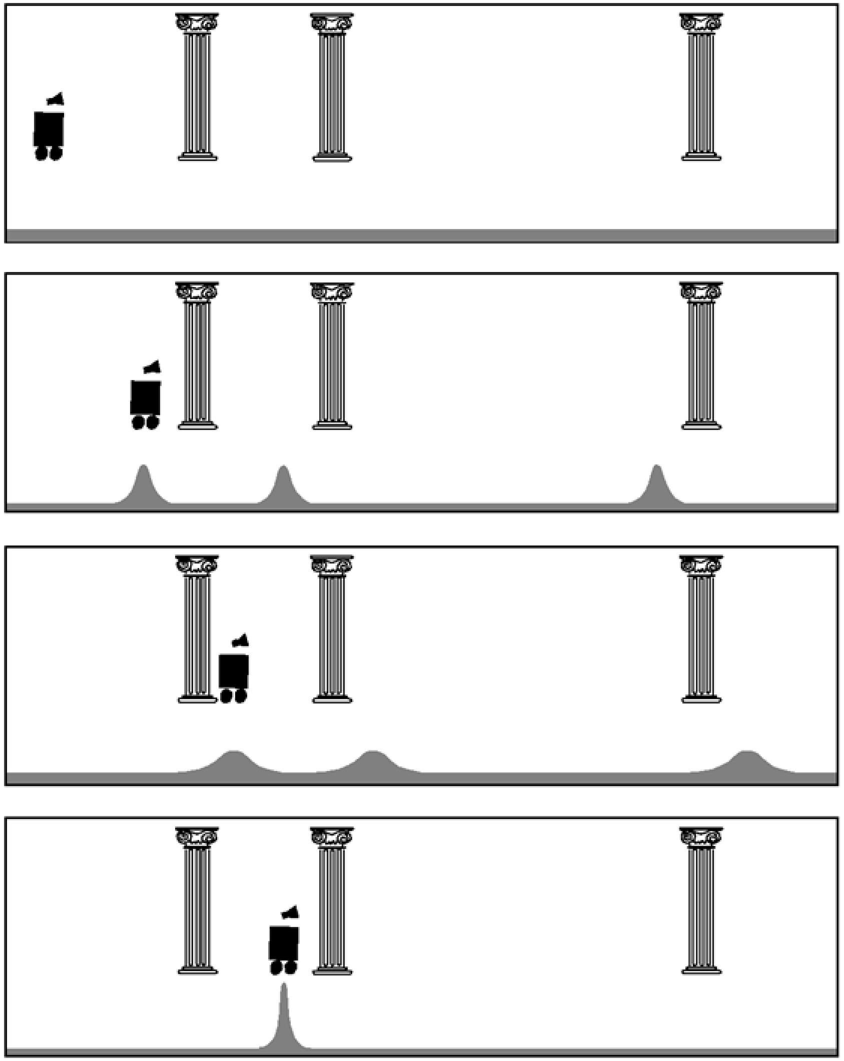
Feature-Based Navigation

Belief representation through particle distribution

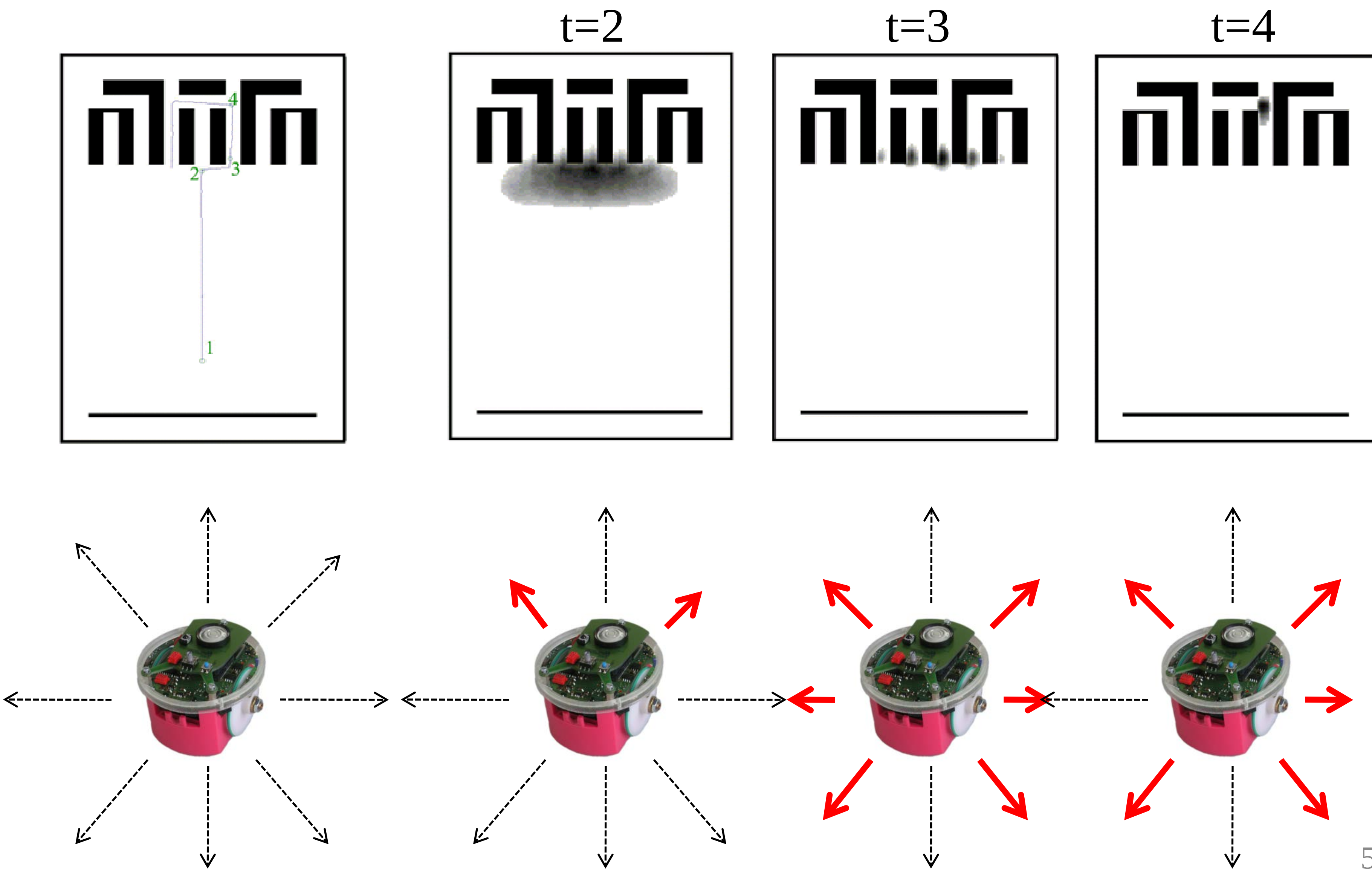
- Advantages:
  - Can model arbitrary beliefs
  - No assumptions on noise characteristic
- Disadvantages:
  - No unique solution
  - Not continuous
  - Computationally expensive
  - Tuning required



Feature-Based Navigation



Feature-Based Navigation



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 positioning method using only proprioceptive sensors but affected by a cumulative error
- Localization error can be modeled and estimated
- The error propagation methods/filtering techniques are tools applicable to a large variety of noisy problems, not just localization and navigation
- Feature-based navigation is a way to compensate odometry limitations

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Additional Literature – Week 4

Books

- Siegwart R., Nourbakhsh I. R., and Scaramuzza D., "Introduction to Autonomous Mobile Robots", MIT Press, 2011 (2nd edition).
- Choset H., Lynch K. M., Hutchinson S., Kantor G., Burgard W., Kavraki L., and Thrun S., "Principles of Robot Motion". MIT Press, 2005.
- Thrun S., Burgard W., and Fox D., "Probabilistic Robotics", MIT Press, 2005.