Autonomous Robot Navigation

Localization and Mapping Techniques for Mobile Robots

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Robots Intelligently Interacting With People
2006 ONASSIS LECTURE SERIES in COMPUTER SCIENCE

Autonomous Navigation
Problem Statement

The ability of robots to navigate safely and reliably within their environments

- Operation in industrial environments
- Tour-guiding visitors in museums/exhibition sites
- Helping in household tasks
- Exploring unfriendly environments
  (volcanoes, sewer systems, underwater)
- Space applications
- …. (the list goes on)

Historical Walkthrough

… in the beginning: Robotics in ancient times - Talos

… and then: a multitude of robotic systems; Industrial robots

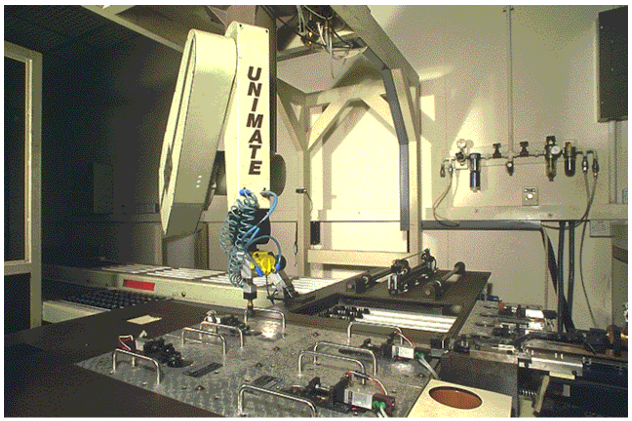
More Recently

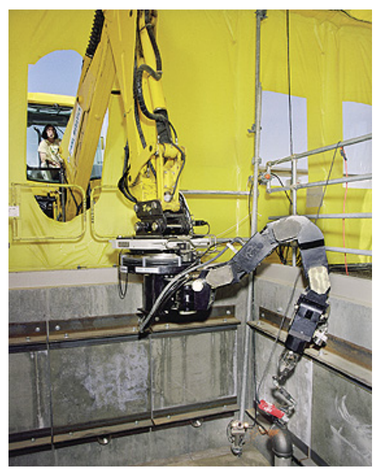
Trend towards intelligent systems

↓

Basic keyword: autonomous systems

Existing, non-autonomous systems…

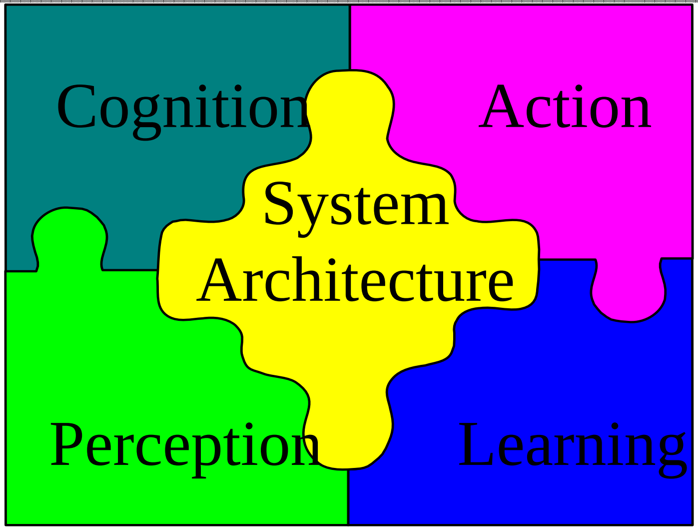




... and non-existent, fully autonomous robots

General research goal

Development of robotic systems able to exhibit autonomous behavior in complex and dynamic environments



An Interesting Research Area

Theoretical interest…

- **Mathematical and computational modeling of perception and action**

… with important applications

- **“Intelligent” robotic wheelchairs**
- **Robotic tour-guides in museums and exhibition sites**
- **Exploration of unknown and, possibly hostile, environments**
- **Routine tasks (surveillance, cleaning, etc)**

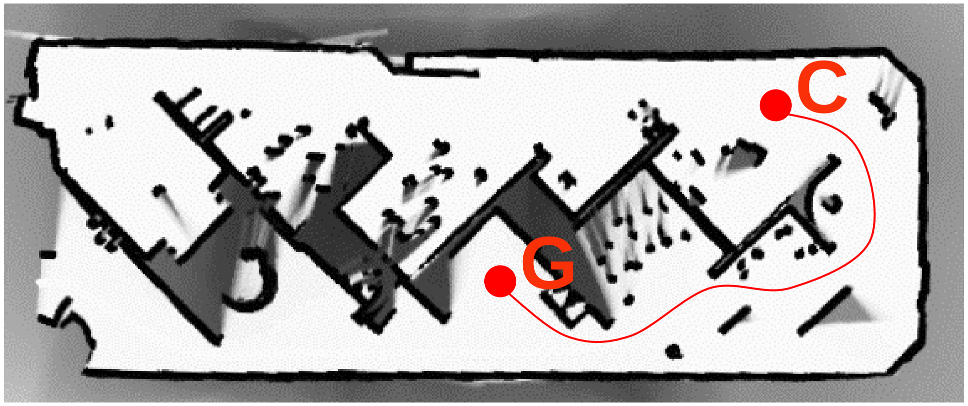
Research Directions

The above are based to a great extent on the ability of <u>autonomous navigation</u>

Autonomous Navigation Research Directions

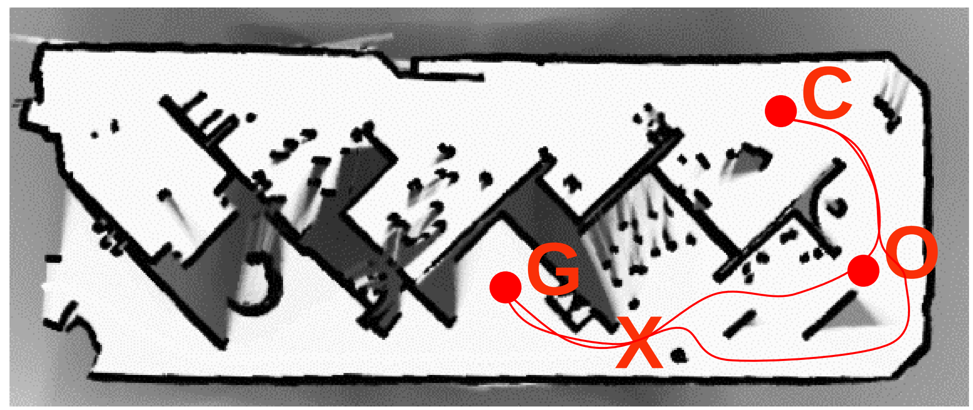
- Given
- An environment representation - Map
- Knowledge of current position C
- Target position G

- A path has to be planned and tracked that will take the robot from C to G



Autonomous Navigation Research Directions

- During execution (run-time)
- Objects / Obstacles O may block the robot
- The planned path is no-longer valid
- The obstacle needs to be avoided and the path may need to be re-planned

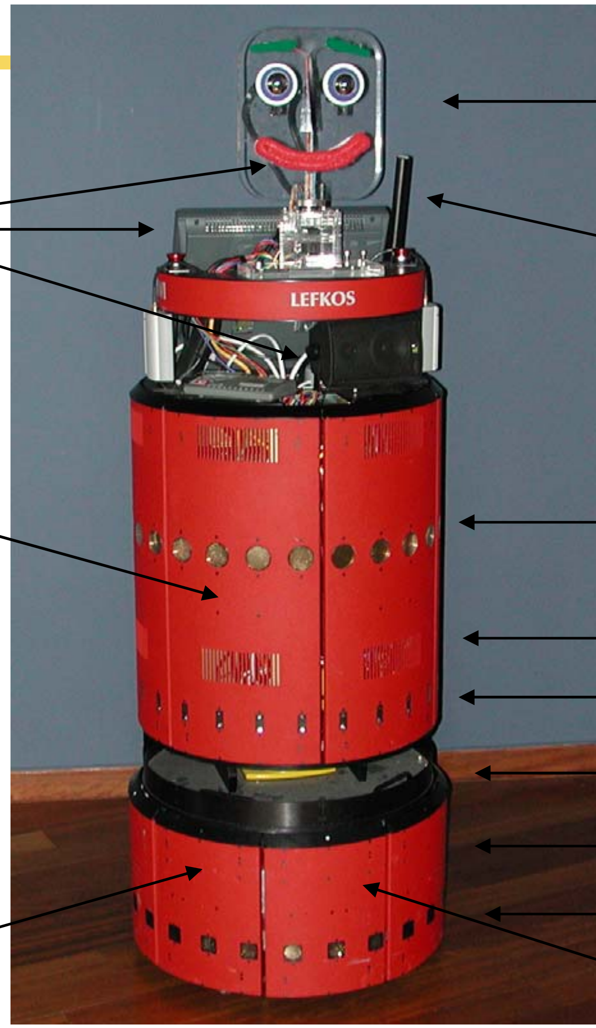


Navigation Issues

Important questions (Levitt et al '91)	*Important navigation issues*
Where am I	Robot localization
Where are other places relative to me	Map building
How do I get to other places from here	Path/m

Wednesday

Navigation Issues – Underlying HW



Interaction

Processing Power

Motors

Sensors

Stereo vision

Communications

Sonars

Bump sensors

Infrared sensors

Laser scanner

Laser Scanner

Bump sensors

Sonars

Odometry

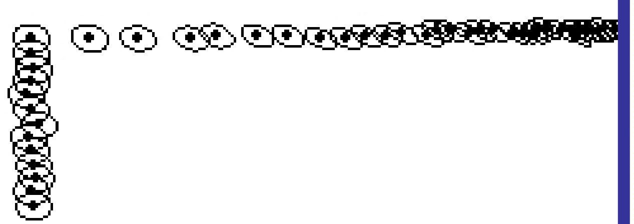
Range Sensor Model

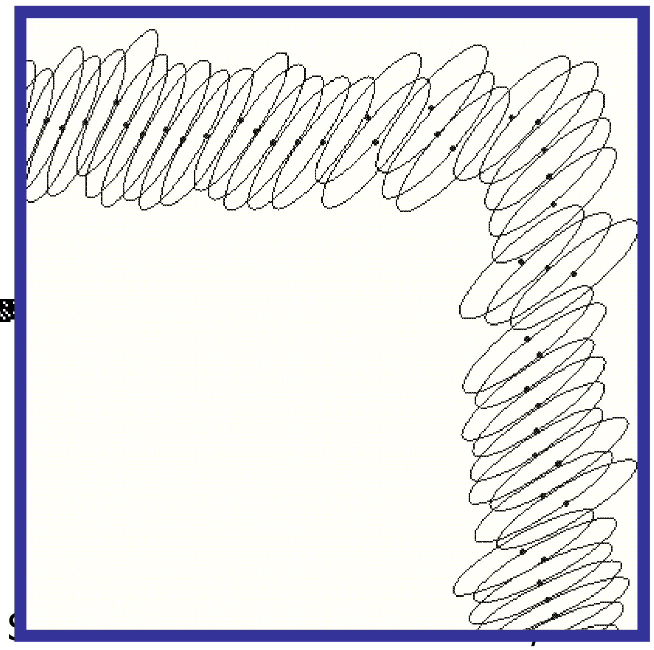
- Laser Rangefinder
- Model range and angle errors.

$$[x, y]^T = Exp\left(R(r,\phi)\right) = \left[r\cos(\phi), r\sin(\phi)\right]^T$$

$$\Sigma_{polar} = \begin{bmatrix} k_{\phi}\phi & 0 \\ 0 & k_{\rho_0} + k_{\rho_1} r \end{bmatrix}$$

$$\Sigma_p = \nabla R \Sigma_{polar} \nabla R^T$$





Need for Modeling

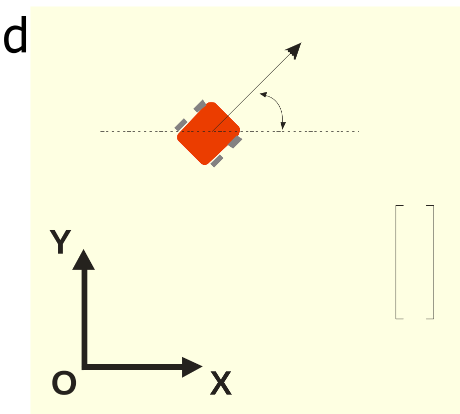
Robot
\+ Environment

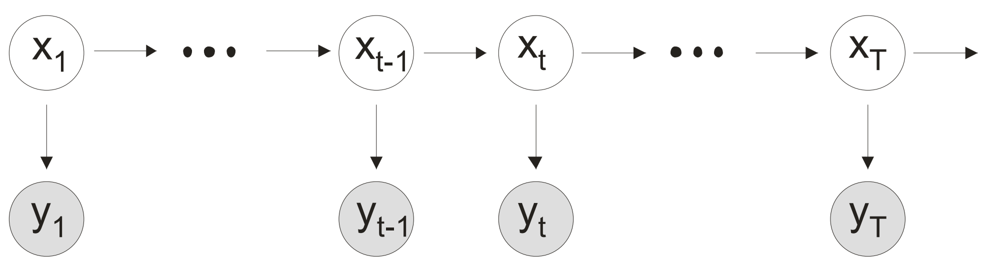
Extremely Complex
Dynamical System

⇨ Need for Appropriate Modeling

Markov Assumption

- State depends only on previous state and observations
- Static world assumption
- Hidden Markov Model (HMM)

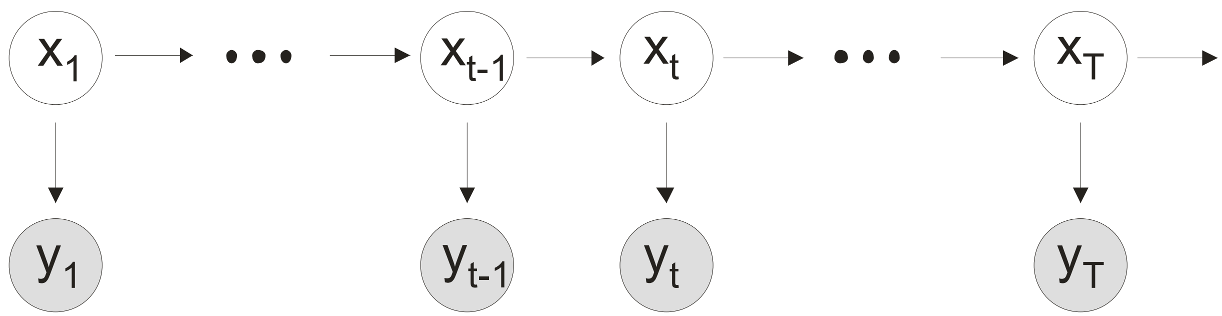




$$P\left(x_t \middle| y_1, y_2, \ldots, y_T\right) \Longrightarrow P(x_1)P\left(y_1 \middle| x_1\right)\prod_{t=2}^{T} P\left(x_t \middle| x_{t-1}\right)P\left(y_t \middle| x_t\right)$$

Bayesian estimation: Attempt to construct the posterior distribution of the state given all measurements

A Dynamic System



- Most commonly - Available:
  - Initial State $\mathbf{x}_1 \leftrightarrow P(\mathbf{x}_1)$
  - Observations $\mathbf{y}_1 .. \mathbf{y}_T$
  - System (motion) Model $\mathbf{x}_k = f_k(\mathbf{x}_{k-1}) \quad \leftrightarrow \quad p(\mathbf{x}_k \mid \mathbf{x}_{k-1})$
  - Measurement (observation) Model

$$\mathbf{y}_k = h_k(\mathbf{x}_k) \quad \leftrightarrow \quad p(\mathbf{y}_k \mid \mathbf{x}_k)$$

Inference - Learning

- Localization (inference task)
  Compute the probability that the robot is at pose z at time t given all observations up to time t (forward recursions only)

$$P\left(x_t = z \middle| y_1, y_2, \ldots, y_t\right)$$

- Map building (learning task)
  Determine the map m that maximizes the probability of the observation sequence.

$$m^* = \arg\max_m P\left(m \middle| y_1, y_2, \ldots, y_T\right)$$

Belief State

$$\boxed{P(x_t \mid y_1, y_2, \ldots, y_t)} = \frac{1}{c_t} P(y_t | x_t) \int_Z P(x_t | x_{t-1} = z) \boxed{P(x_{t-1} = z \mid y_1, y_2, \ldots, y_{t-1})} dz$$

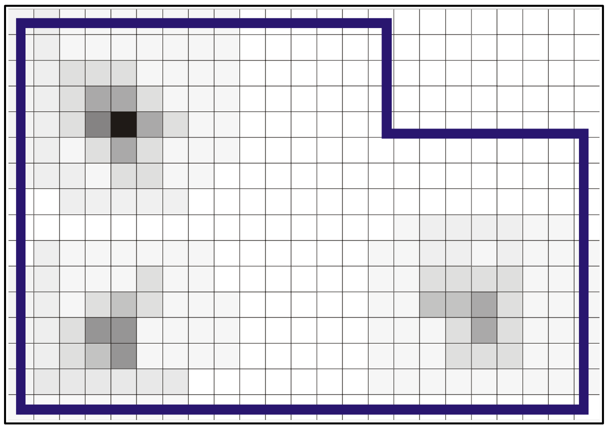
How is the posterior distribution calculated?	How is the prior distribution represented?

- Discrete representation
  - Grid (Dynamic) — (Dynamic) Markov localization (Burgard98)
  - Samples — Monte Carlo localization (Fox99)
- Continuous representation
  - Gaussian distributions — Kalman filters (Kalman60)

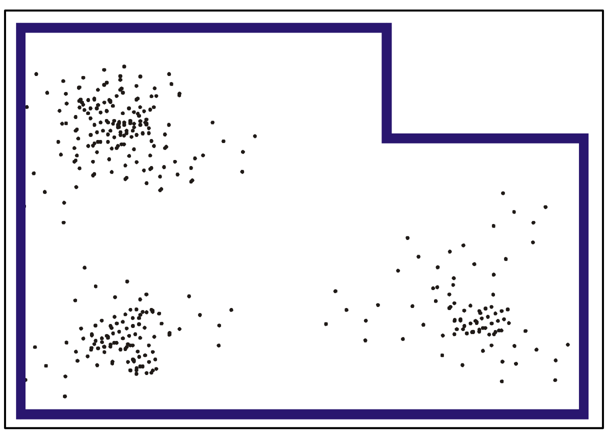
Example: State Representations for Robot Localization

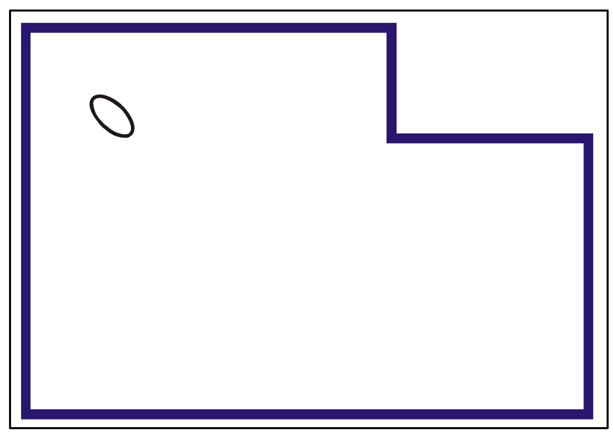
Discrete Representations | *Continuous Representations*

Grid Based approaches (Markov localization)



Particle Filters (Monte Carlo localization)





Kalman Tracking

Kalman Filters - Equations

$$\left.\begin{aligned} P(x_t | x_{t-1}) &\approx N(Ax_{t-1}, \Gamma) \\ P(y_t | x_t) &\approx N(Cx_t, \Sigma) \end{aligned}\right\}$$

A: State transition matrix (n x n)

C: Measurement matrix (m x n)

w: Process noise ($\in R^n$),

v: Measurement noise($\in R^m$)

$$\left.\begin{aligned} x_t &= A_t x_{t-1} + w_t \\ y_t &= C_t x_t + v_t \\ w_t &\approx N(0, \Gamma) \\ v_t &\approx N(0, \Sigma) \end{aligned}\right\}$$

Process dynamics (motion model)

measurements (observation model)

Where : $N(x; m, V) = \dfrac{1}{|2\pi V|^{1/2}} \exp\left(-\dfrac{1}{2}(x-m)^T V^{-1}(x-m) \right)$

Kalman Filters - Update

$$\left.\begin{aligned} x_t &= A_t x_{t-1} + w_t \\ y_t &= C_t x_t + v_t \\ w_t &\approx N(0, \Gamma) \\ v_t &\approx N(0, \Sigma) \end{aligned}\right\}$$

Predict

$$\hat{x}_t^- = A\hat{x}_{t-1}$$

$$P_t^- = AP_{t-1}A^T + \Gamma$$

Compute Gain

$$K_t = P_t^- C^T (CP_t^- C^T + \Sigma)^{-1}$$

Compute Innovation

$$J_t = \hat{y}_t - C\hat{x}_t^-$$

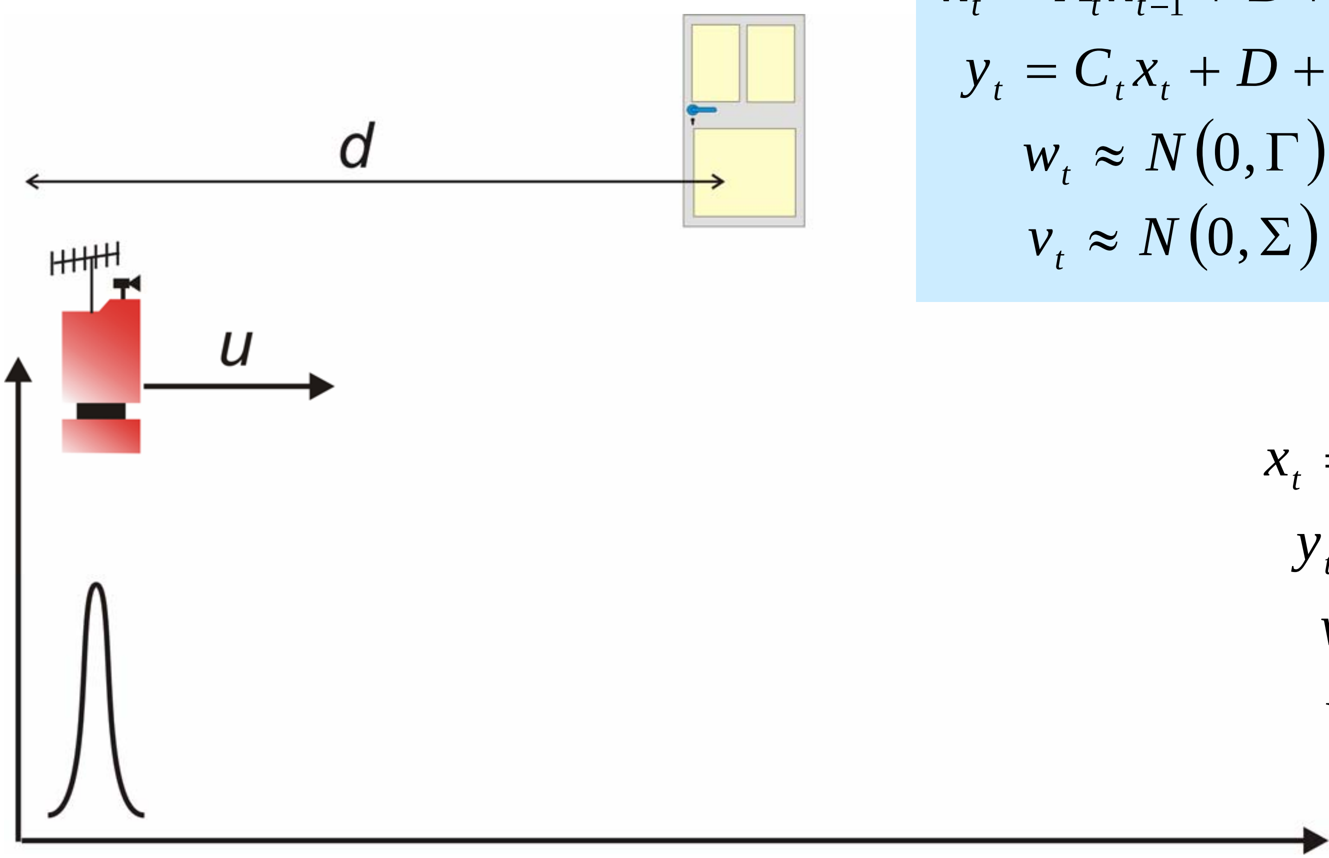
Update

$$\hat{x}_t = \hat{x}_t - \mathrm{K}_t J_t$$

$$P_t = (I - K_t C)P_k^-$$

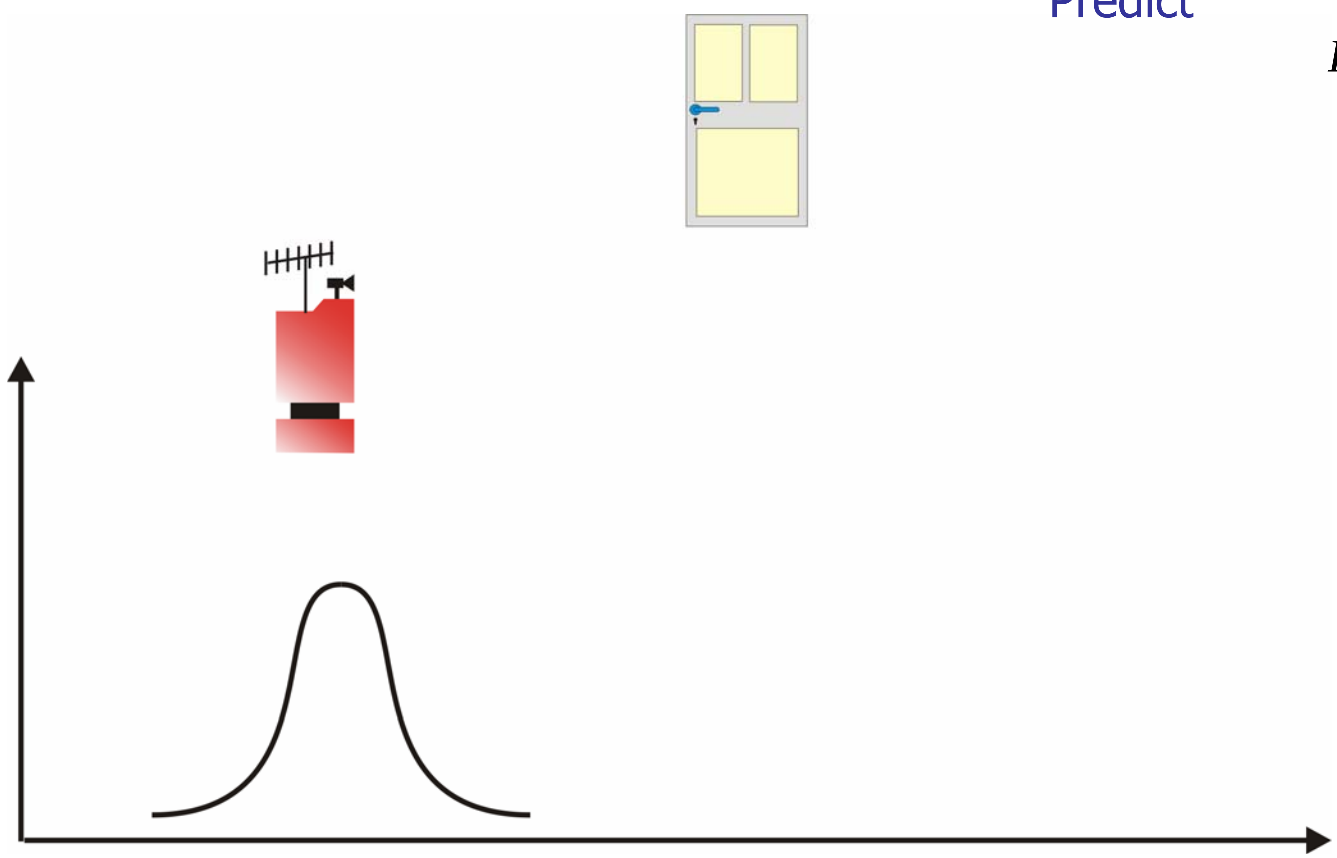
Kalman Filter - Example

$$
\begin{aligned}
x_t &= A_t x_{t-1} + B + w_t \\
y_t &= C_t x_t + D + v_t \\
w_t &\approx N(0, \Gamma) \\
v_t &\approx N(0, \Sigma)
\end{aligned}
\qquad
\begin{aligned}
A_t &= [1] \\
B_t &= [u_t] \\
C_t &= [-1] \\
D_t &= [1]
\end{aligned}
$$



$$
\left.
\begin{aligned}
x_t &= x_{t-1} + u_t + w_t \\
y_t &= d - x_t + v_t \\
w_t &\approx N(0, \Gamma) \\
v_t &\approx N(0, \Sigma)
\end{aligned}
\right\}
$$

Kalman Filter - Example



Predict

$$\hat{x}_t^- = A\hat{x}_{t-1} + B$$

$$P_t^- = AP_{t-1}A^T + \Gamma$$

Kalman Filter - Example

Predict

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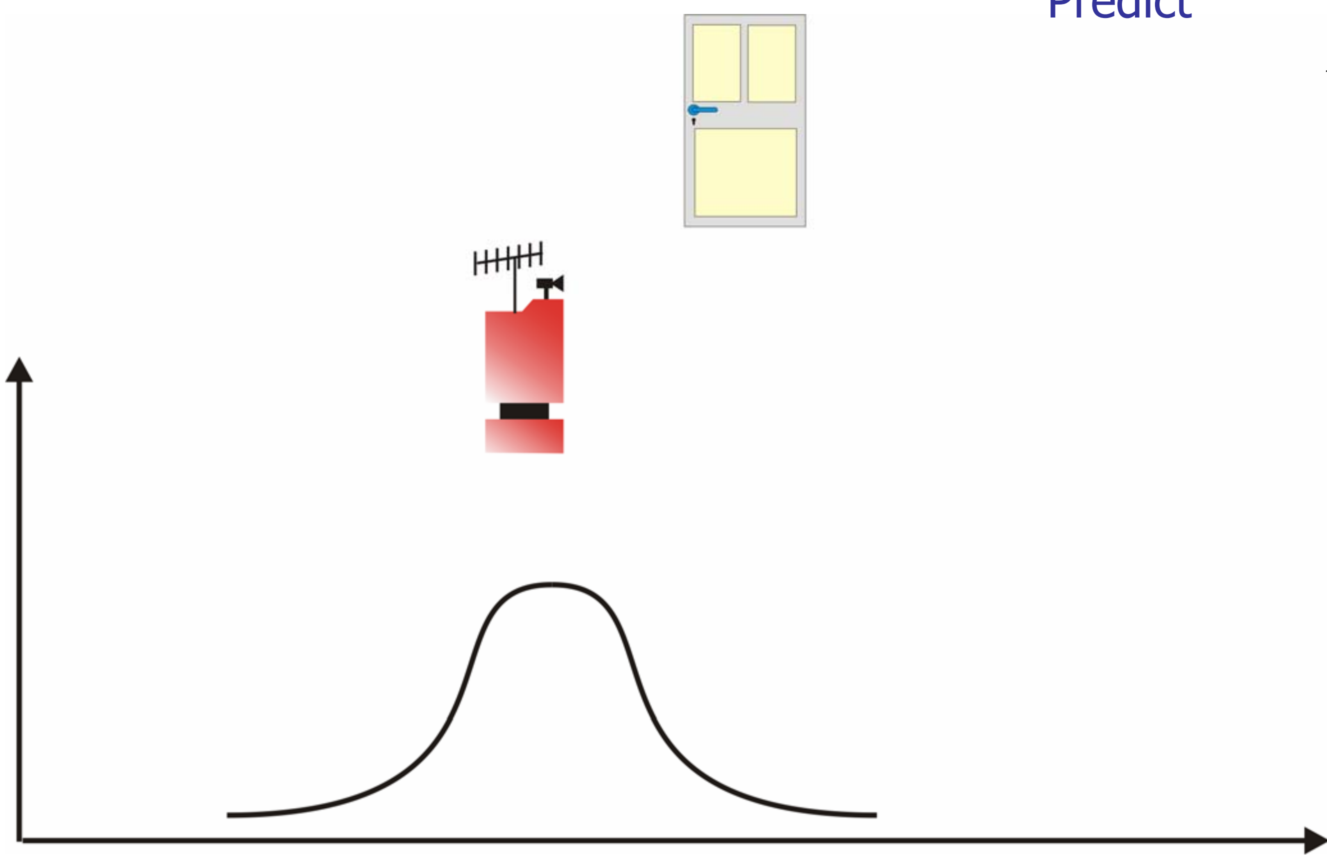
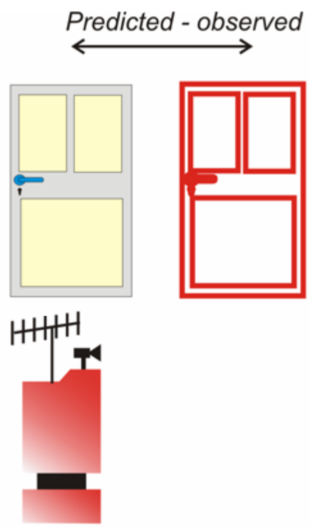


Kalman Filter - Example



Predict

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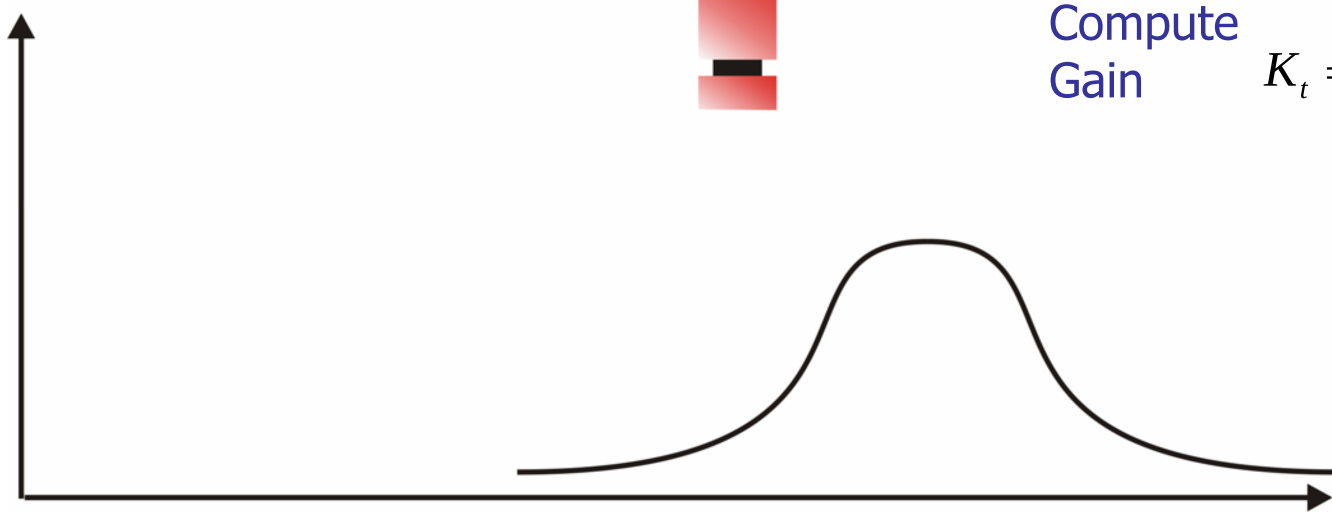
Compute Innovation

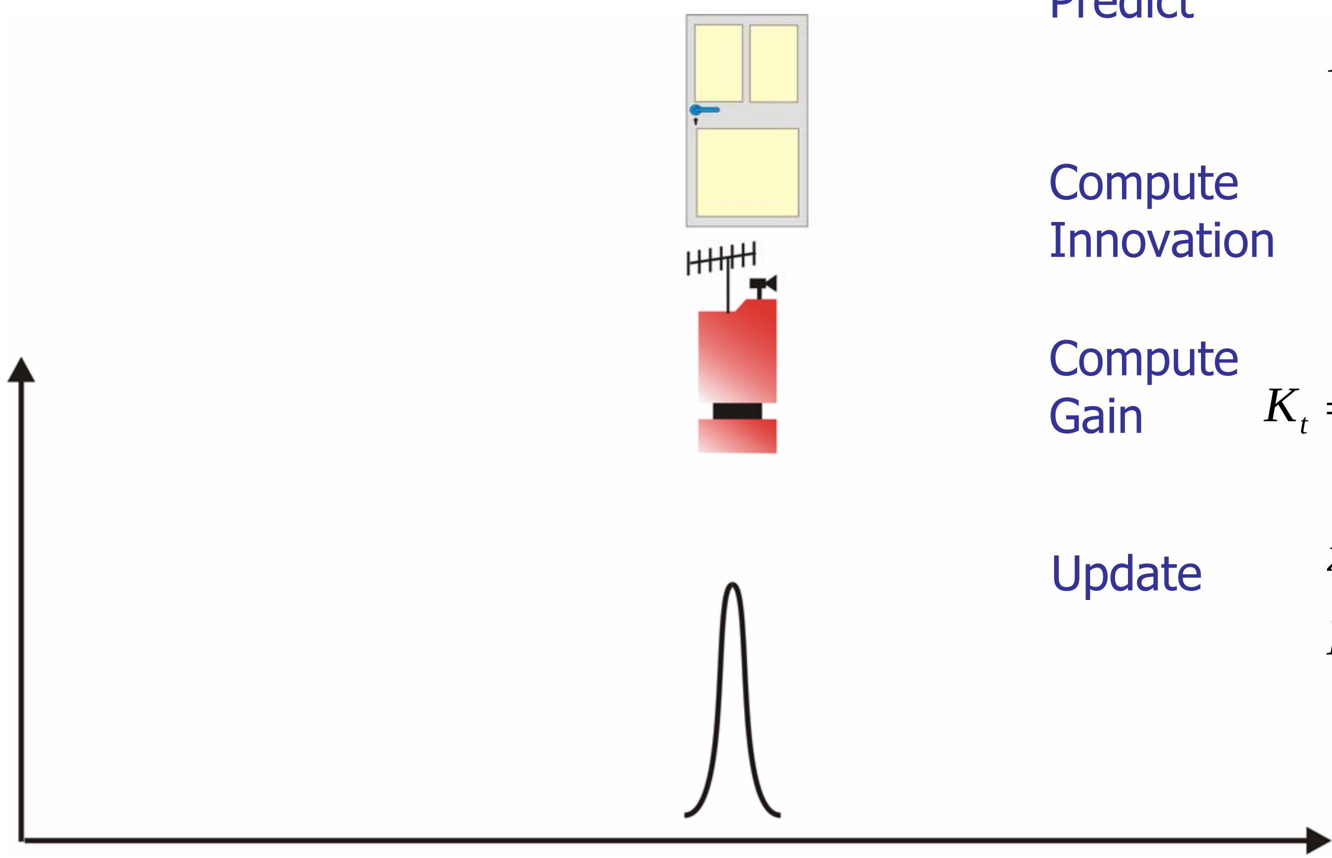
$$J_t = \hat{y}_t - C\hat{x}_t^-$$

Compute Gain

$$K_t = P_t^- C^T (CP_t^- C^T + \Sigma)^{-1}$$



Kalman Filter – Example



Predict

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Compute Innovation

$$J_t = \hat{y}_t - C\hat{x}_t^-$$

Compute Gain

$$K_t = P_t^- C^T (CP_t^- C^T + \Sigma)^{-1}$$

Update

$$\hat{x}_t = \hat{x}_t - \mathrm{K}_t J_t$$

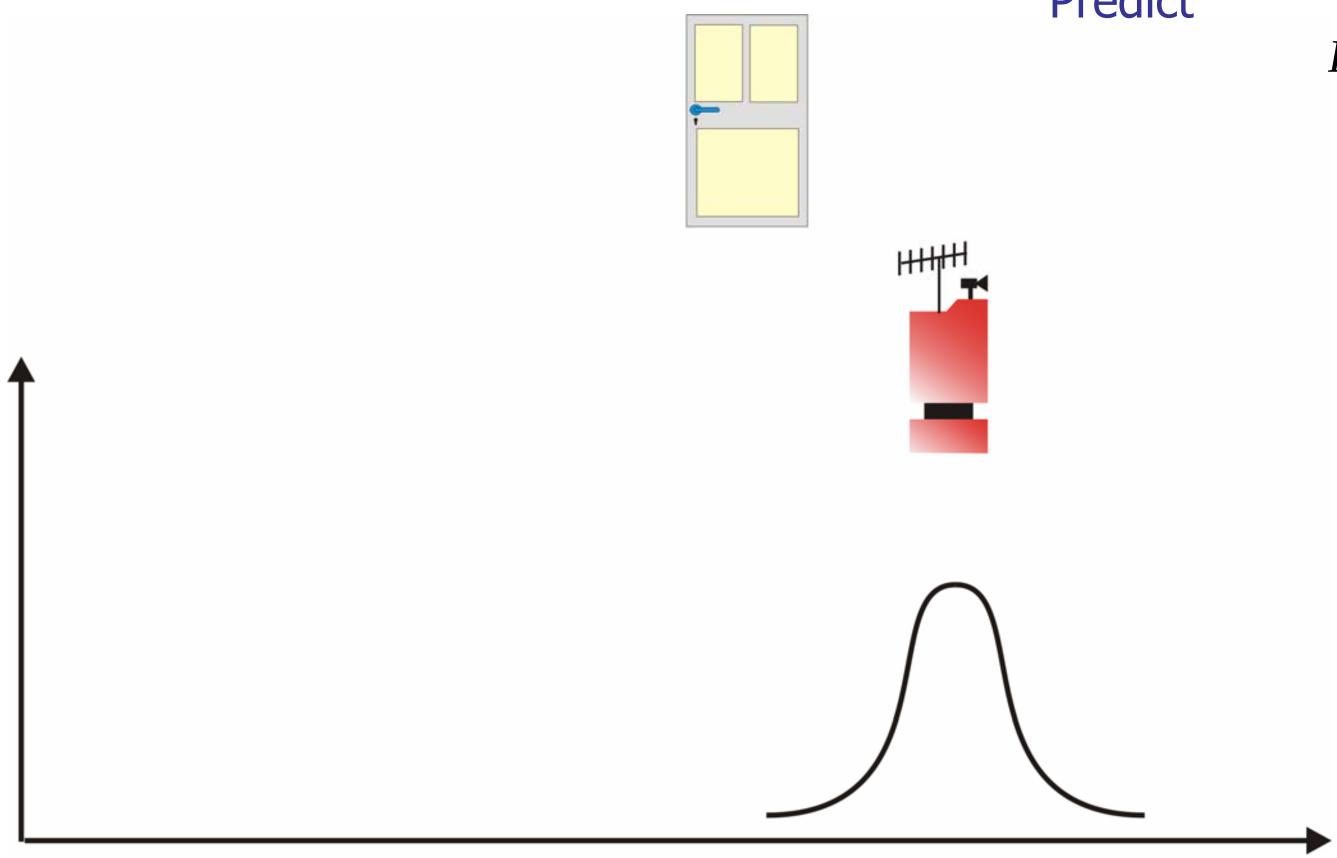
$$P_t = (I - K_t C)P_k^-$$

Kalman Filter – Example

Predict

$$\hat{x}_t^- = A\hat{x}_{t-1} + B$$

$$P_t^- = AP_{t-1}A^T + \Gamma$$

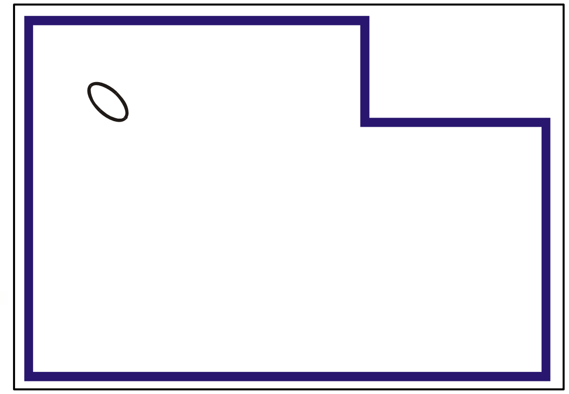


Non-Linear Case

- Kalman Filter assumes that system and measurement processes are linear
- Extended Kalman Filter -> linearized Case

$$\left.\begin{aligned} x_t &= A_t x_{t-1} + w_t \\ y_t &= C_t x_t + v_t \\ w_t &\approx N(0,\Gamma) \\ v_t &\approx N(0,\Sigma) \end{aligned}\right\} \longrightarrow \left.\begin{aligned} x_t &= f(x_{t-1}) + w_t \\ y_t &= g(x_t) + v_t \\ w_t &\approx N(0,\Gamma) \\ v_t &\approx N(0,\Sigma) \end{aligned}\right\}$$

Example: Localization – EKF

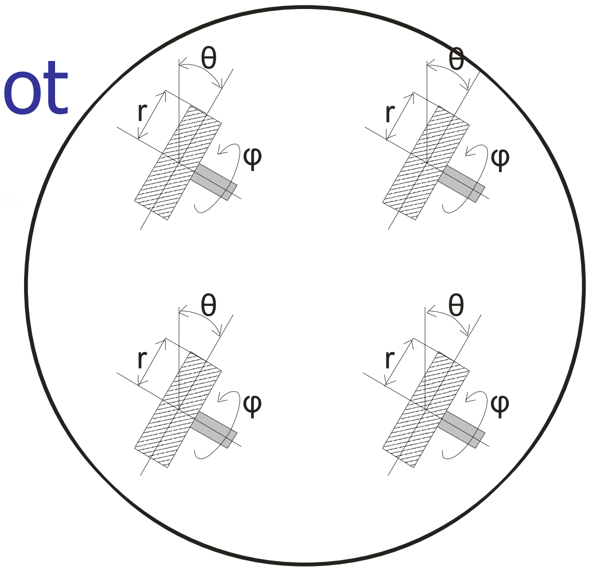


- Initialize State
  - Gaussian distribution centered according to prior knowledge – large variance
- At each time step:
  - Use previous state and motion model to predict new state
    (mean of Gaussian changes - variance grows)
  - Compare observations with what you expected to see from the predicted state – Compute Kalman Innovation/Gain
  - Use Kalman Gain to update prediction

Extended Kalman Filter

Project State estimates forward (prediction step)	$\mu_{x_{t+1}^-} = Exp(F(\mu_{x_t}, \alpha_t))$ $\Sigma_{x_{t+1}^-} = \nabla F_x \Sigma_{x_t} \nabla F_x^T + \nabla F_\alpha \Sigma_{\alpha_t} \nabla F_\alpha^T$
Predict measurements	$l_{t+1}^- = H(\mu_{x_{t+1}^-})$
Compute Kalman Innovation	$r_{t+1} = l_{t+1} - l_{t+1}^-$ $\Sigma_{r_{t+1}} = \nabla F_{x_{t+1}^-} \Sigma_{x_{t+1}^-} \nabla F_{x_{t+1}^-}^T + \Sigma_{l_{t+1}}$
Compute Kalman Gain	$K_{t+1} = \Sigma_{x_{t+1}^-} \nabla F_{x_{t+1}^-} \Sigma_{r_{t+1}^-}^{-1}$
Update Initial Prediction	$\mu_{x_{t+1}} = \mu_{x_{t+1}^-} + K_{t+1} r_{t+1}$ $\Sigma_{x_{t+1}} = \Sigma_{x_{t+1}^-} - K_{t+1} \Sigma_{r_{t+1}} K_{t+1}^T$

EKF – Example
motion model for mobile robot

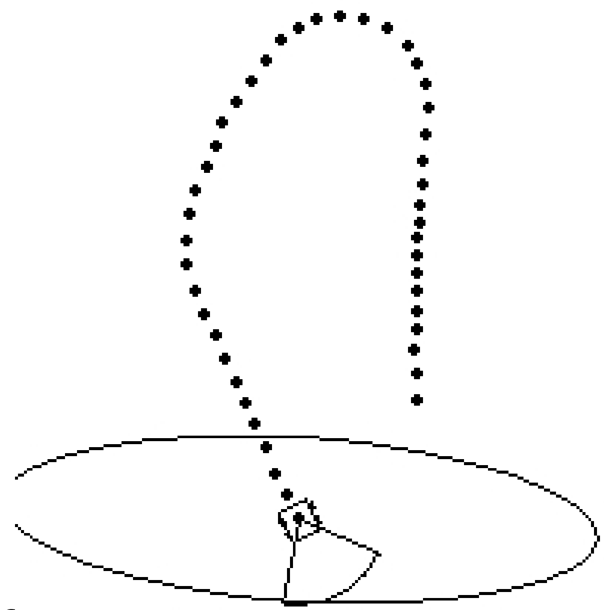


- Synchro-drive robot
- Model range, drift and turn errors

$$\Sigma_{a_t} = \begin{bmatrix} k_r d_t & 0 \\ 0 & k_t f_t + k_d d_t \end{bmatrix}$$

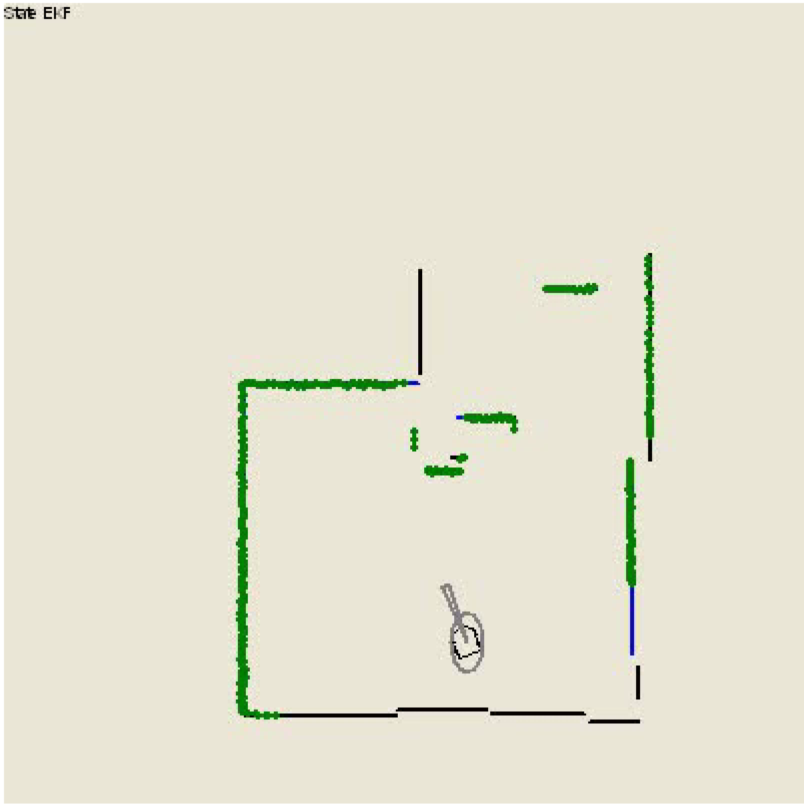
$$\mu_{x_{t+1}} = Exp\big(F(\mu_{x_t}, a_t)\big) = \begin{bmatrix} x_t - d_t \sin(\theta_t) \\ y_t - d_t \cos(\theta_t) \\ \theta_t + d_t \end{bmatrix}$$

$$\Sigma_{x_{t+1}} = \nabla F_x \Sigma_{x_t} \nabla F_x^T + \nabla F_a \Sigma_{a_t} \nabla F_a^T$$



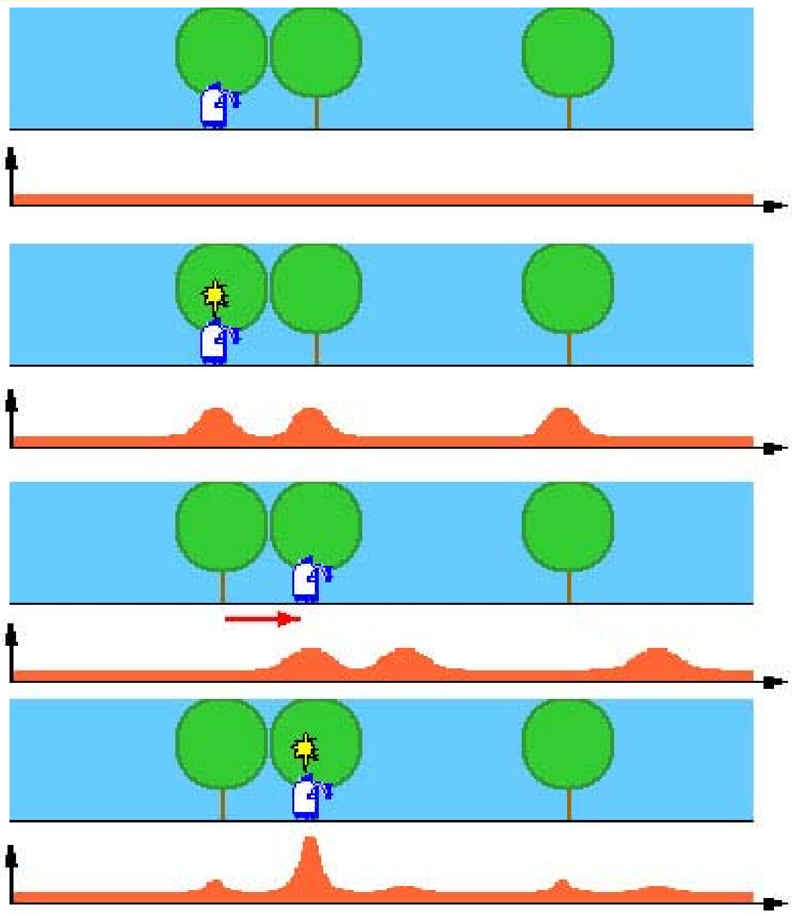
EKF – Example

simulated run



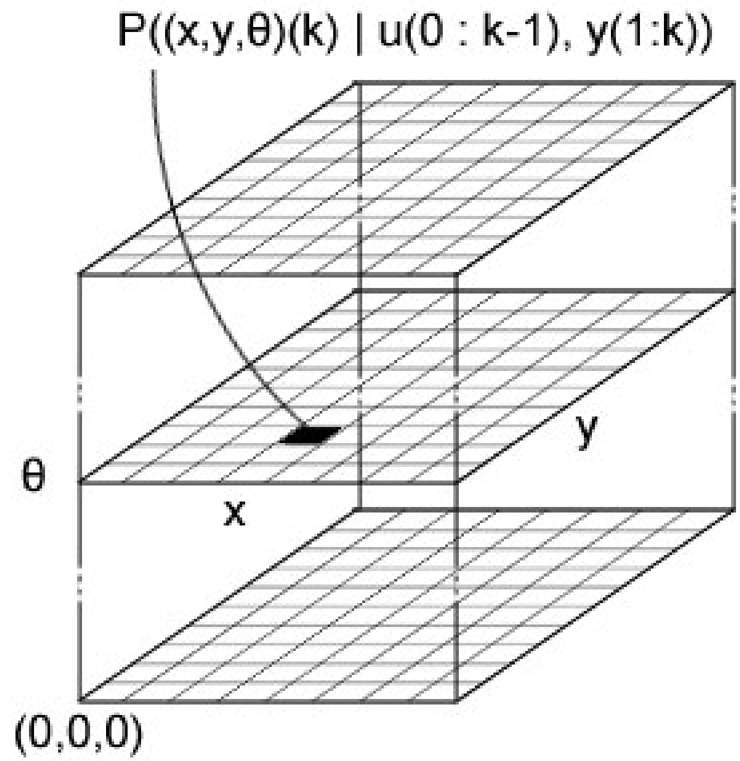
Bayesian Methods
Discrete Representation

Probabilistic localization – the case of global localization



Bayesian Methods
Discrete Approaches

Grid-based representation of the state-space

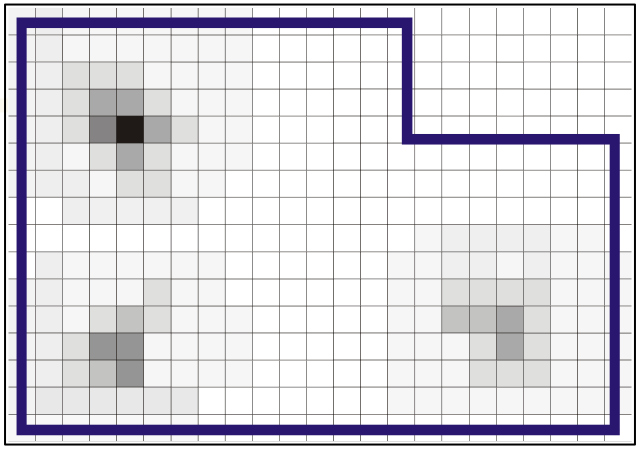


Bayesian Methods
Discrete Approaches

$$\overbrace{P\big(x(k)\,|\,u(0:k-1),y(1:k)\big)}^{\textbf{Posterior}} = n(k)\overbrace{P\big(y(k)\,|\,x(k)\big)}^{\textbf{Sensor model}} \bullet$$

$$\sum_{x(k-1)\in X}\Big[\underbrace{P\big(x(k)\,|\,u(k-1),x(k-1)\big)}_{\textbf{Motion model}}\underbrace{P\big(x(k-1)\,|\,u(0:k-2),y(1:k-1)\big)}_{\textbf{Past history}}\Big]$$

Example: Localization – Grid Based



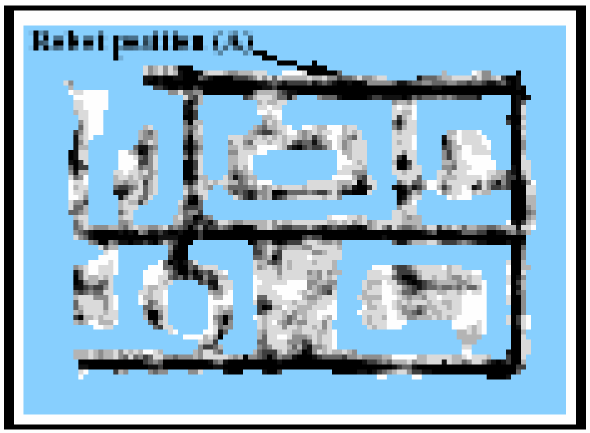
- Initialize Grid
  (Uniformly or according to prior knowledge)
- At each time step:
  - For each grid cell
    - Use observation model to compute $P\big(y(k)\,|\,x(k)\big)$
    - Use motion model and probabilities to compute

$$\sum_{x(k-1)\in X}\Big[P\big(x(k)\,|\,u(k-1),x(k-1)\big)\,P\big(x(k-1)\,|\,u(0:k-2),y(1:k-1)\big)\Big]$$

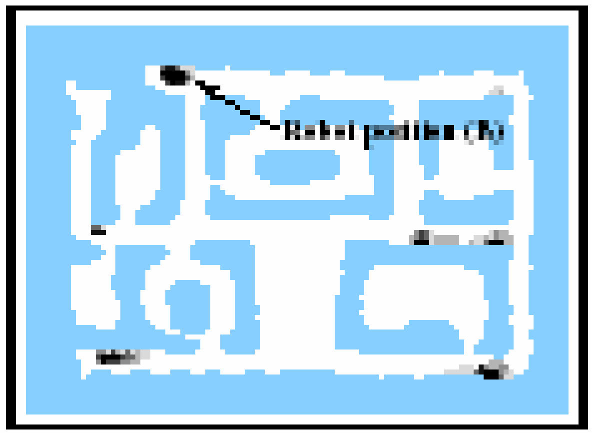
  - Normalize

Bayesian Methods
Discrete Approaches

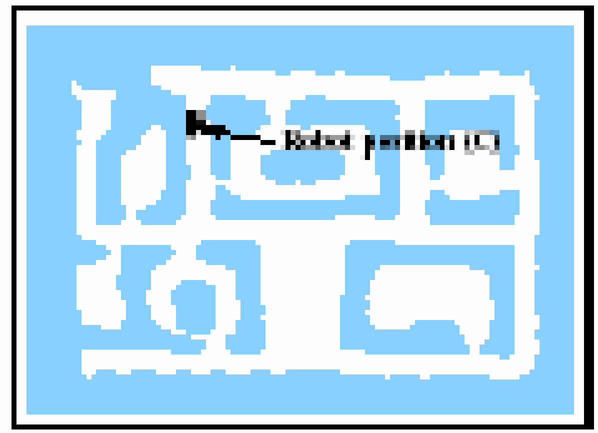
Density plots of the robot state



… beginning

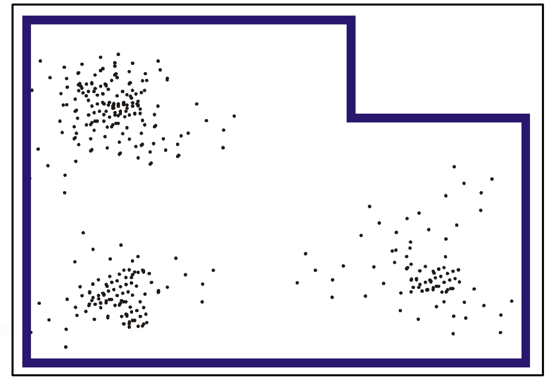


small No of cycles



sufficient No of cycles

Particle Filters



- Often models are non-linear and noise in non gausian.
- Use particles to represent the distribution
- "Survival of the fittest"

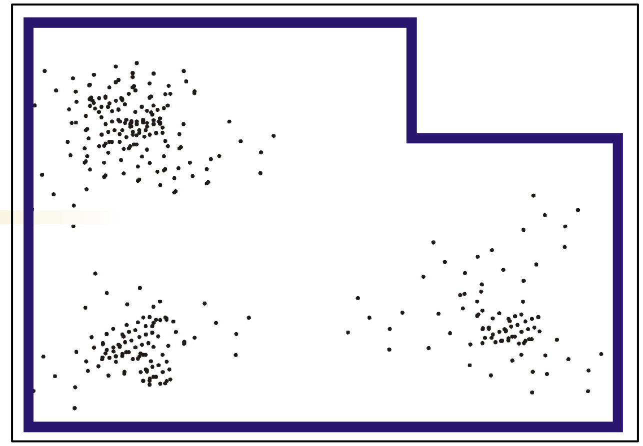
$$P(x_t \mid y_{1:t}) = \frac{1}{c_t} P(y_t | x_t) \boxed{\int_Z P(x_t | x_{t-1} = z) P(x_{t-1} = z \mid y_{1:t-1}) dz}$$

Motion model

Observation model (=weight)

Proposal distribution

Particle Filters
SIS-R algorithm



- Initialize particles randomly
  (Uniformly or according to prior knowledge)
- At each time step:

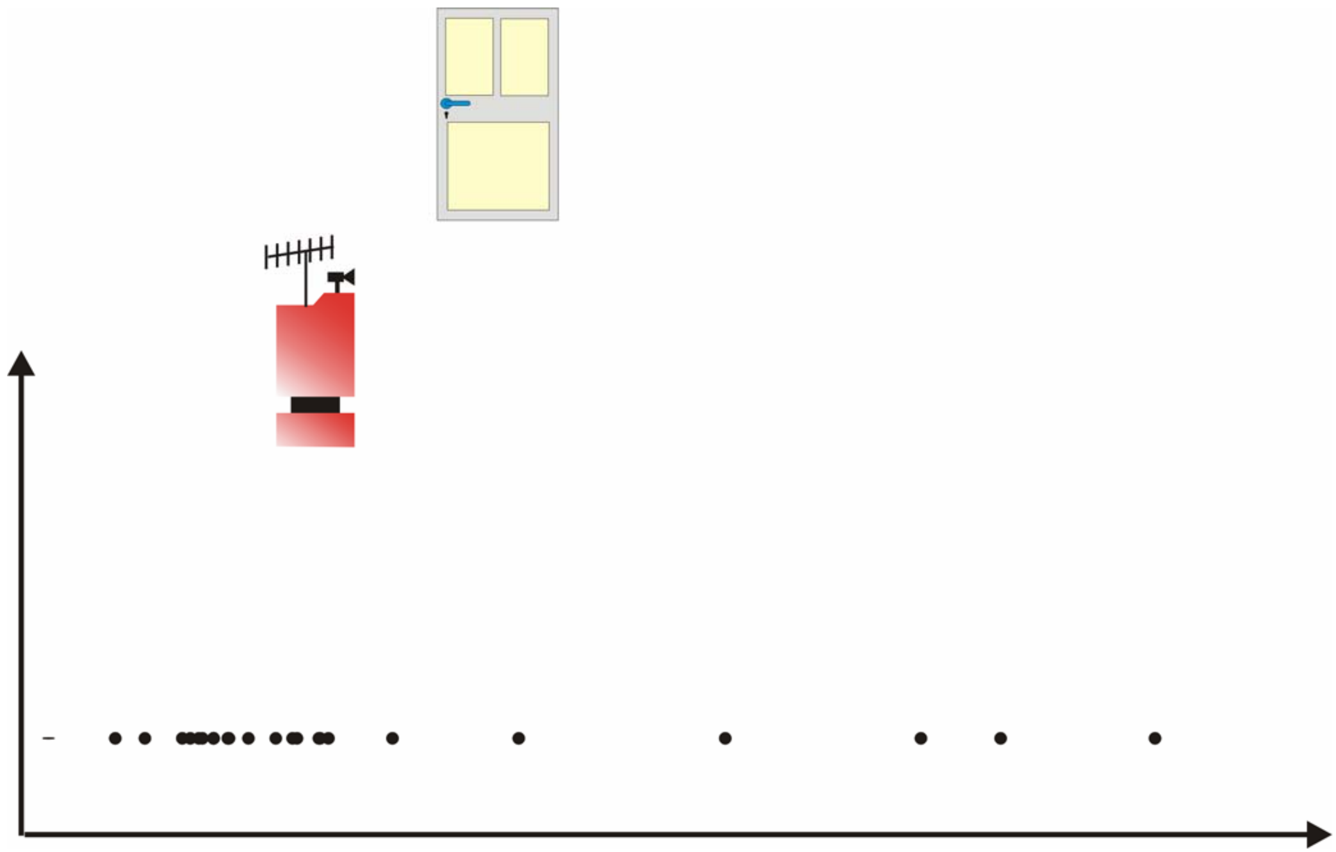
Sequential importance sampling

- For each particle:
  - Use motion model to predict new pose (sample from transition priors)
  - Use observation model to assign a weight to each particle (posterior/proposal)

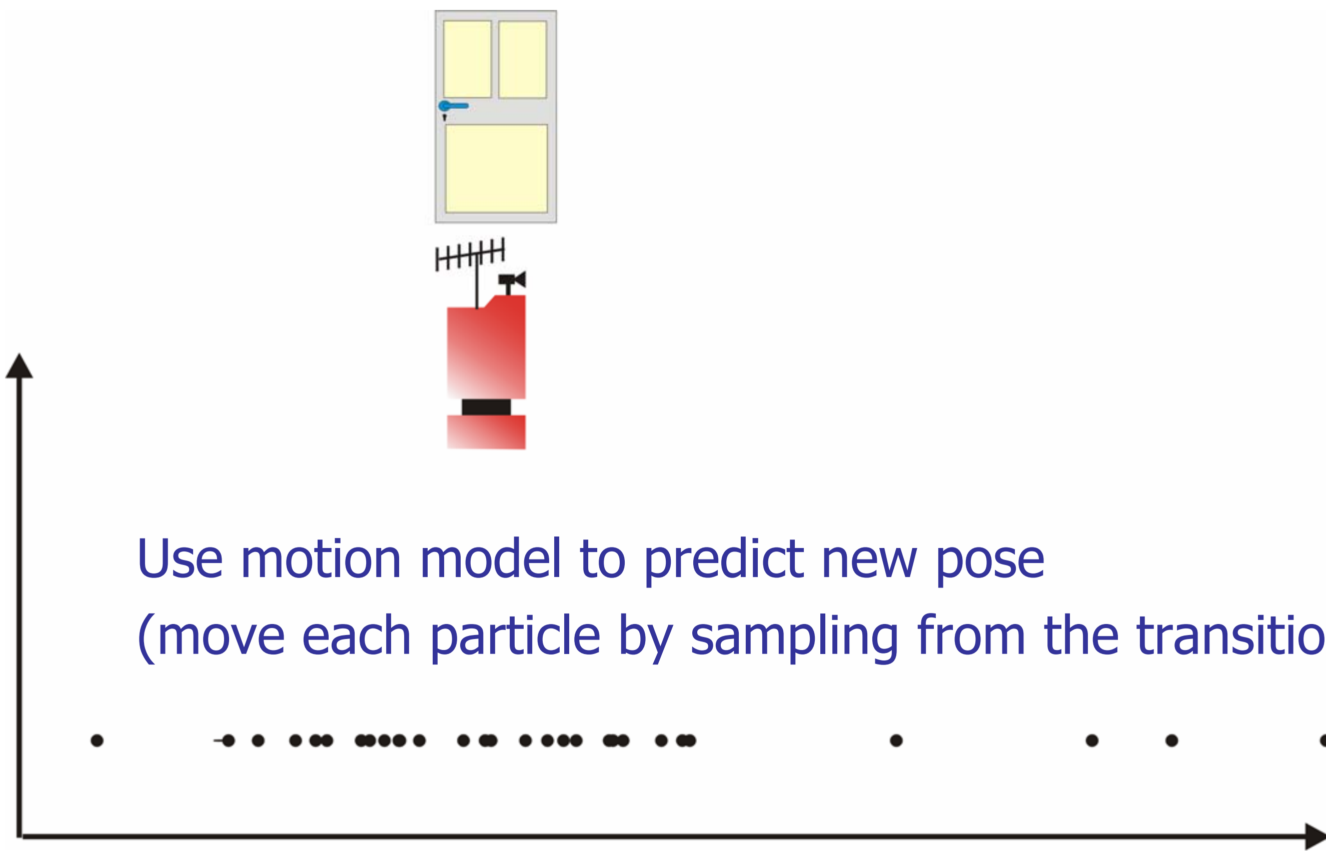
Selection: Re-sampling

- Create A new set of equally weighted particles by sampling the distribution of the weighted particles produced in the previous step.

Particle Filters – Example 1

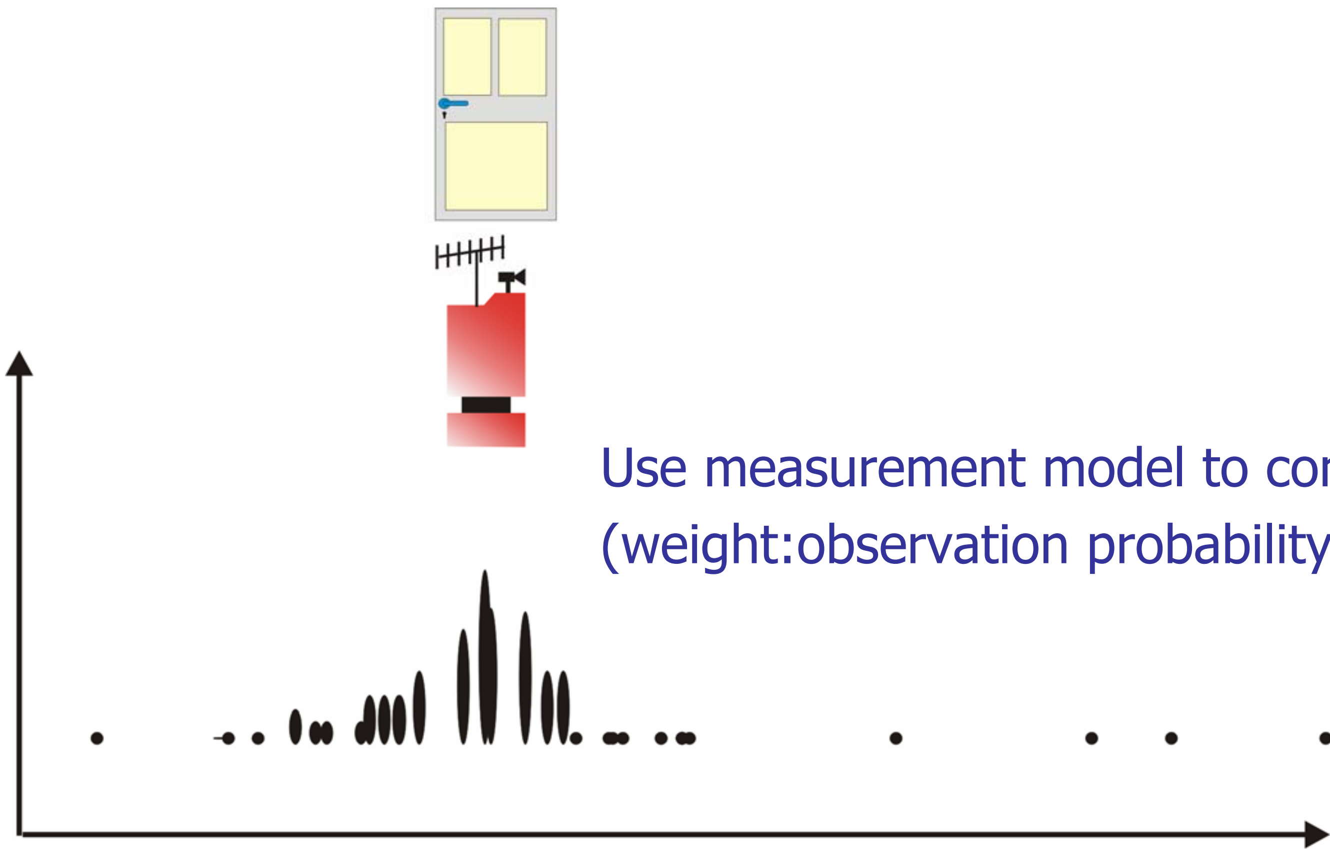


Particle Filters – Example 1



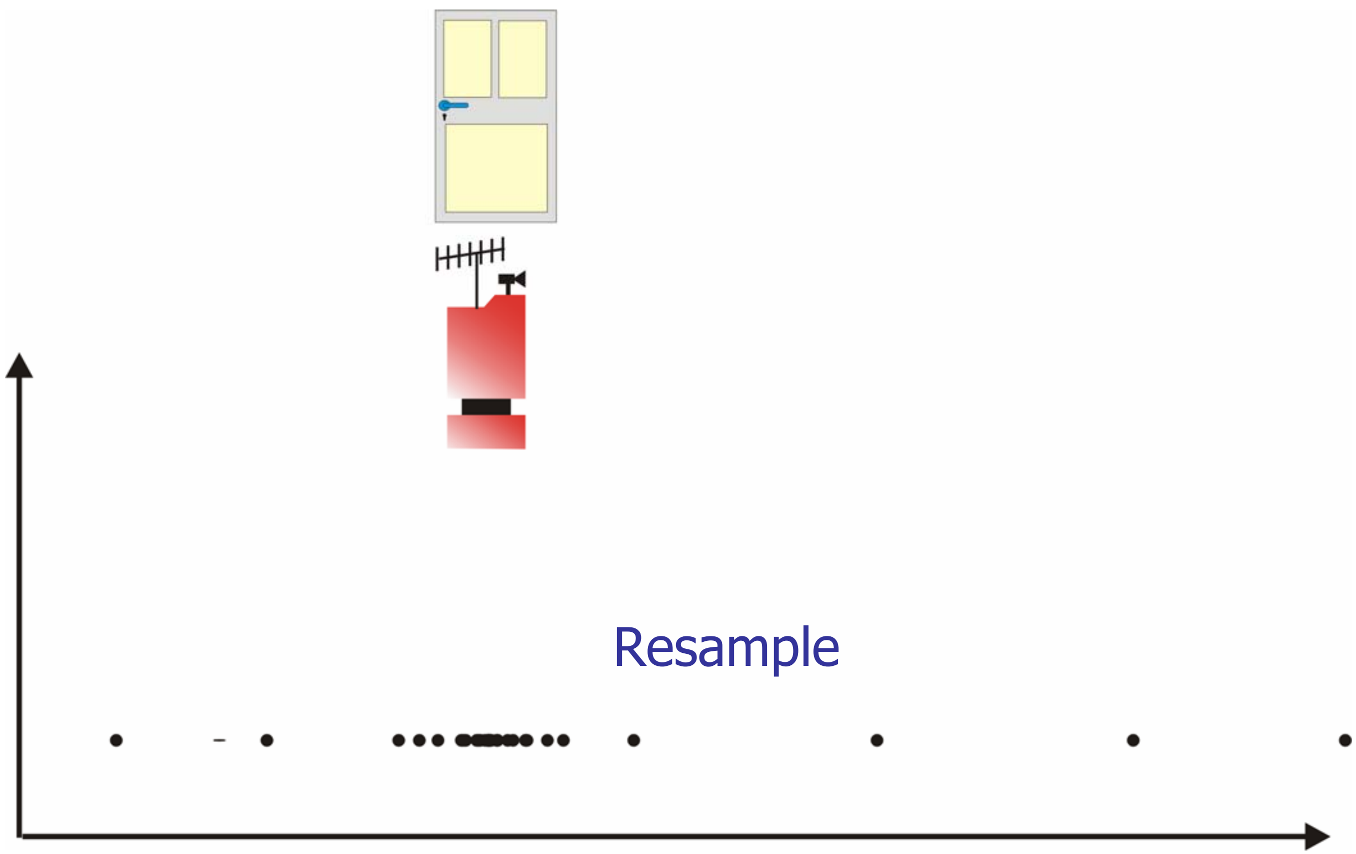
Use motion model to predict new pose
(move each particle by sampling from the transition prior)

Particle Filters – Example 1

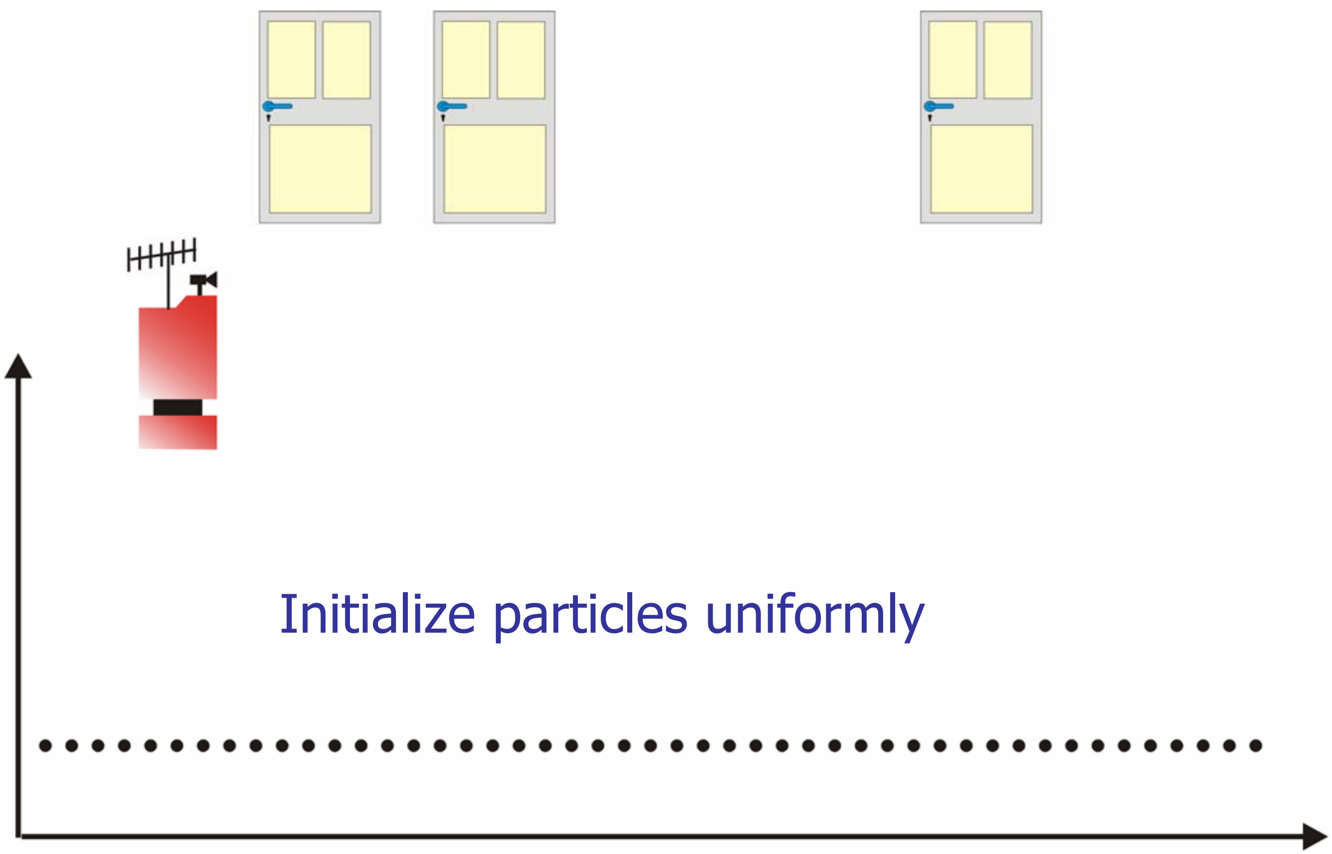


Use measurement model to compute weights (weight:observation probability)

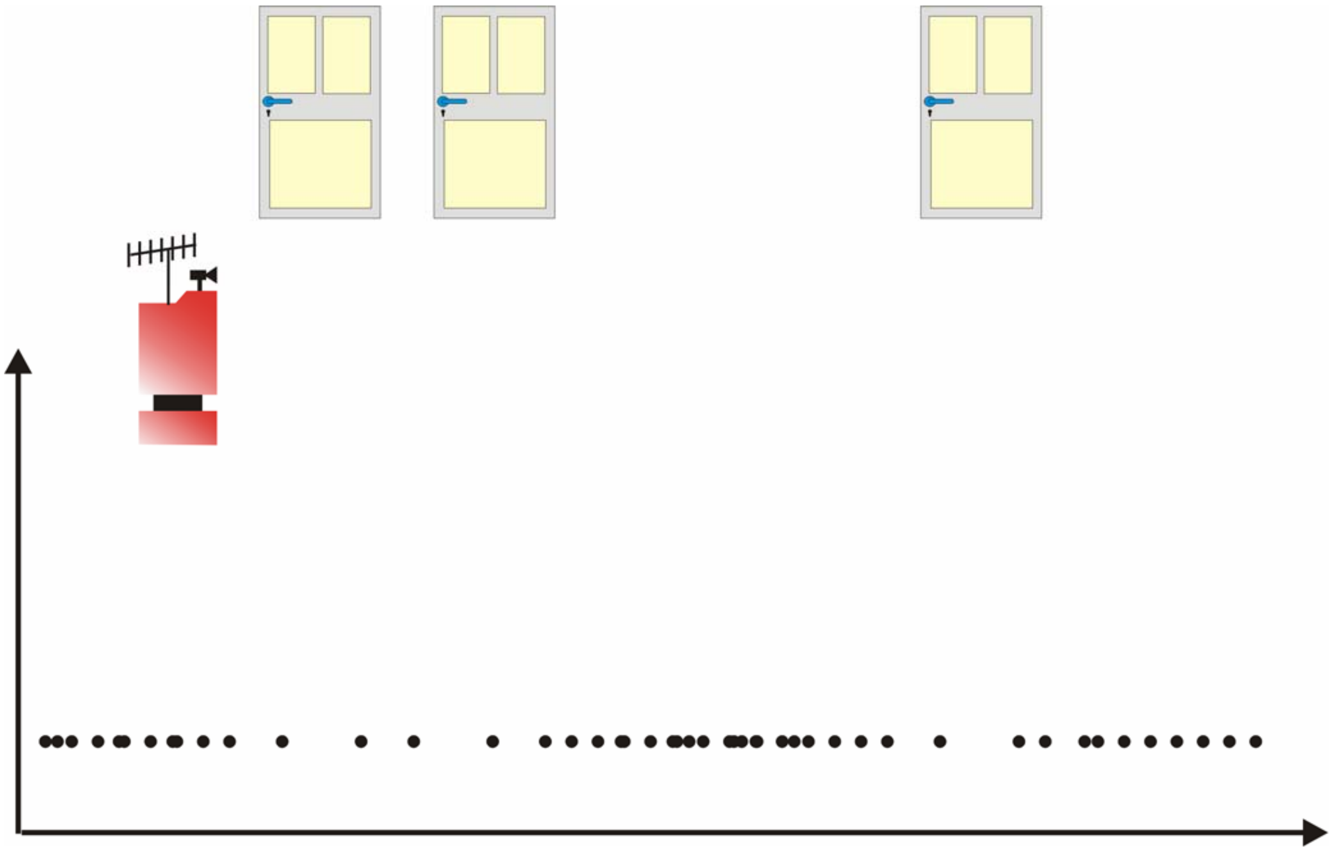
Particle Filters – Example 1



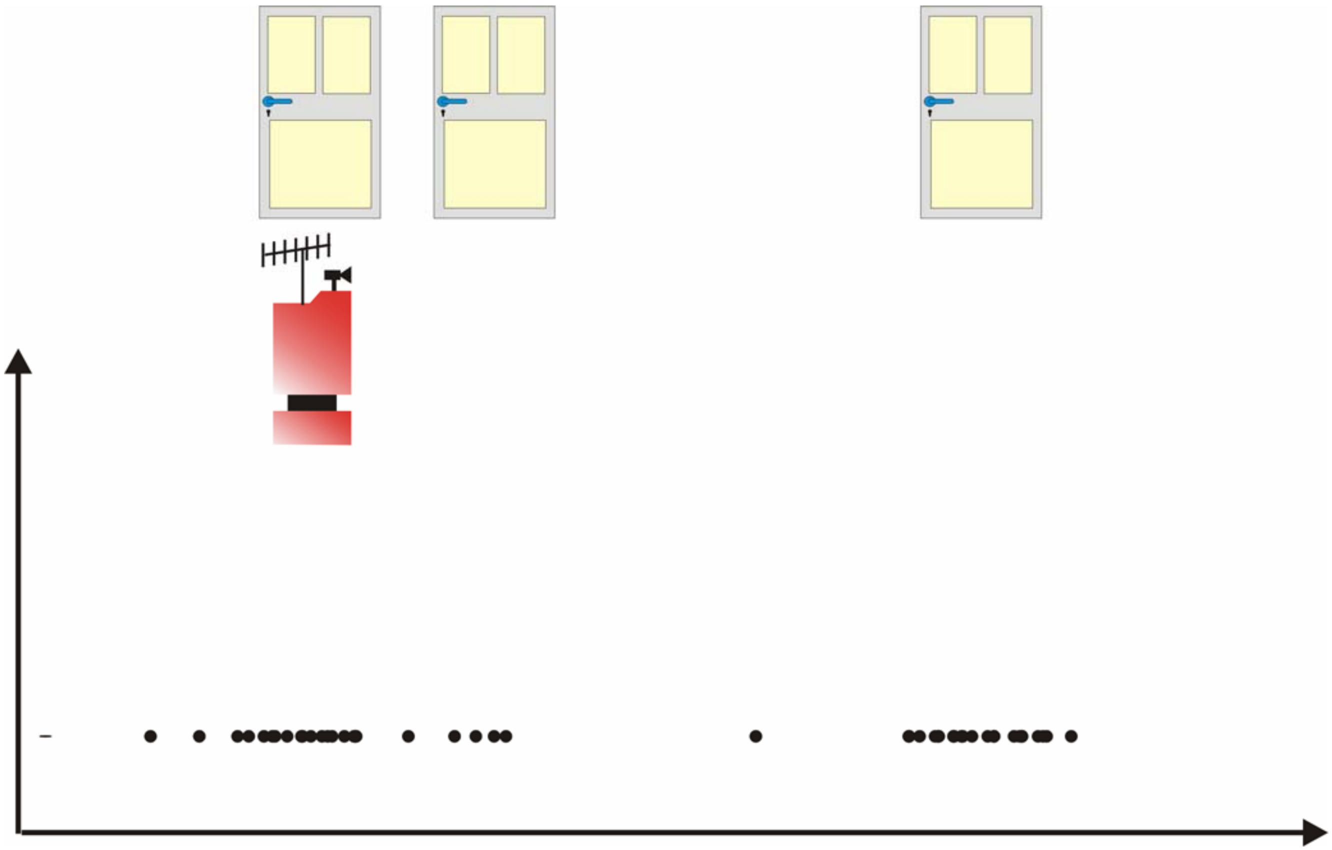
Particle Filters – Example 2



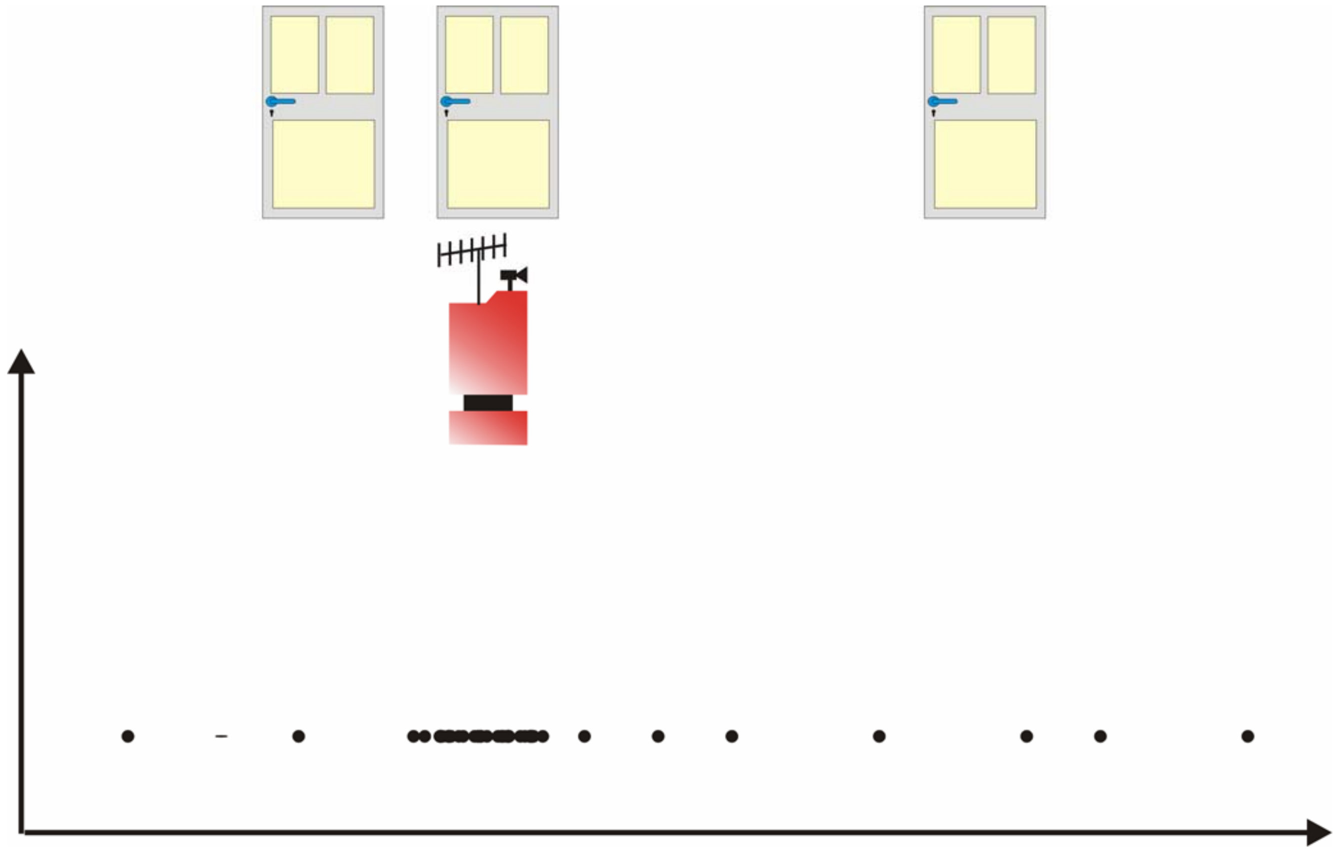
Particle Filters – Example 2



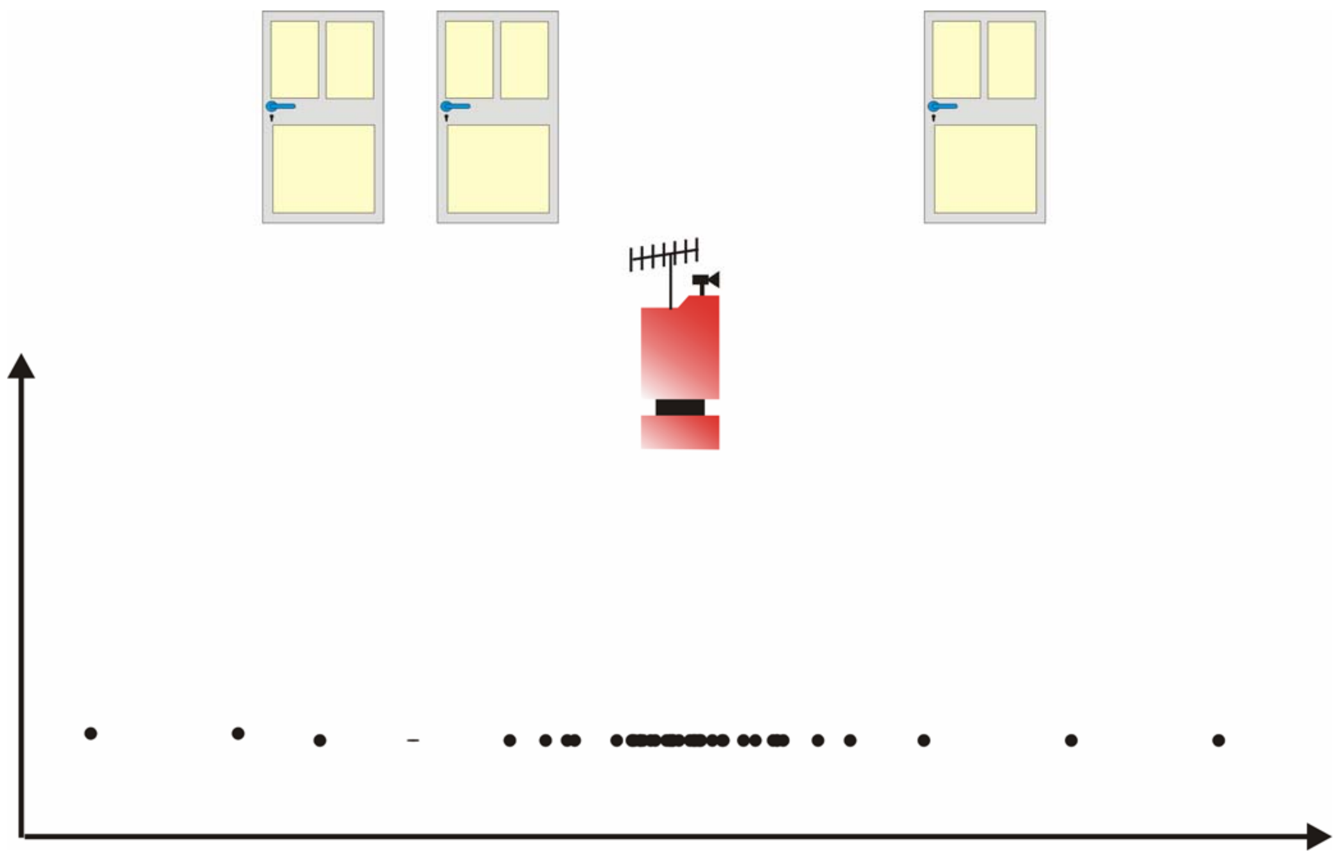
Particle Filters – Example 2



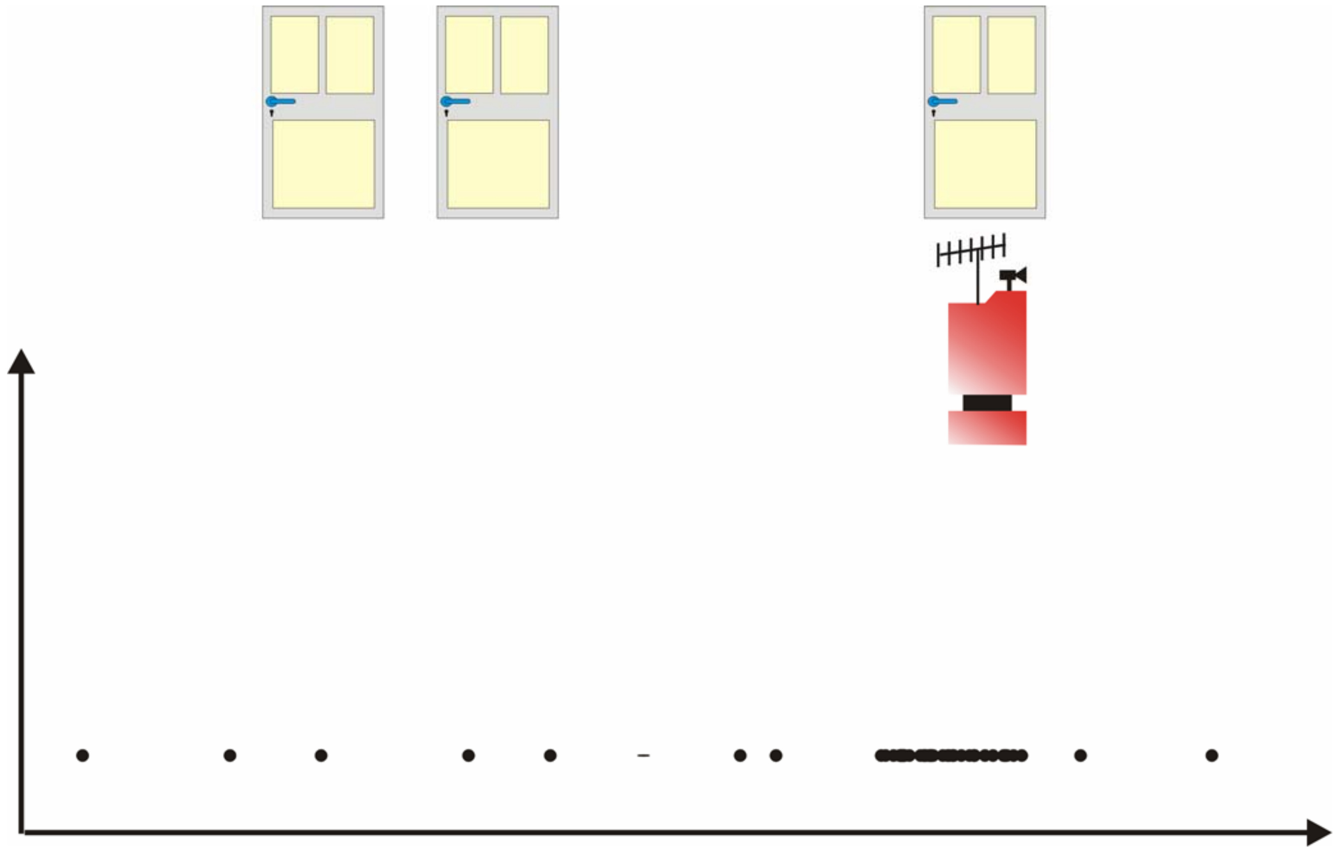
Particle Filters – Example 2



Particle Filters – Example 2



Particle Filters – Example 2



Discrete State Approaches

- Ability (to some degree) to localize the robot even when its initial pose is unknown.
- Ability to deal with noisy measurements, such as from ultrasonic sensors.
- Ability to represent ambiguities.
- Computational time scales heavily with the number of possible states (dimensionality of the grid, size of the cells, size of the map).
- Localization accuracy is limited by the size of the grid cells.

Continuous State Approaches

- Perform very accurately if the inputs are precise (performance is optimal in the linear case).
- Computational efficiency.

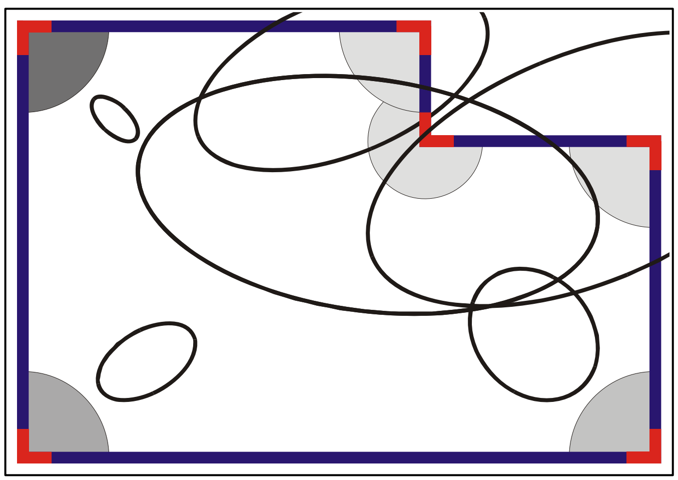
- Requirement that the initial state of the robot is known.
- Inability to recover from catastrophic failures caused by erroneous matches or incorrect error models.
- Inability to track Multiple Hypotheses about the location of the robot.

Hybrid Approaches

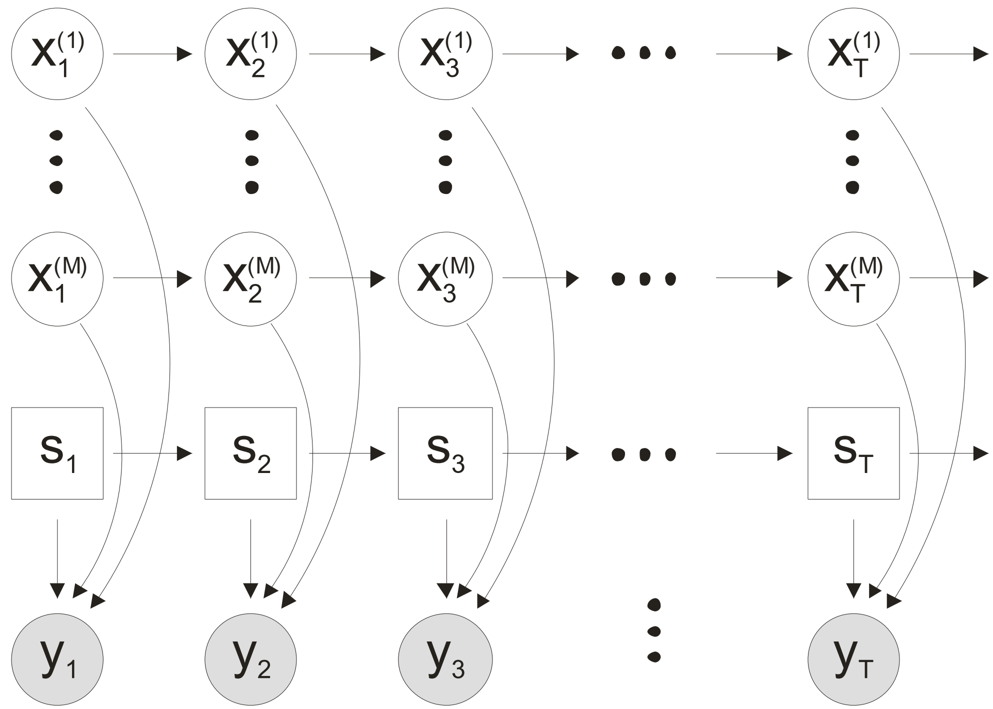
- Combination of characteristics from both methods
- Hybrid methods very popular in many scientific areas
  - Control theory
  - Economics

Proposed Model
switching state-space model (SSSM)

The Switching State-Space model
- M continuous State Vectors
- One discrete "switch" variable



Example Belief State



H. Baltzakis and P. Trahanias, Autonomous Robots 2003

Switching state-space Model

Combines both models

Inherits strengths
Eliminates weaknesses

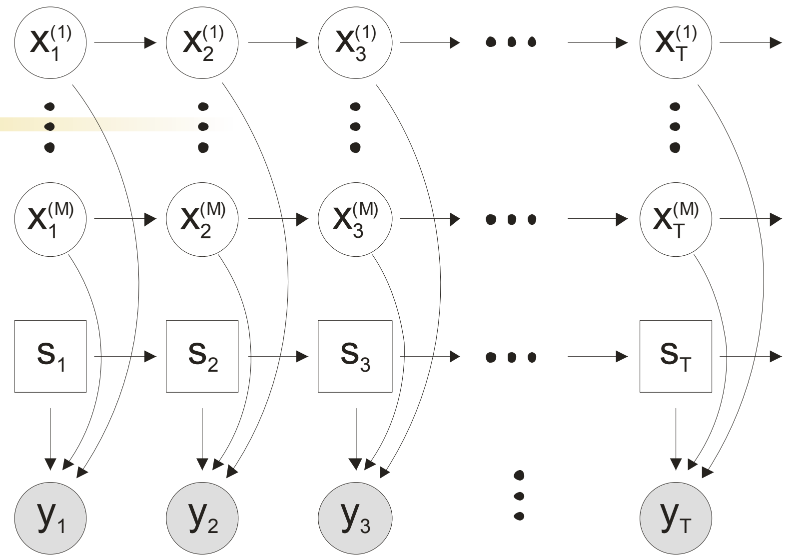
Continuous Model

- Accurate performance
- Computational efficiency
- ~~Initial state must be known~~
- ~~Inability to recover from catastrophic failures~~
- ~~Inability to track Multiple Hypotheses~~

Discrete Model

- Perform even when initial pose is unknown
- Deal with noisy measurements
- Represent ambiguities
- ~~Computational time scales heavily~~
- ~~Localization accuracy limited~~

Localization



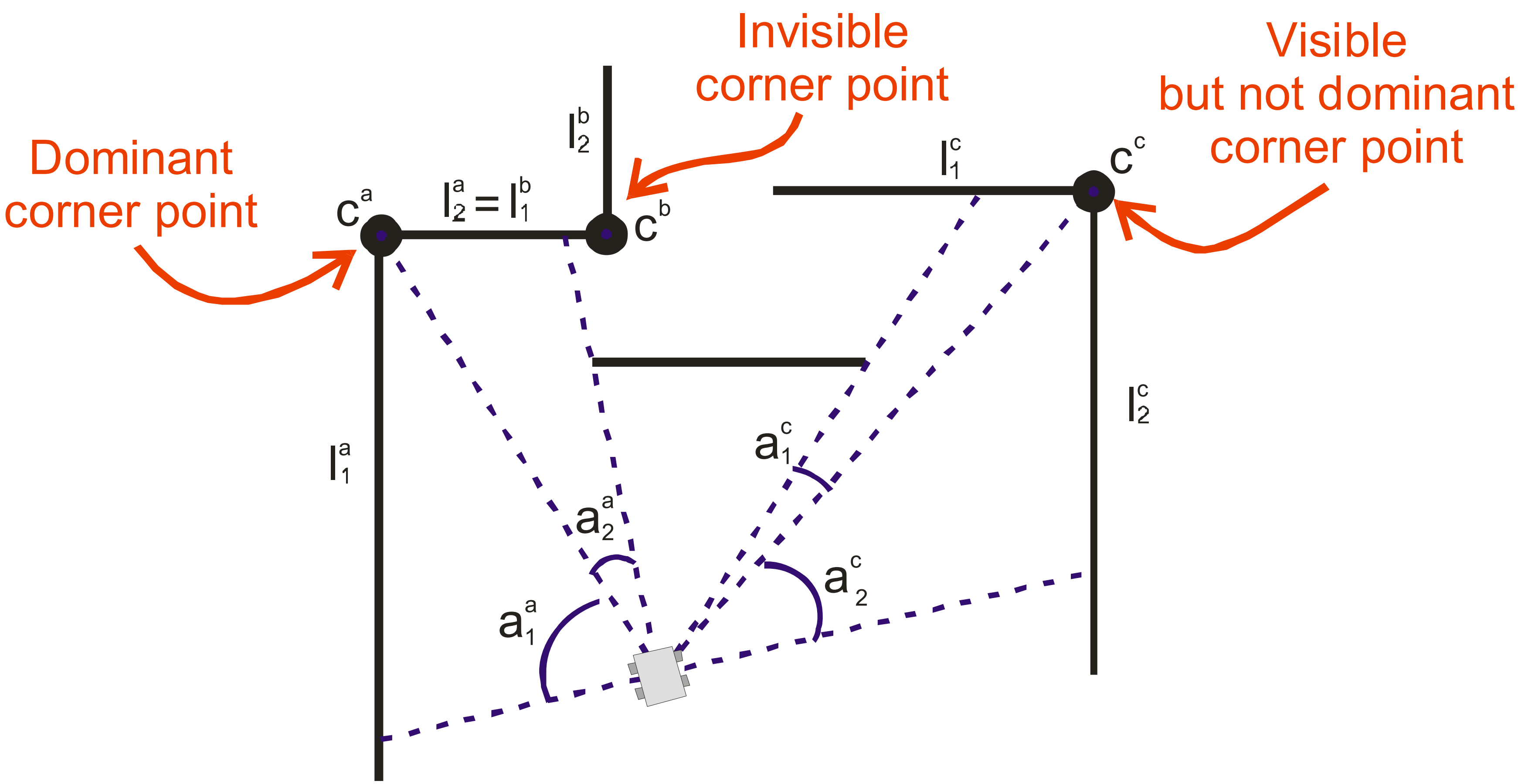
Belief state is intractable

- Mixture of M^T Gaussians
- Grows exponentially with time

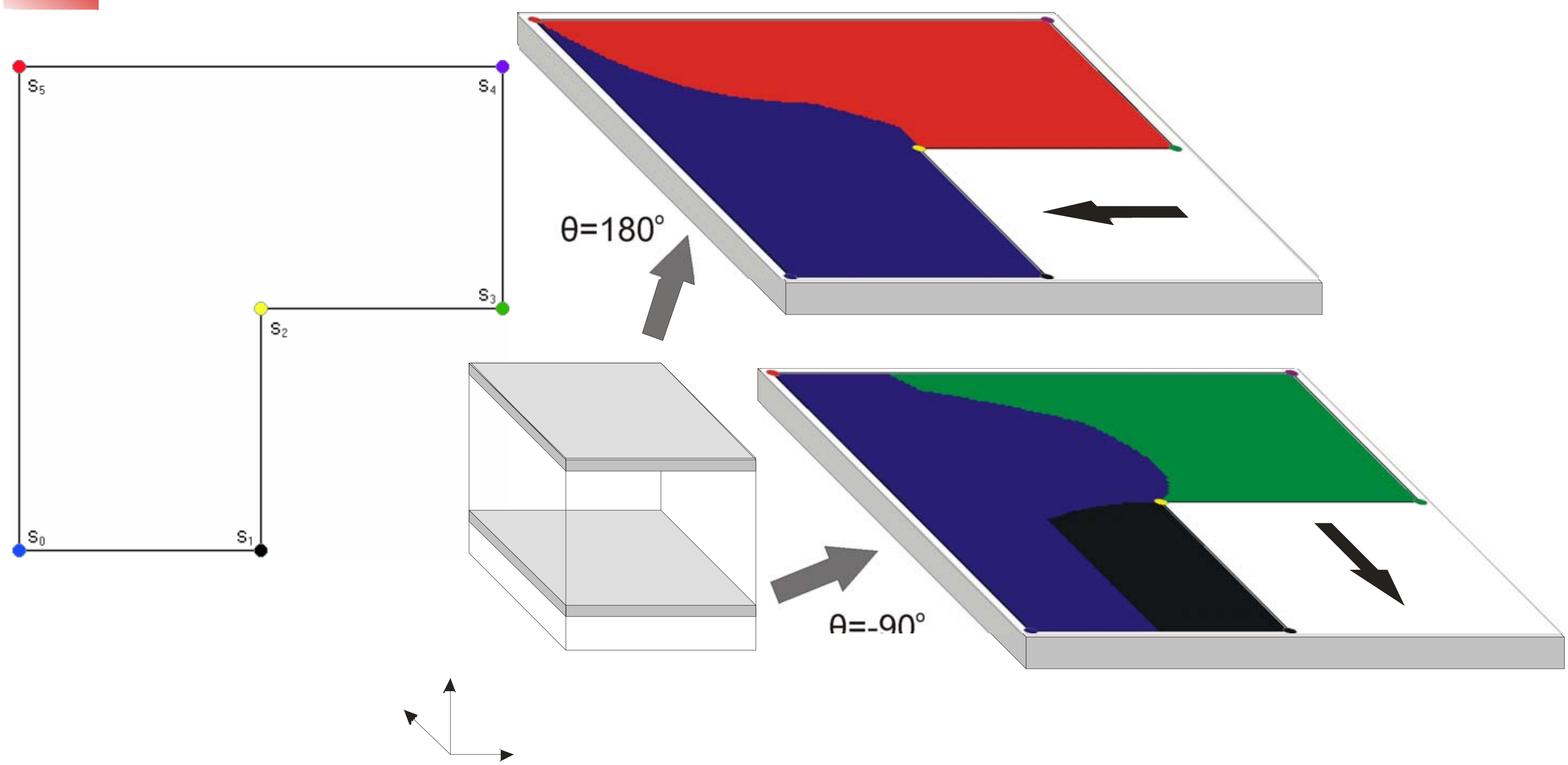
Solution

- Selection (eg. Cox94, Jensfelt99, Roumeliotis00 ,Duckett01)
  Only keep the most probable paths in model histories (Multiple Hypothesis Tracking)
- <u>Collapsing (eg. Murphy98)</u>
  Approximate the mixture of M^T Gaussians with a mixture of M^r Gaussians (r: small number, eg. 1,2,3)

Localization – Discrete Model Corner Point Visibility

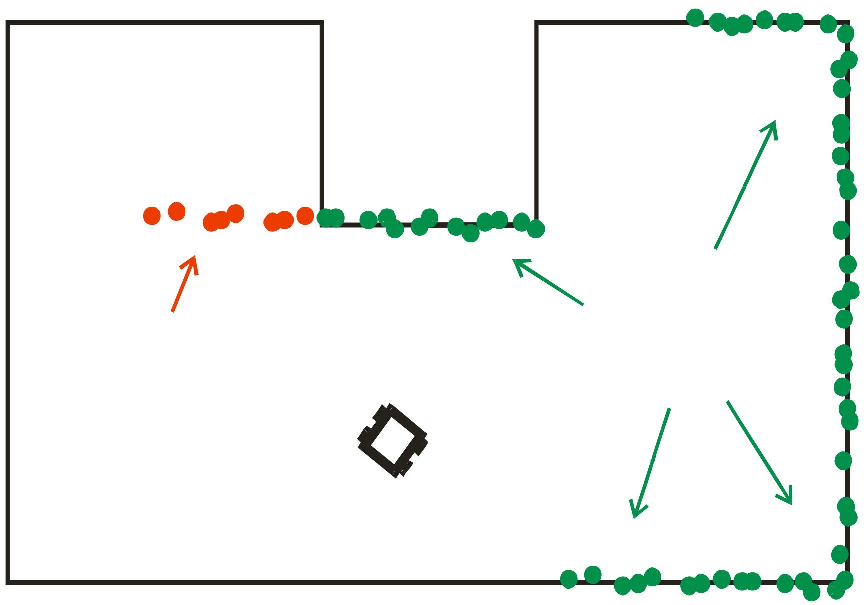


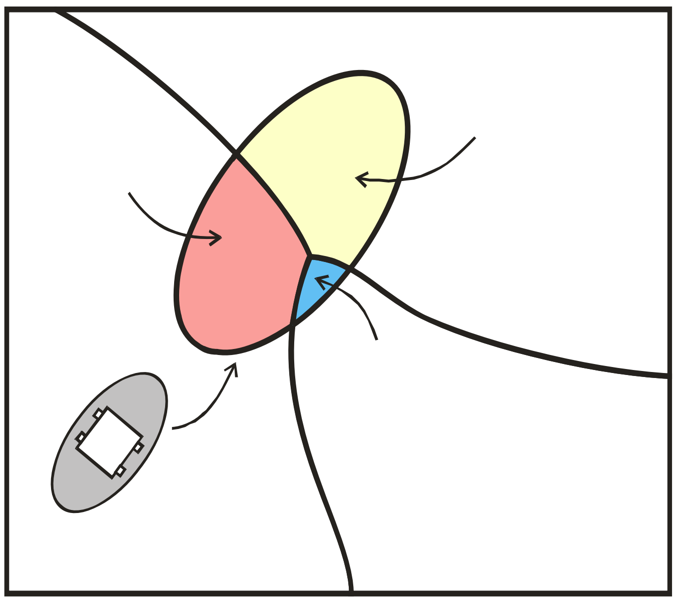
Localization – Discrete Model
Corner Point Visibility



Localization - Discrete Model (Observation – Transition)

$$P\left(s_t^k \mid y_1, y_2, \ldots, y_t\right) = \frac{1}{c_t} P\left(y_t \middle| s_t^k\right) \int_i P\left(s_t^k \middle| s_{t-1}^i\right) P\left(s_{t-1}^i \mid y_1, y_2, \ldots, y_{t-1}\right)$$

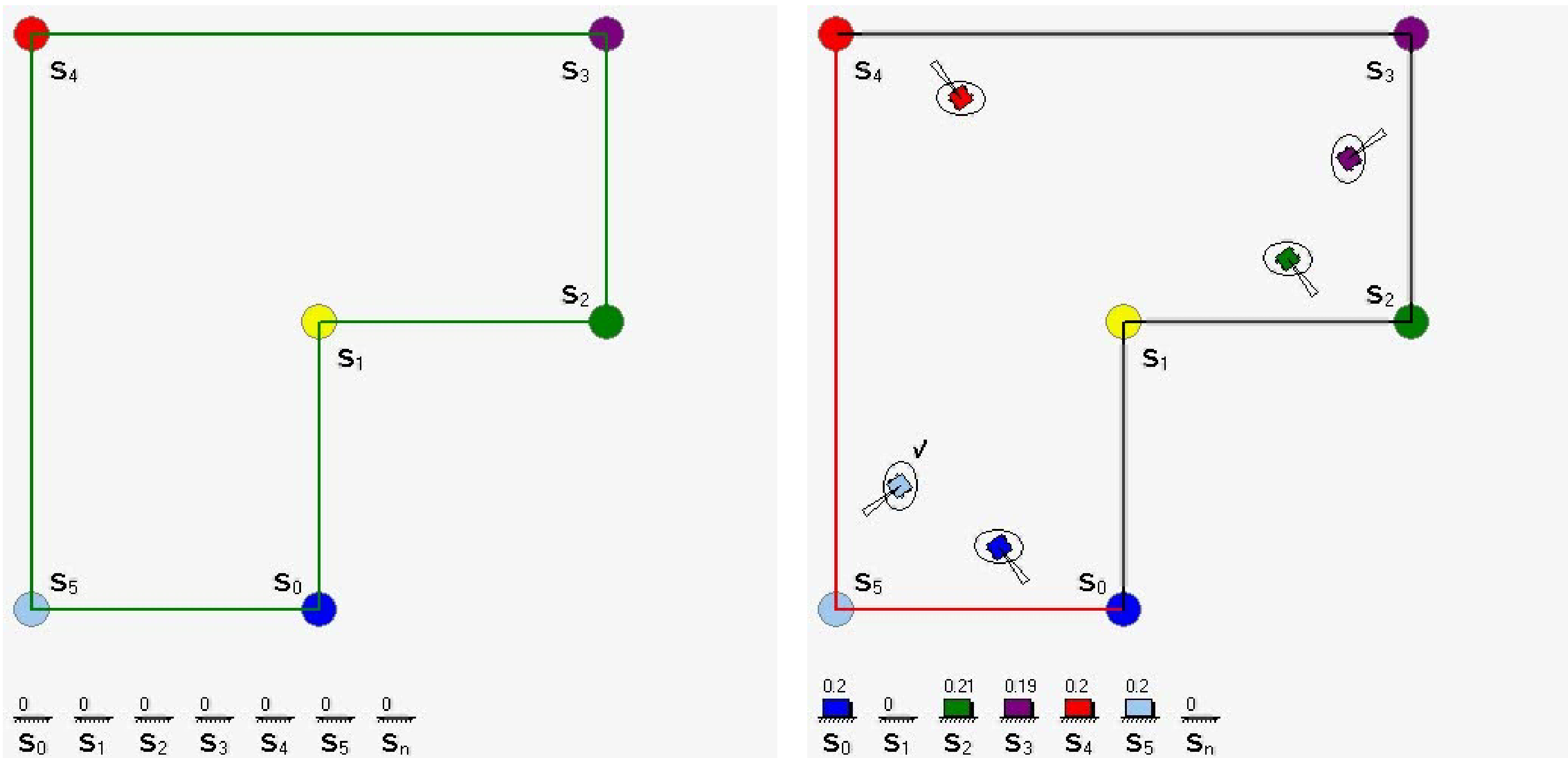




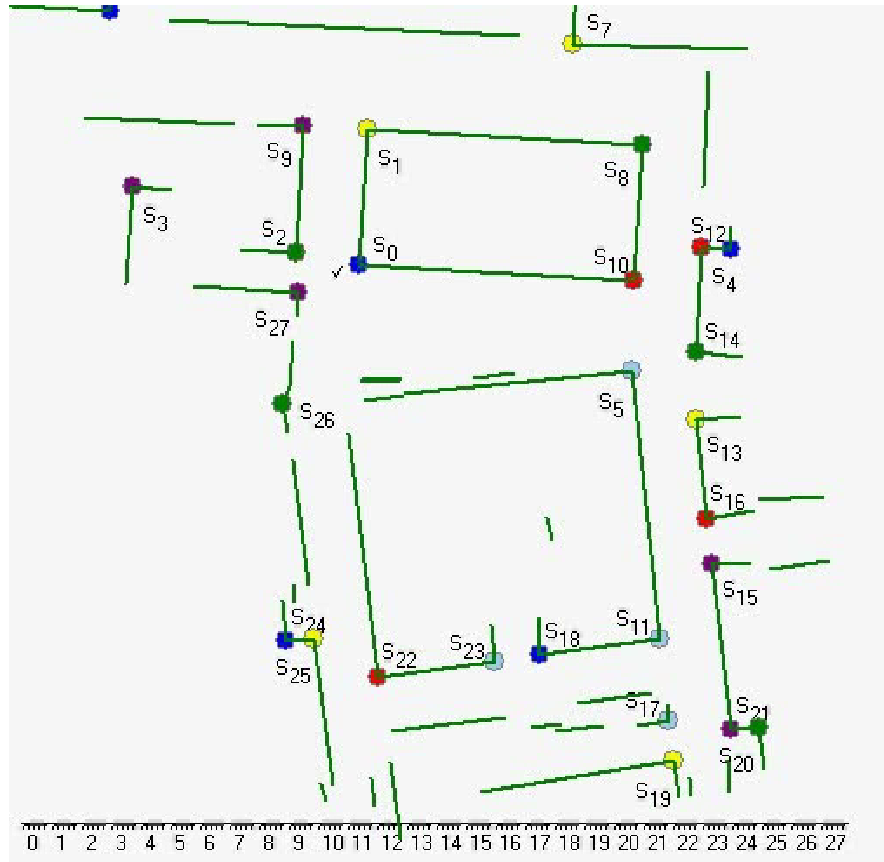
Localization – Continuous Model (EKF)

Project State estimates forward (prediction step)	$\mu_{x_{t+1}^-} = Exp(F(\mu_{x_t}, \alpha_t))$ $\Sigma_{x_{t+1}^-} = \nabla F_x \Sigma_{x_t} \nabla F_x^T + \nabla F_\alpha \Sigma_{\alpha_t} \nabla F_\alpha^T$
Predict already mapped features to the predicted state	$l_{t+1}^- = H(\mu_{x_{t+1}^-})$
Compute Kalman Innovation	$r_{t+1} = l_{t+1} - l_{t+1}^-$ $\Sigma_{r_{t+1}} = \nabla F_{x_{t+1}^-} \Sigma_{x_{t+1}^-} \nabla F_{x_{t+1}^-}^T + \Sigma_{l_{t+1}}$
Compute Kalman Gain	$K_{t+1} = \Sigma_{x_{t+1}^-} \nabla F_{x_{t+1}^-} \Sigma_{r_{t+1}^-}^{-1}$
Update Initial Prediction	$\mu_{x_{t+1}} = \mu_{x_{t+1}^-} + K_{t+1} r_{t+1}$ $\Sigma_{x_{t+1}} = \Sigma_{x_{t+1}^-} - K_{t+1} \Sigma_{r_{t+1}} K_{t+1}^T$

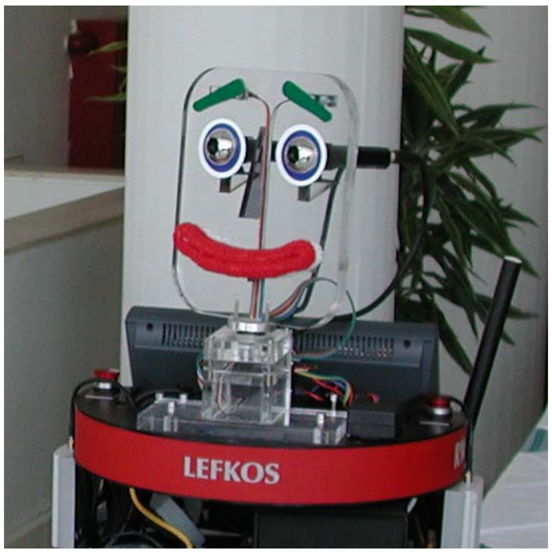
Localization - Results
(Simulated)

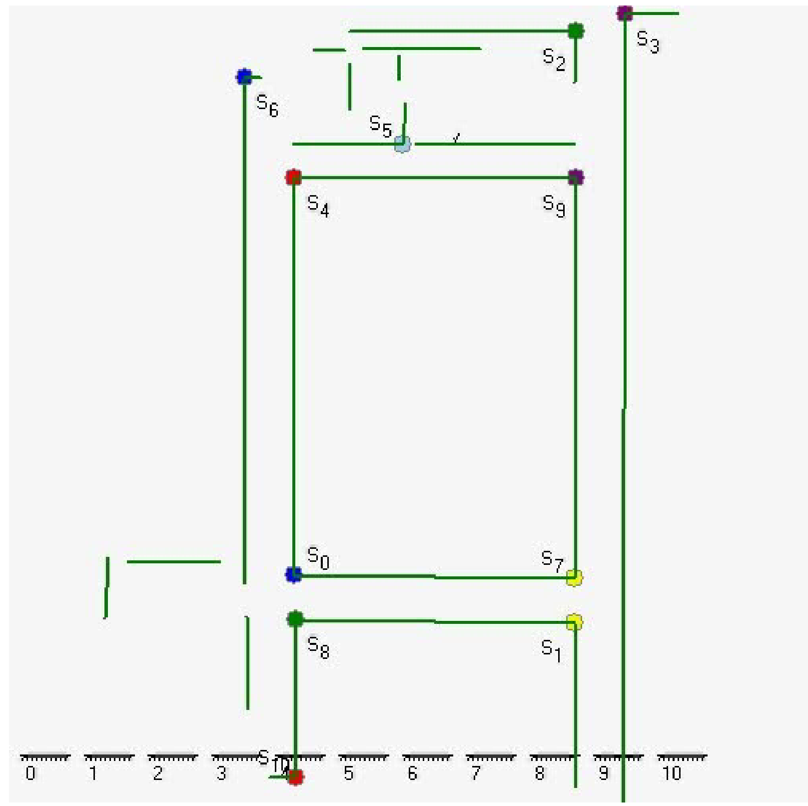


Localization - Results
(Real world – FORTH 1st floor)

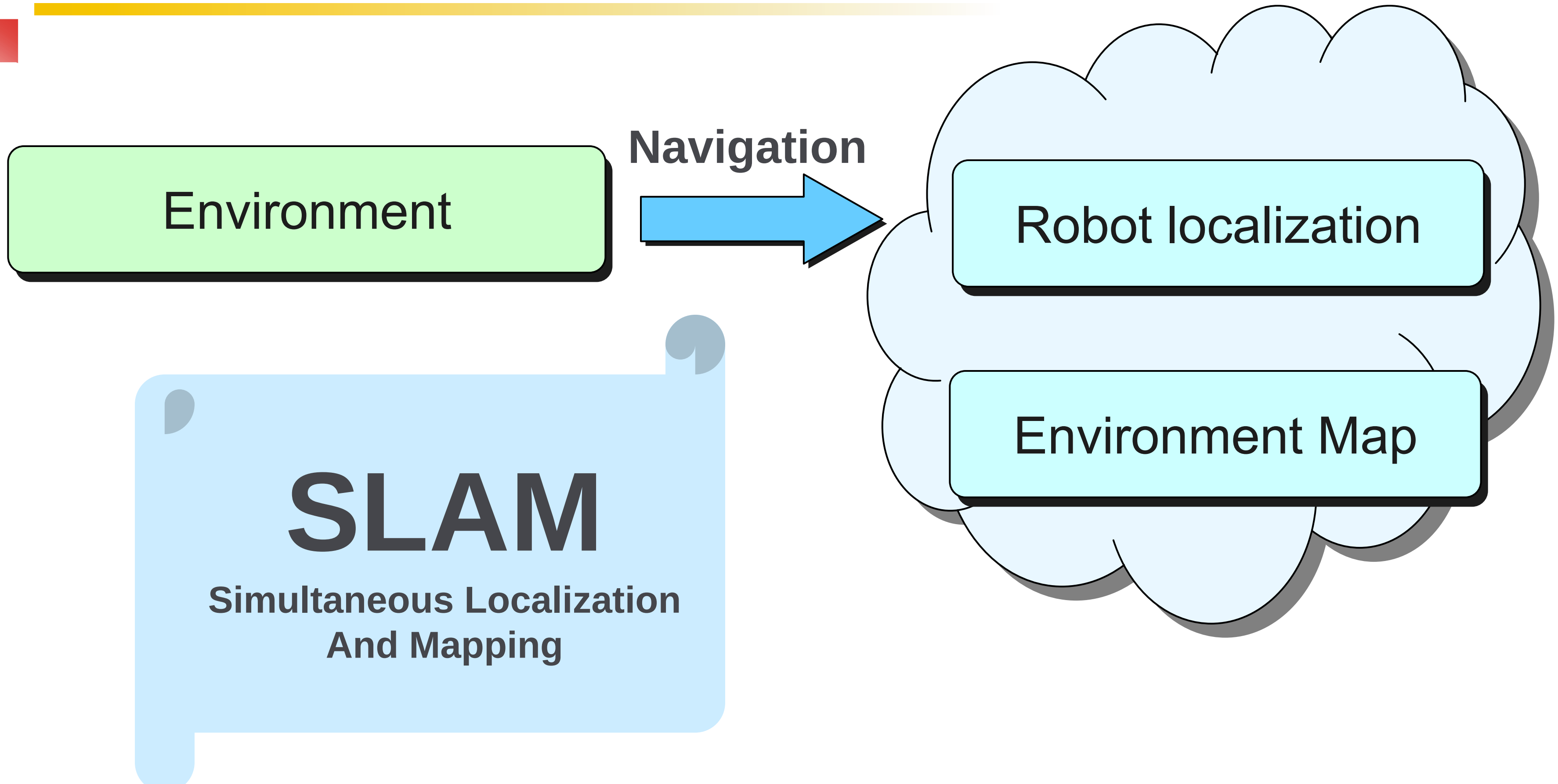


Localization - Results
(Real world – Outside our lab)





Mapping
Problem Statement



Mapping – Kalman Tracker

- Simultaneously estimate the robot position as well as the positions of landmarks (stochastic mapping)
  - Augment state vector to also include landmark positions

$$x = \begin{bmatrix} x_r & y_r & x_{l1} & y_{l1} & x_{l2} & y_{l2} & \cdots & x_{\ln_l} & y_{\ln_l} \end{bmatrix}^T$$

Mapping – Kalman Tracker

$$x(k+1) = x(k) + \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \end{pmatrix} \begin{pmatrix} u_x(k) \\ u_y(k) \end{pmatrix} + \begin{pmatrix} v_{rx}(k) \\ v_{ry}(k) \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$x(k+1) = Fx(k) + Gu(k) + v(k)$$

Mapping – Discrete Bayesian Approach

- Recursive Bayesian filtering for estimating the robot positions along with a map of the environment

$$P(x(1:k), m \mid u(0:k-1), y(1:k))$$
$$= aP(y(k) \mid x(k), m) \int A \bullet B \bullet dx(1:k-1)$$

$$A = (P(x(k) \mid u(k-1), x(k-1))$$
$$B = P(x(1:k-1), m \mid u(0:k-2), y(1:k-1)))$$

Mapping – Discrete Bayesian Approach

- Estimating the full posterior is not tracktable
- Incremental scan matching

- Let at time k-1 the localization and map estimates:

$$\hat{x}(k-1) \qquad \hat{m}(\hat{x}(1:k-1), y(1:k-1))$$

- At time k – after moving and getting a new measurement y(k)

$$\hat{x}(k) = \arg\max_{x(k)} \left\{ P(y(k) \mid x(k), \hat{m}(\hat{x}(1:k-1), y(1:k-1))) P(x(k) \mid u(k-1), \hat{x}(k-1)) \right\}$$

Mapping – Discrete Bayesian Approach

- $\boxed{\text{Estimating the full posterior is not tracktable}}$
- FastSLAM

$$P(x(1:k), m \mid u(0:k-1), y(1:k))$$
$$= P(m \mid u(0:k-1), y(1:k)) \bullet P(x(1:k) \mid u(0:k-1), y(1:k))$$

- Usually implemented via particle filters

Mapping Challenge: Loops in the robot’s path

- As the robot moves and maps features, errors in both the state and the mapped features tend to increase with time
- When already mapped areas are visited (a loop is detected), the mapping algorithm should be able to correct its state and eliminate the accumulated errors

- Complicated robot paths, nested loops or loops that close simultaneously are difficult cases.

Our approach

Off-line Feature-mapping algorithm:

Loop detection is accomplished via a hybrid localizer with global localization capabilities (SSSM) that creates hypotheses whenever known areas (corner points) are visited

- All hypotheses created by the localizer, whenever loops are detected, are tracked individually within their own copy of the map.
- The best path through hypotheses histories is selected, a Kalman smoother redistributes errors and an iterative procedure corrects the map

H. Baltzakis and P. Trahanias, ICRA 2006

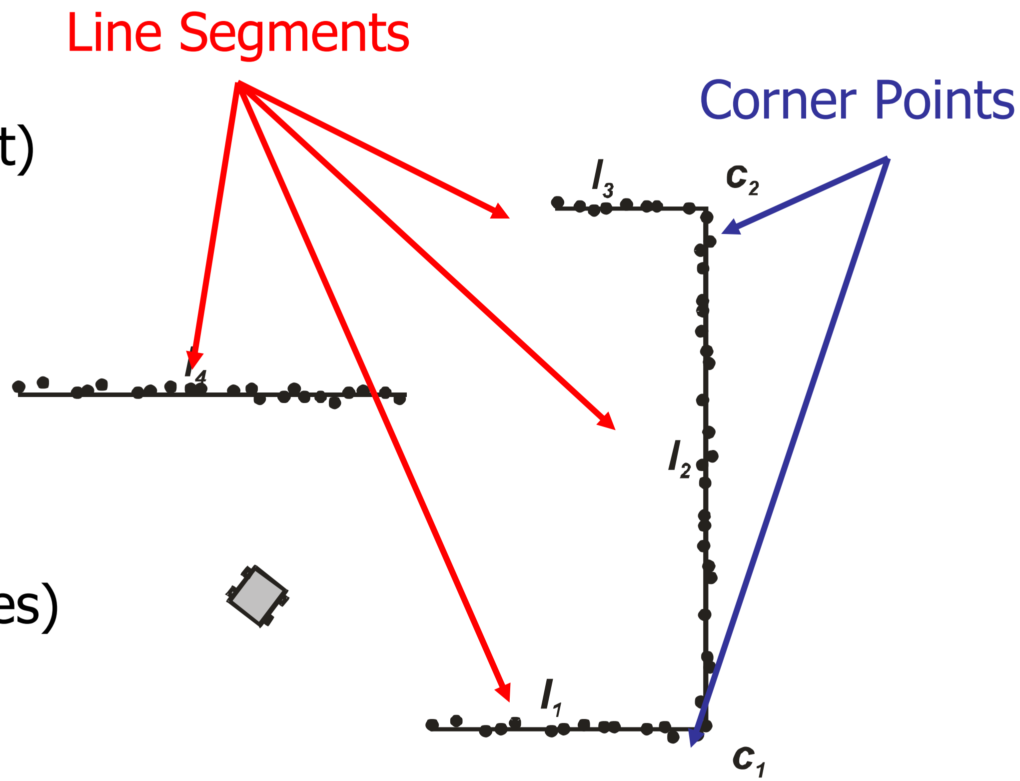
Features

- **Line Segments**
  (used to localize the robot)

$$l \approx N\left((l_f, l_d), \Sigma_f\right)$$

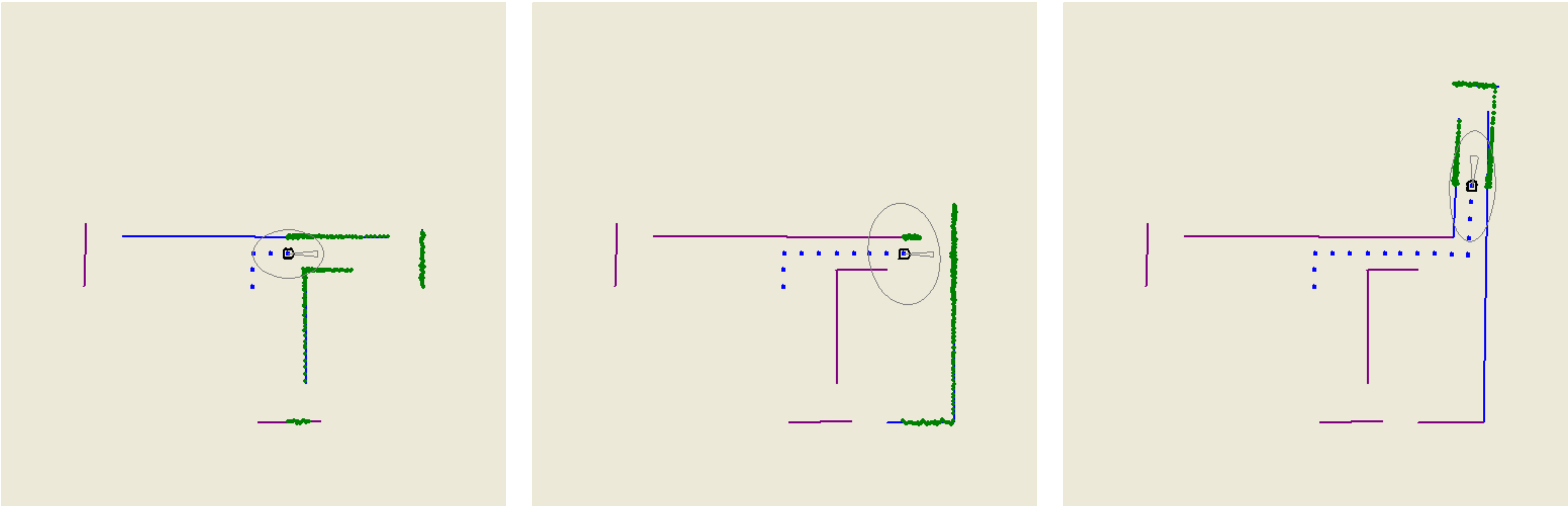
- **Corner Points**
  (used to create hypotheses)

$$c \approx N\left((c_x, c_y), \Sigma_c\right)$$



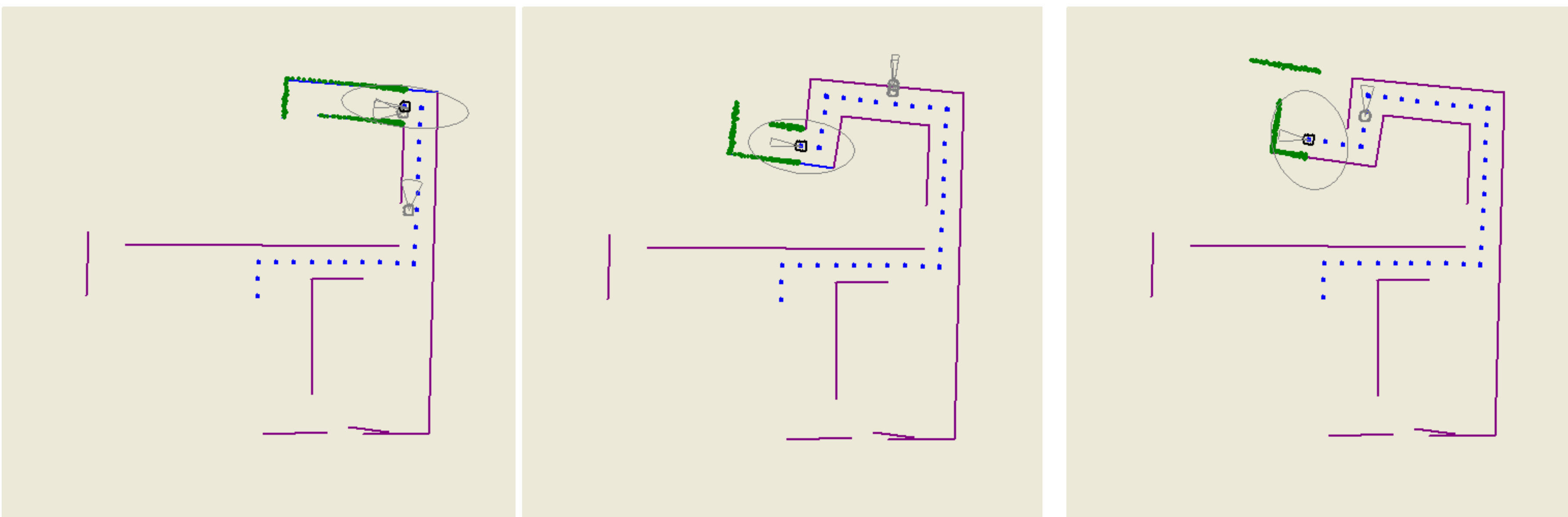
Algorithm overview 1

- Mapping starts with one hypothesis (dominant)
- Existing line segments used for localization while the map is created.
- Non existing segments are inserted in the map



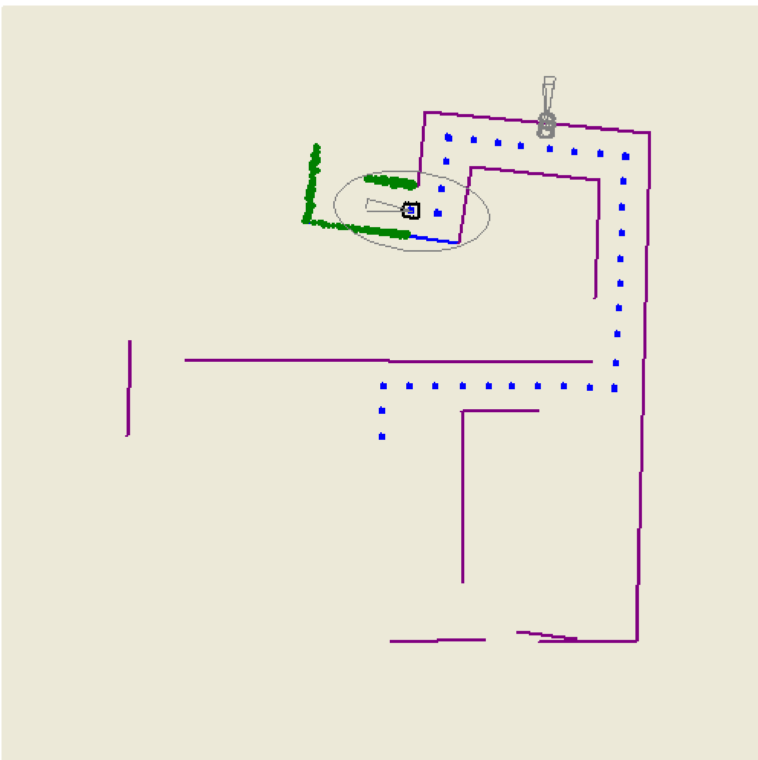
Algorithm overview 2

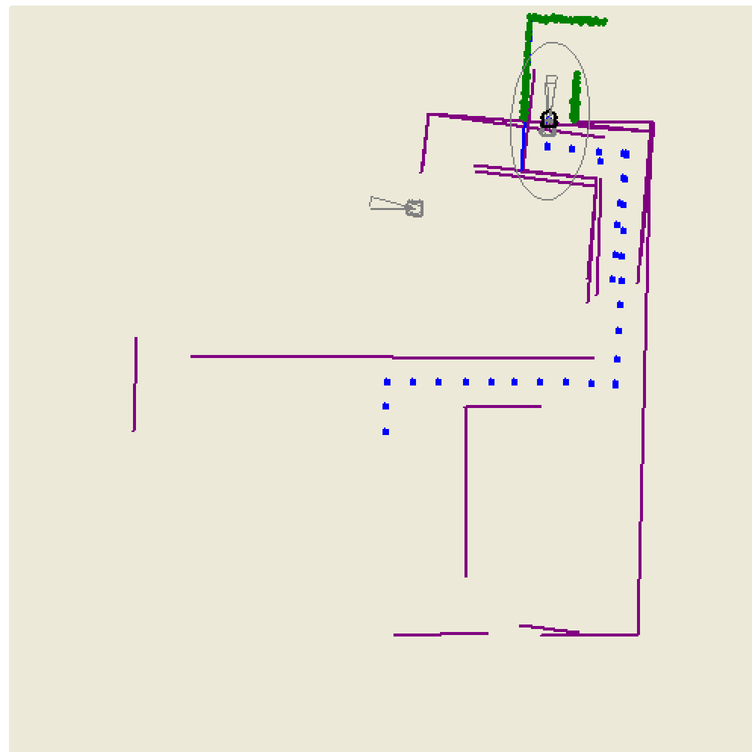
- Detected corner points result in creation of new hypotheses
- Hypotheses eventually vanish if observation sequences do not confirm their validity



Algorithm overview 3

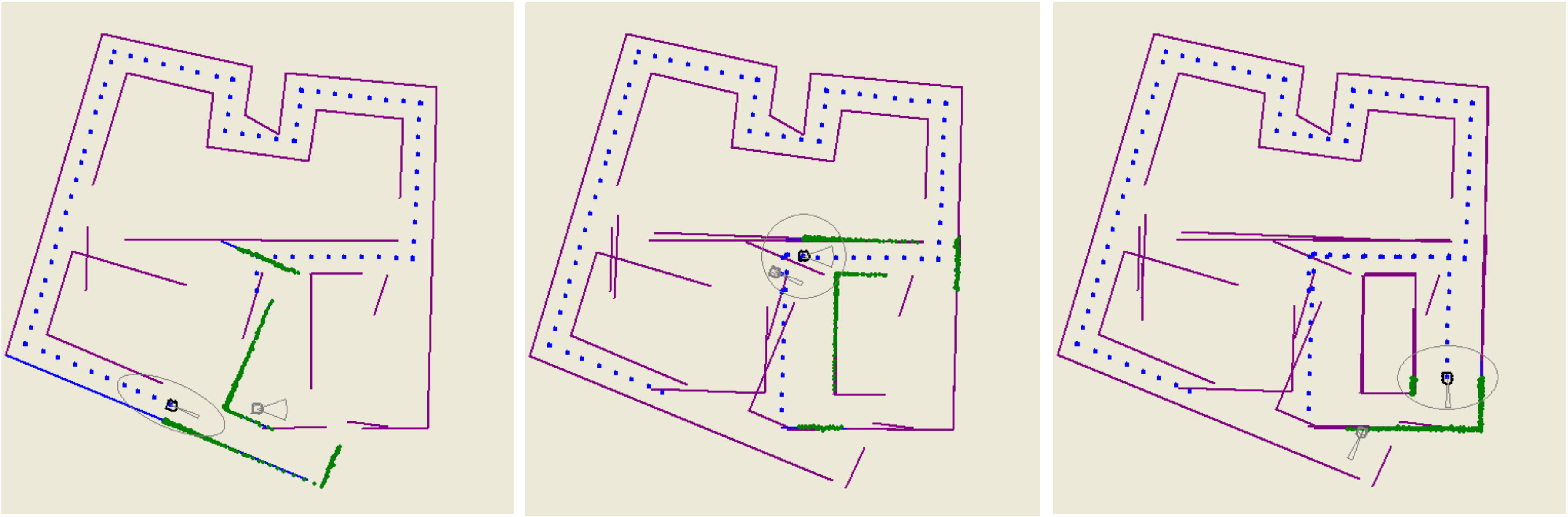
- Hypotheses maintain their own copy of the map (as many maps as hypotheses)





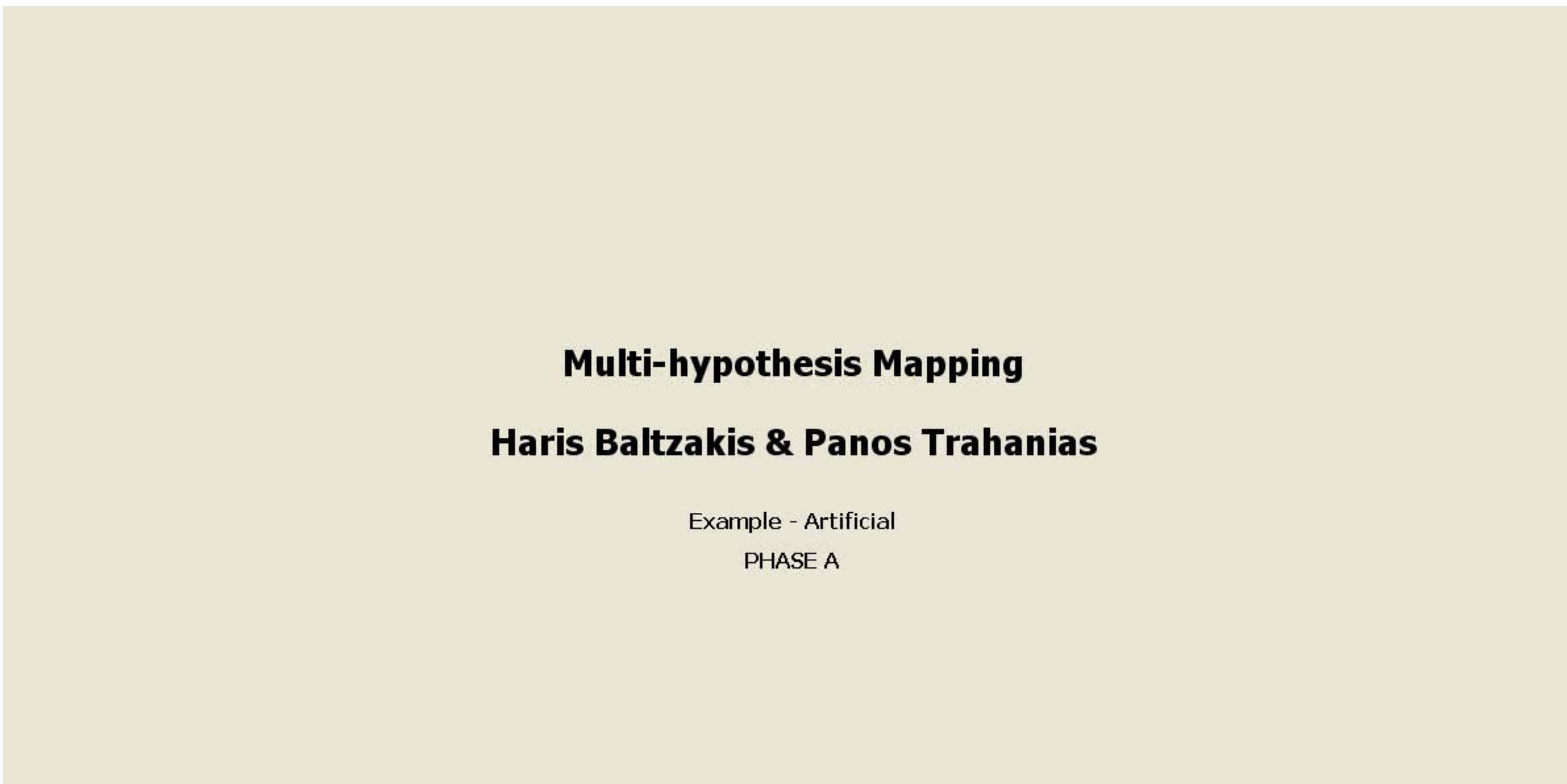
Algorithm overview 4

- Upon entering previously mapped areas (corners detected), new hypotheses are created at the correct robot poses
- Correct hypotheses will eventually become more probable since observations confirm their validity



Algorithm overview 5

- All hypotheses are tracked within their own copy of the map.

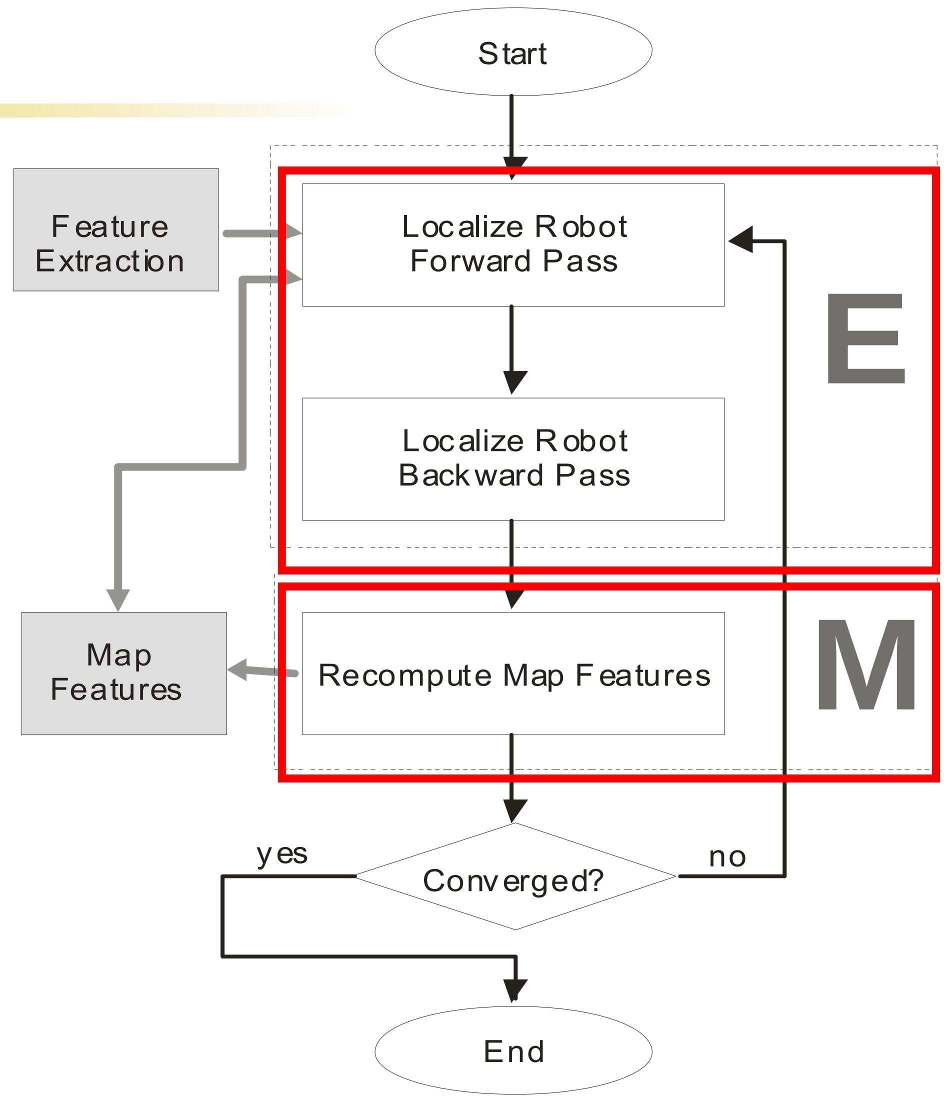


Map Rectification - Iterative Algorithm

Treat map features as parameters of the dynamical system according to which the robot's state evolves

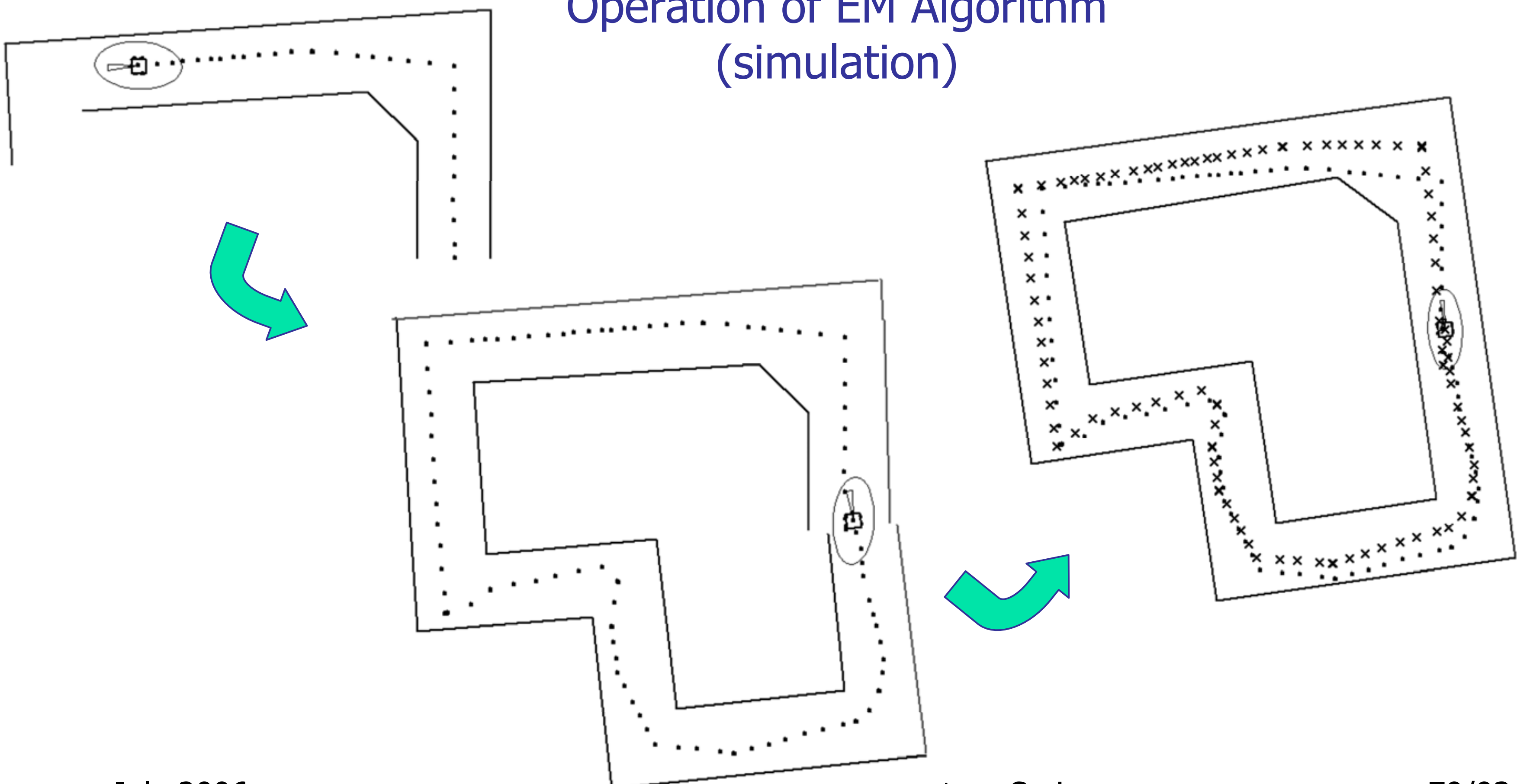
- E-STEP: Localize the robot using all available measurements. (obtain max a-posteriori estimates of robot states)

- M-STEP: Recalculate map features



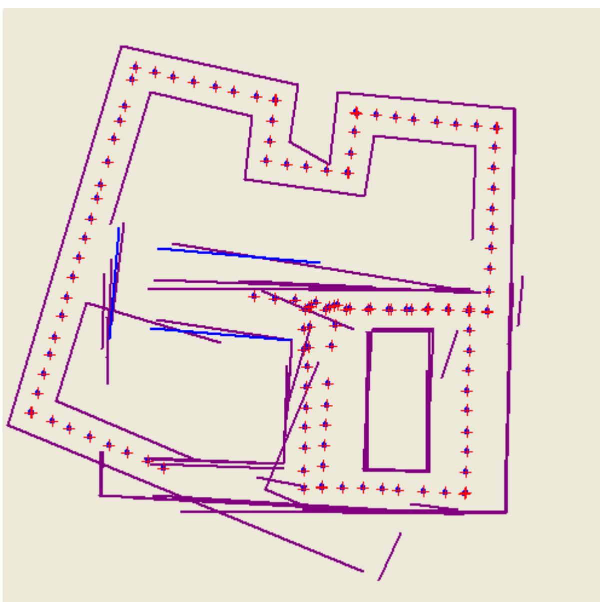
EM Algorithm - Example

Operation of EM Algorithm
(simulation)



Results (simulated running example)

Initial map



Multi-hypothesis Mapping

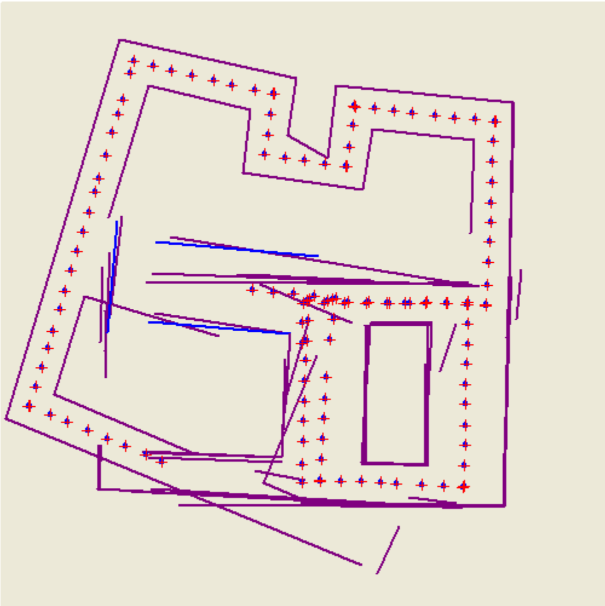
Haris Baltzakis & Panos Trahanias

Example - Artificial

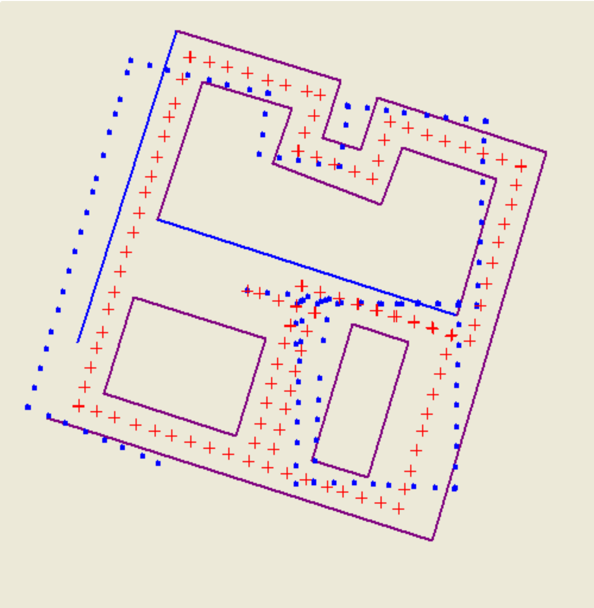
PHASE B

Results (simulated running example)

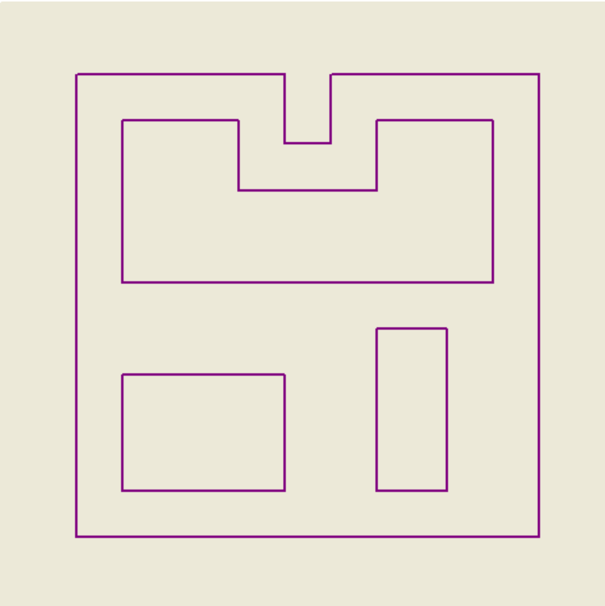
Initial Map



Rectified Map

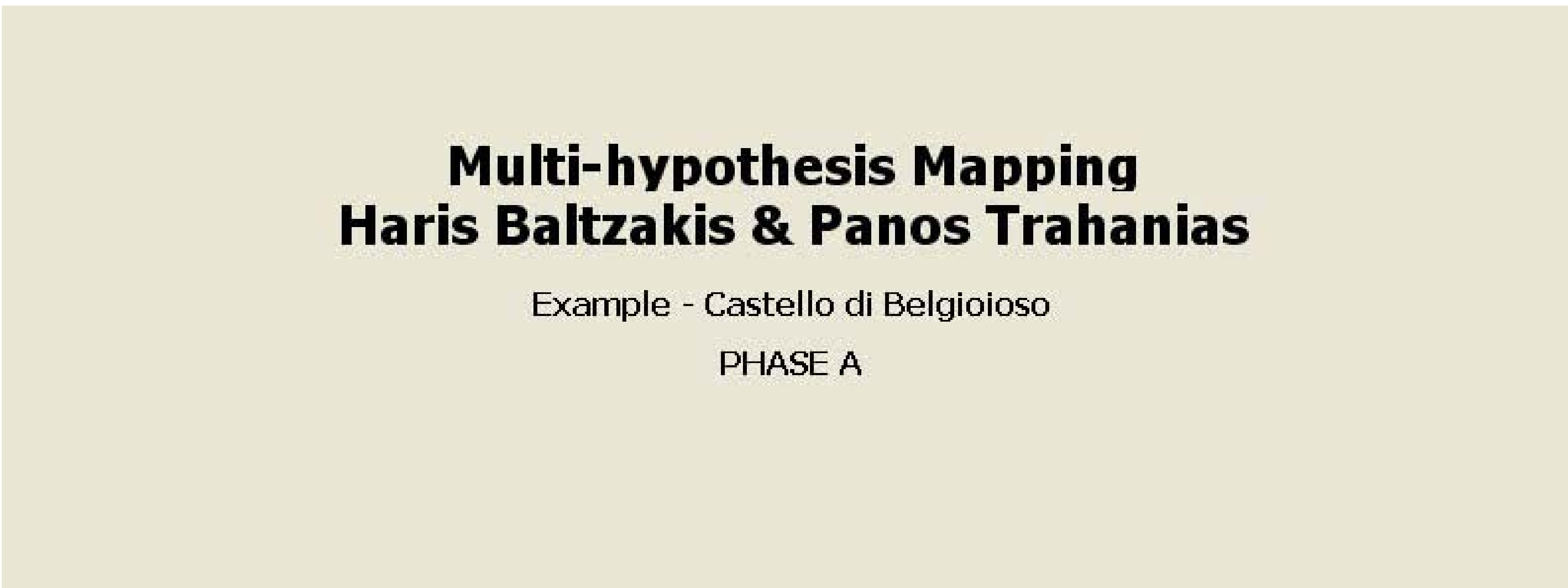


Ground Truth



Results (Di Castello Belgioioso)

Phase A



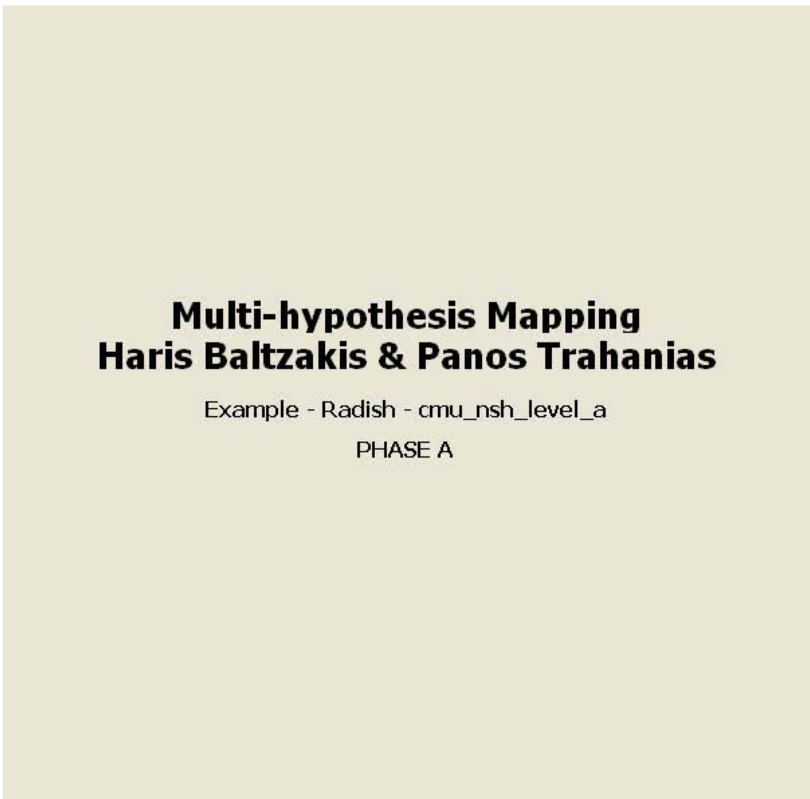
Belgioioso dataset available from university of Freiburg

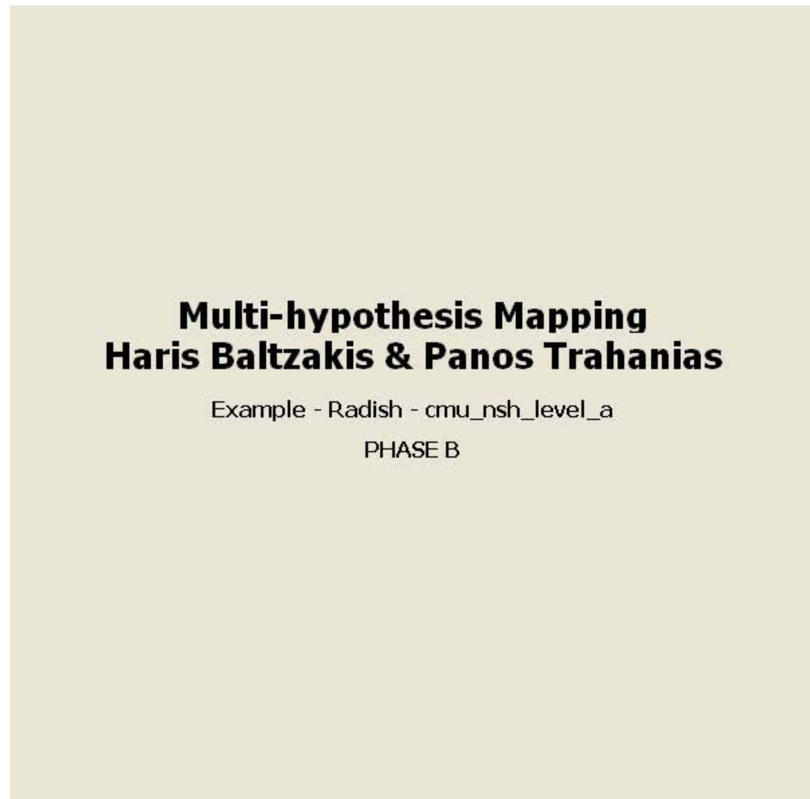
Results (Di Castello Belgioioso)

Phase B

Belgioioso dataset available from university of Freiburg

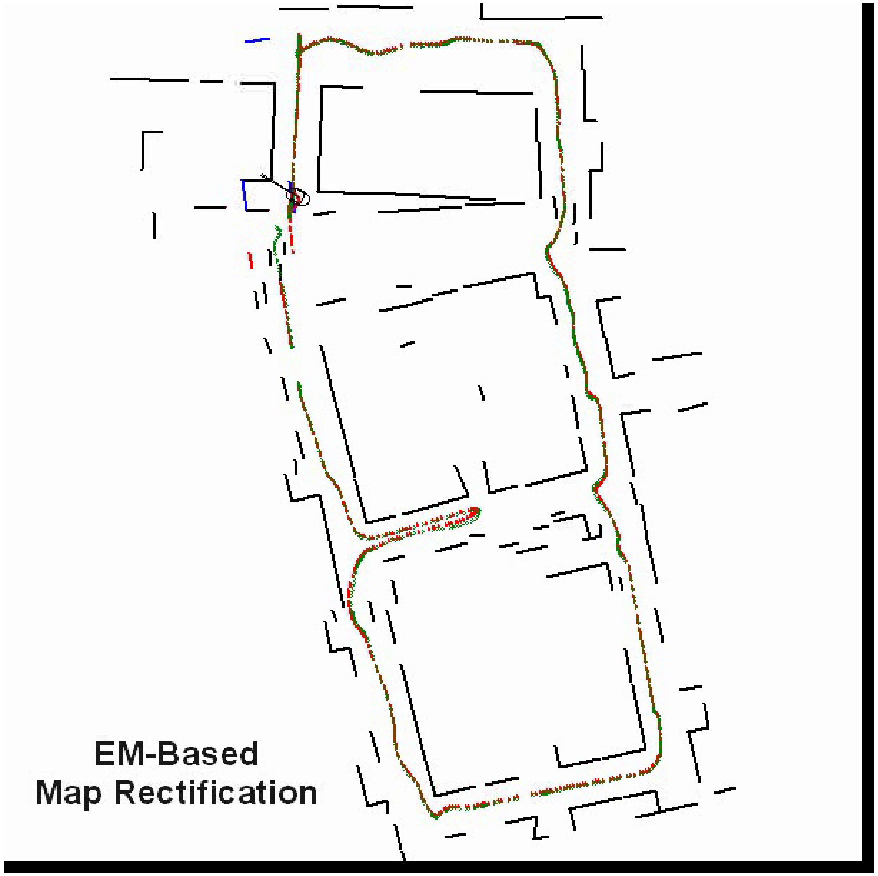
Results (Radish - cmu_nsh_level_a)





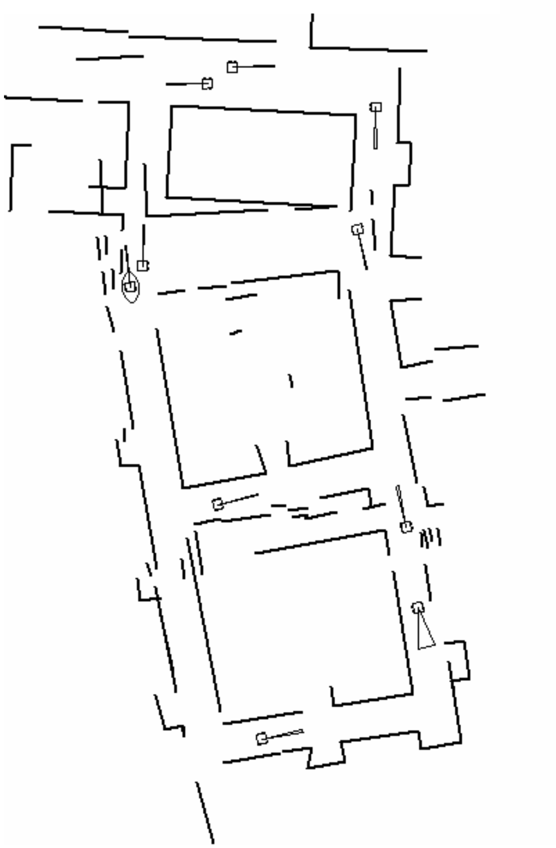
Radish cmu_nsh_level_a data set submitted by Nick Roy

Mapping - Results
(Real world – FORTH 1st floor)

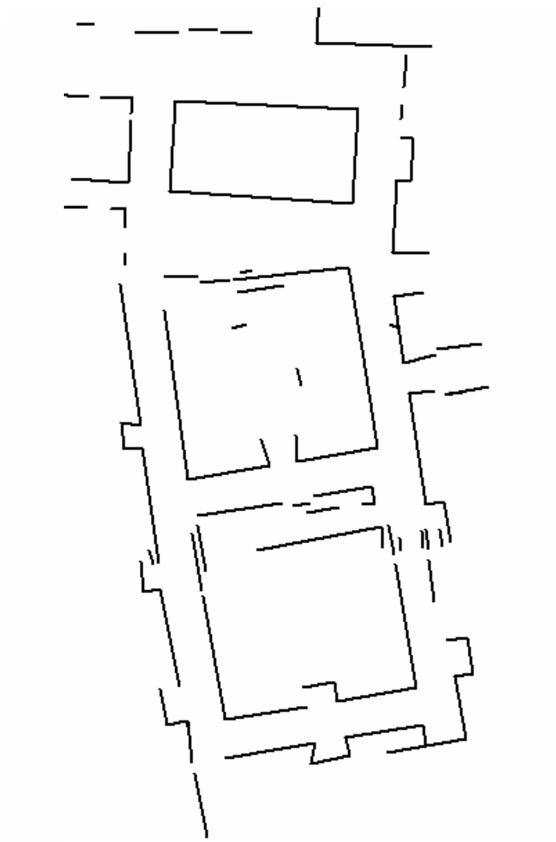


Mapping - Results
(Real world – FORTH 1st FLOOR)

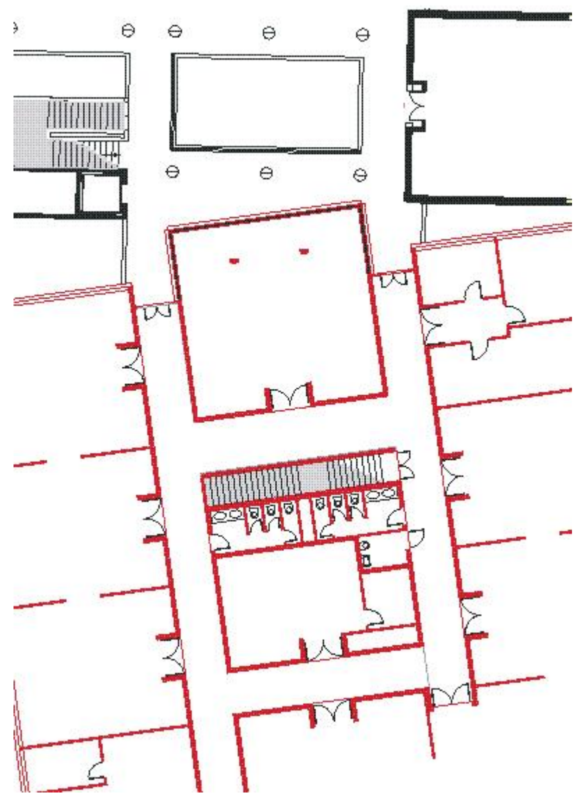
Initial Map



Rectified Map

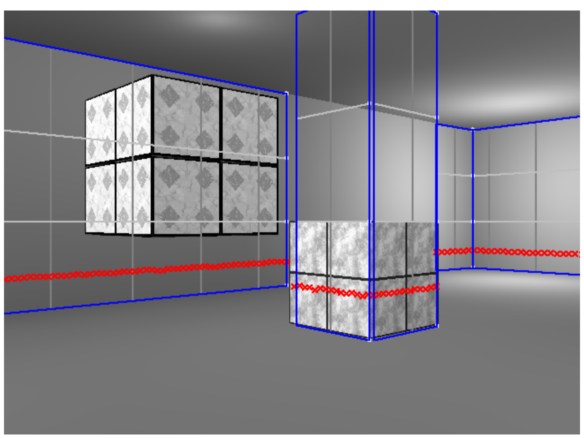


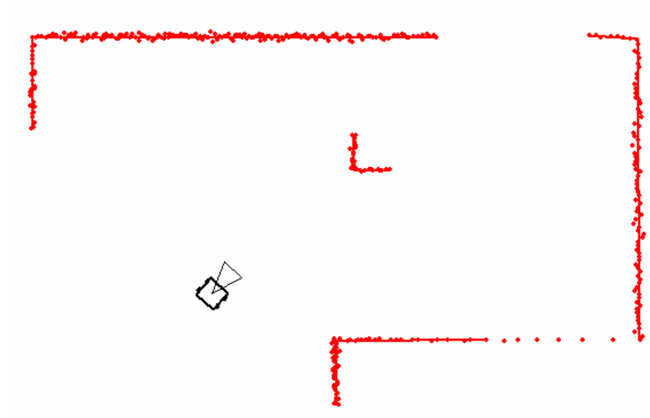
Ground Truth



Visual Information Processing

- Laser range finders provide fast and accurate depth information for 2D slices of the environment
- Various objects are invisible to the laser range finder.
- Vision can provide extra information for crucial tasks such as obstacle avoidance.



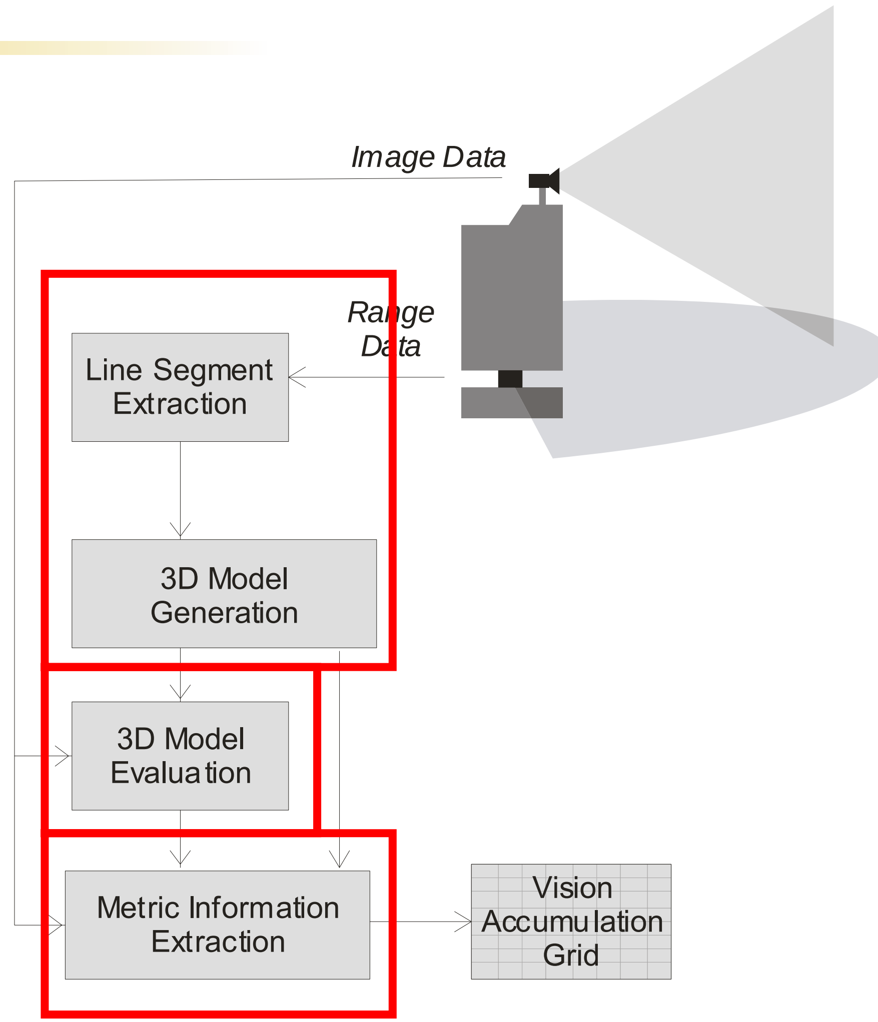


Visual Information Processing

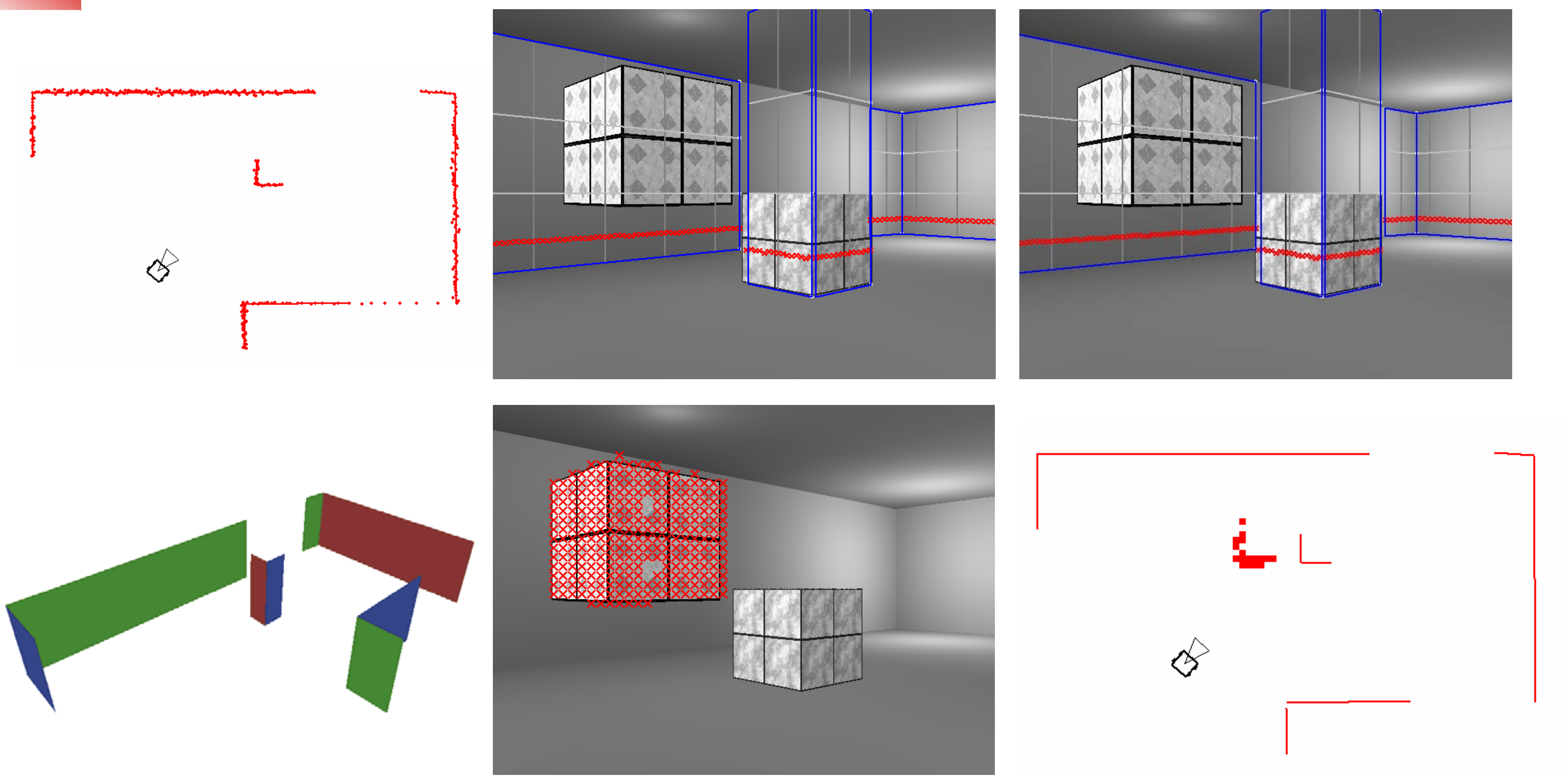
Step 1: From 2D laser measurements, form 3D model hypothesis

Step 2: From 1^{st} camera visual data and 3D model hypothesis predict visual data at the 2^{nd} camera. Then, compare actual and predicted visual data to evaluate the 3D model

Step 3: Wherever 3D model hypothesis is invalid, extract metric structure information



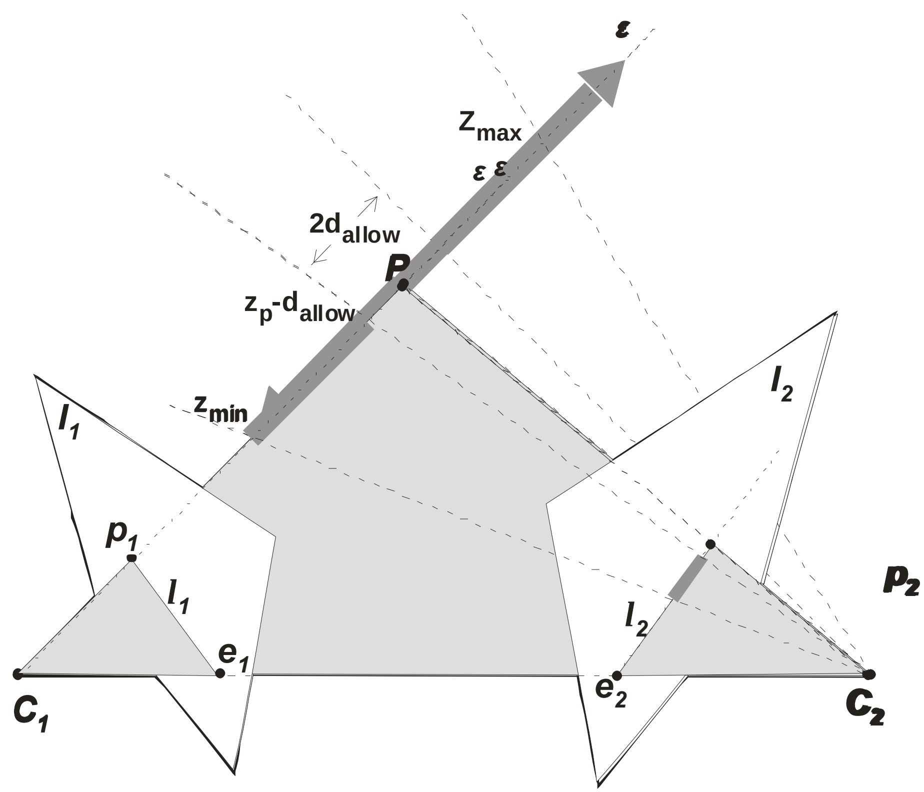
Visual Information Processing
(simulated example)



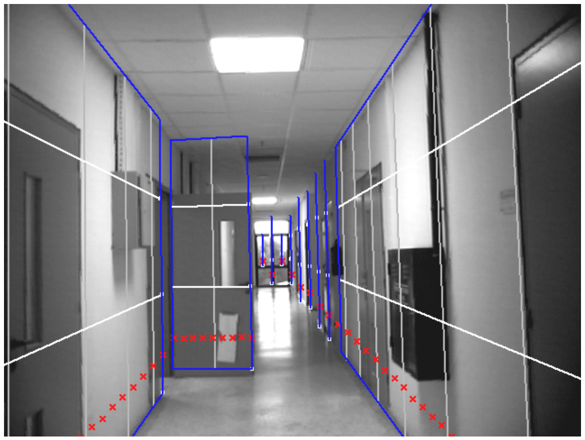
Visual Information Processing (Efficiency considerations)

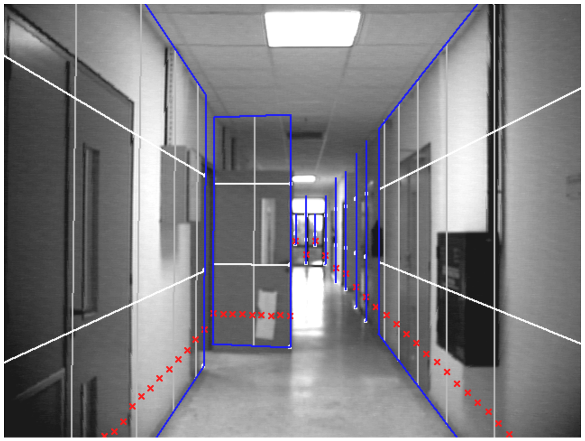
- Depth computations take place only where inconsistencies are detected
- For collision avoidance depth computations can be further eliminated.
  - Criterion 1. Visual range defers significantly to laser range data
  - Criterion 2. Visual range is shorter that corresponding laser suggests
  - Criterion 3. Visual range is neither too far nor to close to the robot.

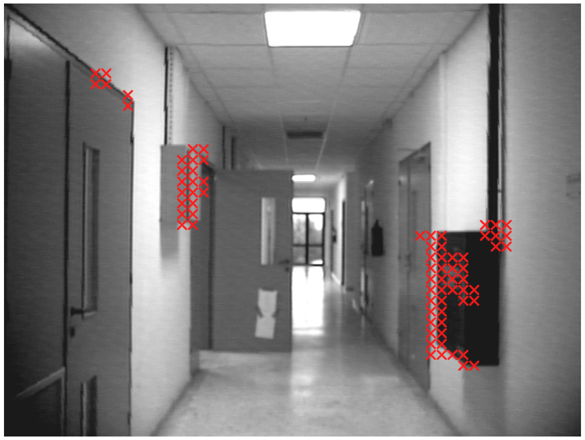
Crit Combination of Criteria max low

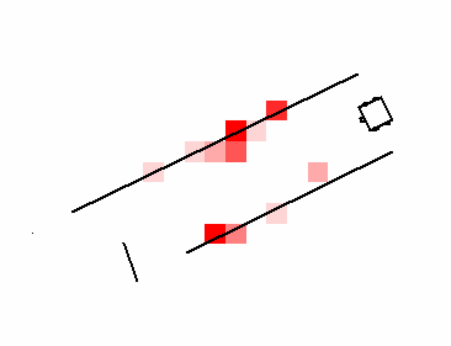


Visual Information Processing
(Real world example – outside our lab)









H. Baltzakis, A. Argyros and P. Trahanias, MVA 2003

Real Application
(Robotic Tour-guide in exhibition site)

The TOURBOT & WebFAIR Projects:

- Autonomous mobile robots in populated environments (serving real-visitors)
- Also operating over the web (serving web-visitirs)

P. Trahanias et al, IEEE RAM 2005

Thanks!

Thanks for your attention! Time for a break…