KFUPM

COE 584: Robotics

Presentation 1

Particle Filter Localization

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Outline

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- Bayesian Filtering
- Particle Filters
- Monte-Carlo Localization
- Visually…
- The Use of Negative information
- Localization Architecture in GT
- What Next?

References

- Sebastian Thrun, Dieter Fox, Wolfram Burgard. **“Monte Carlo Localization With Mixture Proposal Distribution”**.
- Wolfram Burgard. **“Recursive Bayes Filtering”,** PPT file
- Jan Hoffmann, Michael Spranger, Daniel Gohring, and Matthias Jungel. “Making Use of What you Don’t See: Negative Information in Markov Localization.
- Dieter Fox, Jeffrey Hightower, Lin Liao, and Dirk Schulz

Introduction

MOTIVATION

- Where am I?

Localization Problem

- **"Using sensory information to locate the robot in its environment is the most fundamental problem to providing a mobile robot with autonomous capabilities."** *[Cox '91]*

- **Given**
  - Map of the environment: **Soccer Field**
  - Sequence of percepts & actions: **Camera Frames, Odometry, etc**

- **Wanted**
  - Estimate of the robot's state (pose):

$$Pose = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix}$$

Probabilistic State Estimation

- Advantages
  - Can accommodate inaccurate models
  - Can accommodate imperfect sensors
  - Robust in real-world applications
  - Best known approach to many hard robotics problems
- Disadvantages
  - Computationally demanding
  - False assumptions
  - Approximate!

Bayesian Filter

May 2008

Bayesian Filters

- Bayes' Rule

$$P(x|y) = \frac{P(y|x) \cdot P(x)}{P(y)} = \frac{\text{Likelihood} \cdot \text{Prior}}{\text{Evidence}}$$

- with background knowledge

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

- Total Probability

$$P(x) = \sum_{\forall z} P(x|z)P(z)$$

BAYESIAN FILTERS

- Let
  - ***x(t)*** be pose of robot at time instant ***t***
  - ***o(t)*** be robot observation (sensor information)
  - ***a(t)*** be robot action (odometry)

- The Idea in Bayesian Filtering is
  - to find ***Probability Density (distribution)*** of the **Belief**

$$Bel(x(t)) = P\left(x(t) \middle| o(t), a(t-1), o(t-1), a(t-2), \ldots, o(0)\right)$$

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

Bayesian Filters

- So, by Bayes Rule

$$Bel\big(x(t)\big) = \frac{P(o(t)|x(t), a(t-1), \dots) \cdot P(x(t)|a(t-1), \dots)}{P(o(t)|a(t-1), \dots)}$$

- **Markov Assumption**:
  - *Past & Future data are independent if current state known*

$$Bel\big(x(t)\big) = \frac{P(o(t)|x(t)) \cdot P(x(t)|a(t-1), \dots)}{P(o(t)|a(t-1), \dots)}$$

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

Bayesian Filters

$$Bel(x(t)) = \frac{P(o(t)|x(t)) \cdot P(x(t)|a(t-1),\dots)}{P(o(t)|a(t-1),\dots)}$$

- **Denominator** is not a function of x(t), then it is replaced with *normalization* constant
- With Law of **Total Probability** for rightmost term in numerator; and further simplifications
  - We get the **Recursive Equation**

$$Bel(x(t)) = \eta P(o(t)|x(t)) \sum_{\forall x(t-1)} P(x(t)|x(t-1),a(t-1))Bel(x(t-1))$$

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

Bayesian Filters

$$Bel(x(t)) = \eta P(o(t)|x(t)) \sum_{\forall x(t-1)} P(x(t)|x(t-1), a(t-1)) Bel(x(t-1))$$

- So we need for ***any*** Bayesian Estimation problem:
  1. Initial Belief distribution, $Bel(x(0))$
  2. Next State Probabilities, $P(x(t)|x(t-1), a(t-1))$
  3. Observation Likelihood, $P(o(t)|x(t))$

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

Particle Filter

Particle Filter

$$Bel(x(t)) = \eta P(o(t)|x(t)) \sum_{\forall x(t-1)} P(x(t)|x(t-1), a(t-1)) Bel(x(t-1))$$

- The **Belief** is modeled as the **discrete** distribution

$$Bel(x) = \{x_i, w_i\}$$

- $i = 1, \ldots, m$ as ***m*** is the number of particles
- x_i hypothetical state estimates
- w_i weights reflecting a "confidence" in how well is the particle

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

Particle Filter

- Estimation of non-Gaussian, nonlinear processes

- It is also called:
  - Monte Carlo filter,
  - Survival of the fittest,
  - Condensation,
  - Bootstrap filter,

$$P(x|y,z) = \frac{P(y|x,z) \cdot P(x|z)}{P(y|z)}$$

Monte-Carlo Localization

- Framework

$$Bel(x(t)) = \eta P(o(t)|x(t)) \sum_{m} P\big(x(t)\big|x(t-1), a(t-1)\big) Bel(x(t-1))$$

Observation Model

Motion Model

Previous Belief

Monte-Carlo Localization

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MONTE-CARLO LOCALIZATION

- **Algorithm**

1. Using previous samples, project ahead by generating a new samples by the motion model
2. Reweight *each sample* based upon the new sensor information
   - **One approach** is to compute $w_i = P(o(t)|x_i(t))$ for each *i*
3. Normalize the weight factors for all ***m*** particles
4. Maybe resample or not! And go to <u>*step 1*</u>

- The normalized weight defines the potential **distribution** of state

Monte-Carlo Localization

- **Algorithm**

$$Bel(x(t)) = \eta P(o(t)|x(t)) \sum_m P\big(x(t)\big|x(t-1), a(t-1)\big) Bel(x(t-1))$$

Step 2&3 for all m

Step 1 for all m after **Step 4**

Monte-Carlo Localization

- **State Estimation,** i.e. Pose Calculation
  - Mean
  - particle with the highest weight
  - find the cell (particle subset) with the highest total weight, and calculate the mean over this particle subset. GT2005

- Most crucial thing about MCL is the **calculation of weights**
- Other alternatives can be imagined

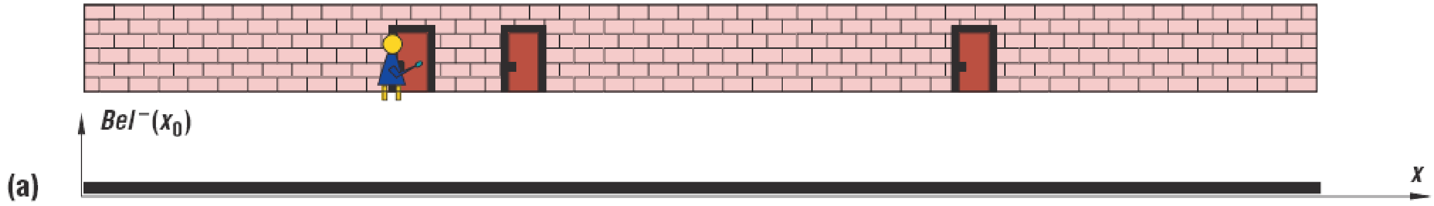
MONTE-CARLO LOCALIZATION

- **Advantages** to using particle filters (MCL)
  - Able to model non-linear system dynamics and sensor models
  - No Gaussian noise model assumptions
  - In practice, performs well in the presence of large amounts of noise and assumption violations (e.g. Markov assumption, weighting model…)
  - Simple implementation

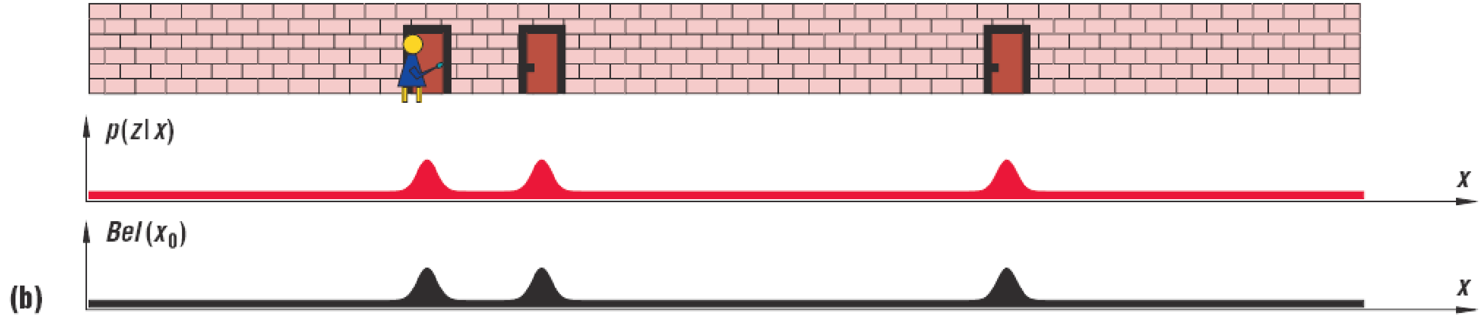
- **Disadvantages**
  - Higher computational complexity
  - Computational complexity **increases exponentially** compared with increases in state dimension
  - In some applications, the filter is more likely to diverge with more accurate measurements!!!!

… Visually

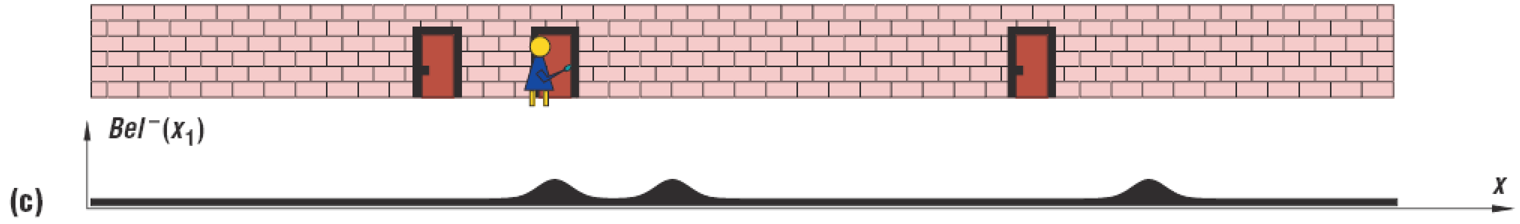
One – Dimensional illustration of Bayes Filter



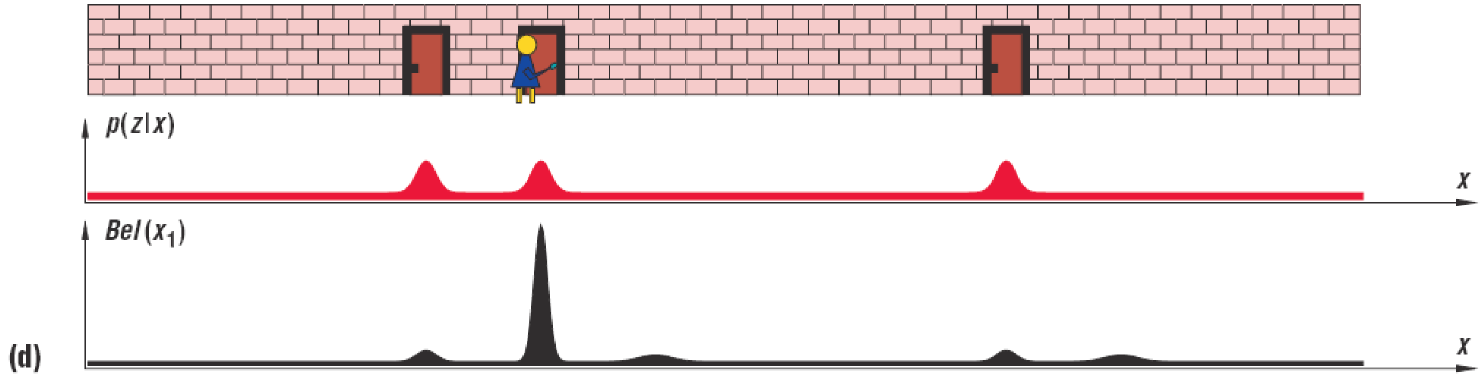
One – Dimensional illustration of Bayes Filter



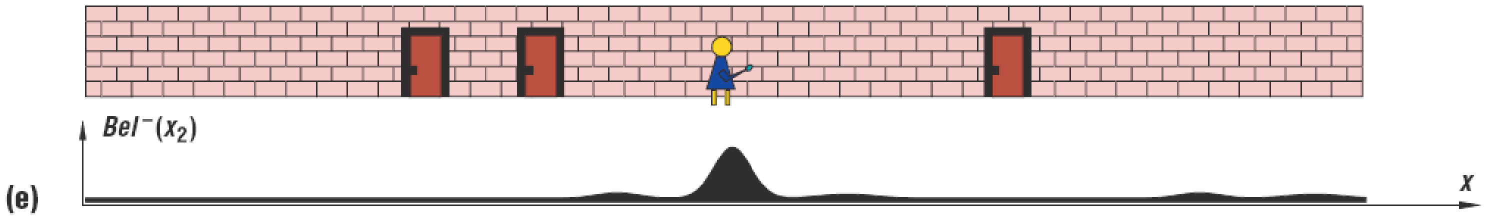
One – Dimensional illustration of Bayes Filter



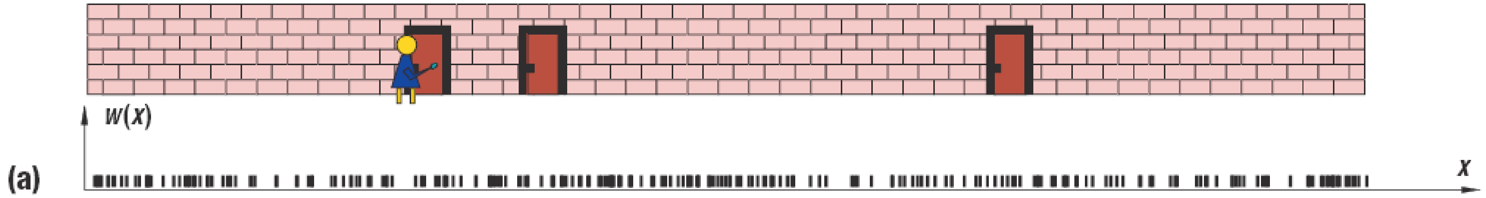
One – Dimensional illustration of Bayes Filter



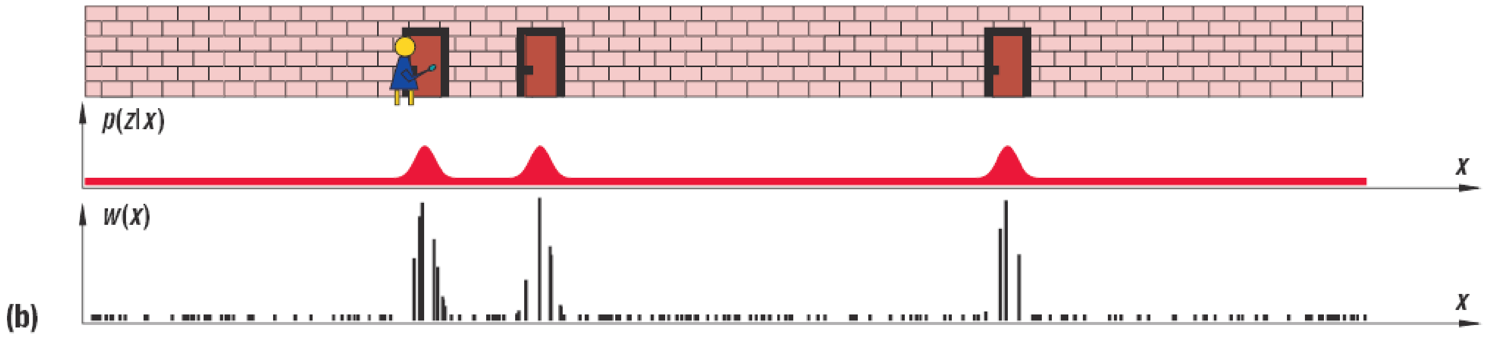
One – Dimensional illustration of Bayes Filter



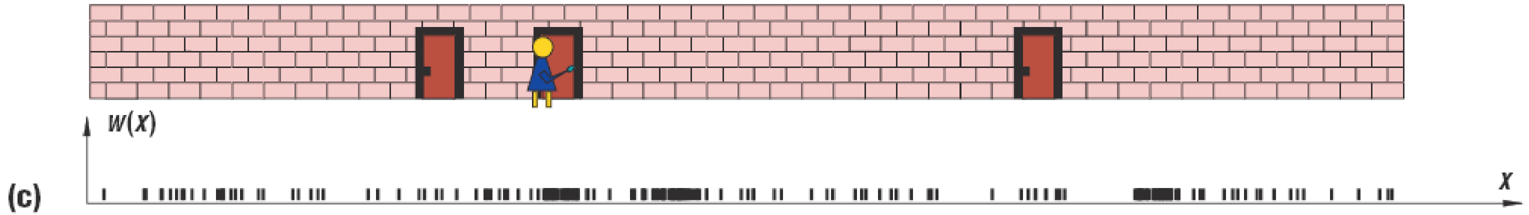
Applying Particle Filters to Location Estimation



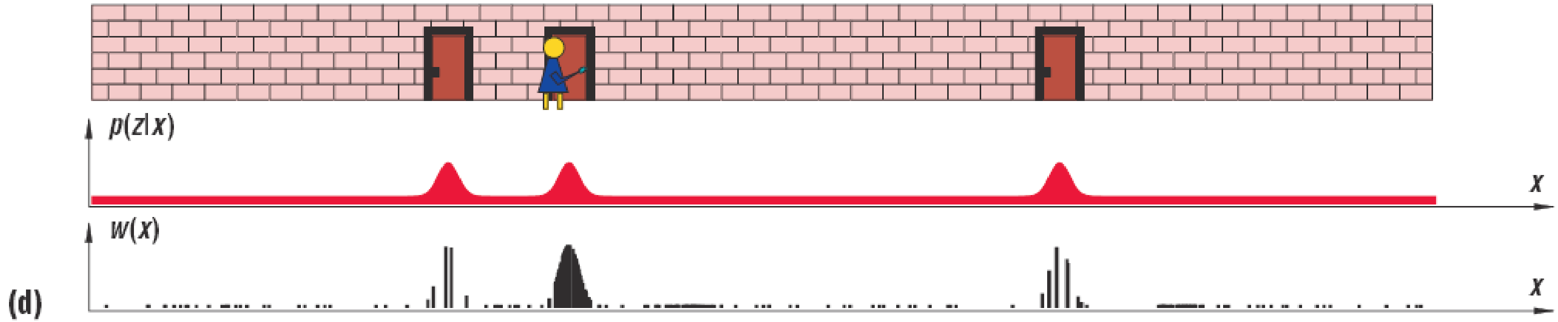
APPLYING PARTICLE FILTERS TO LOCATION ESTIMATION



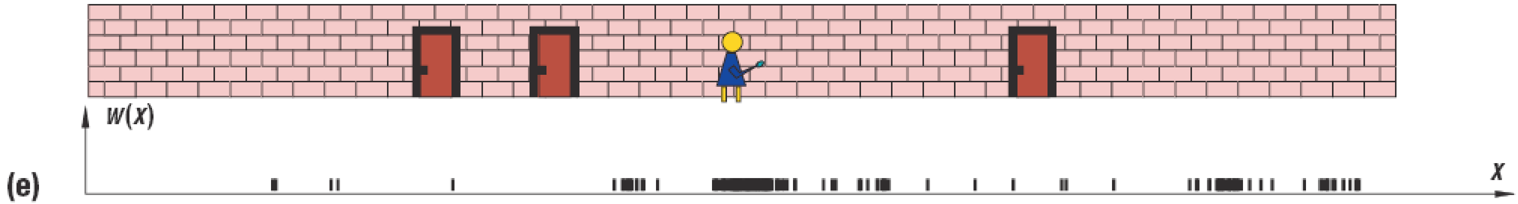
APPLYING PARTICLE FILTERS TO LOCATION ESTIMATION



Applying Particle Filters to Location Estimation



APPLYING PARTICLE FILTERS TO LOCATION ESTIMATION



Negative Information

Making Use of Negative Information

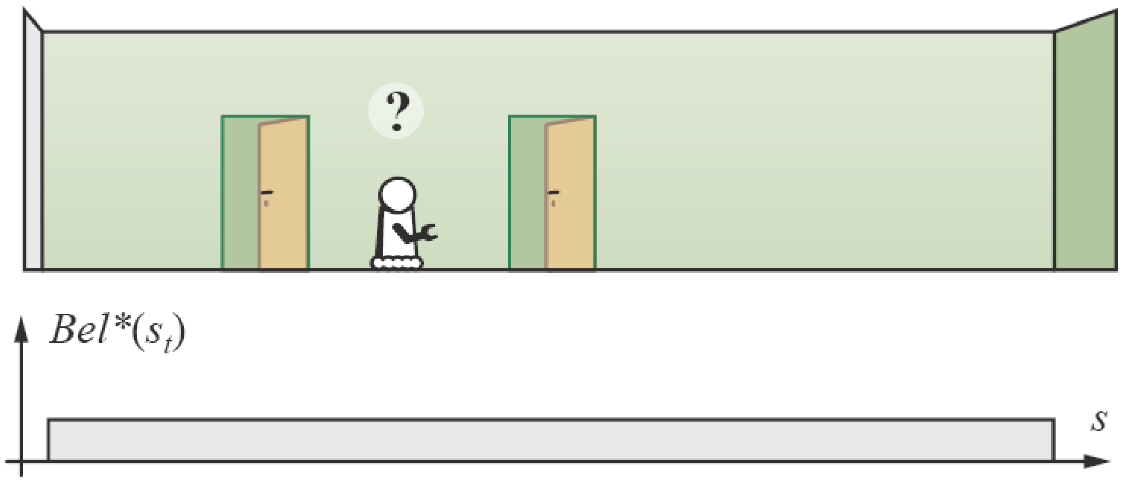


Fig. 1a. ($t = t_0$) Illustration of a robot localizing in an office hallway. The robot has a sensor to detect doors. At the beginning, the robot does not know its position in the hallway (uniform belief distribution $Bel^\star(s_t)$). At this time, no sensing of the world takes place.

Making Use of Negative Information

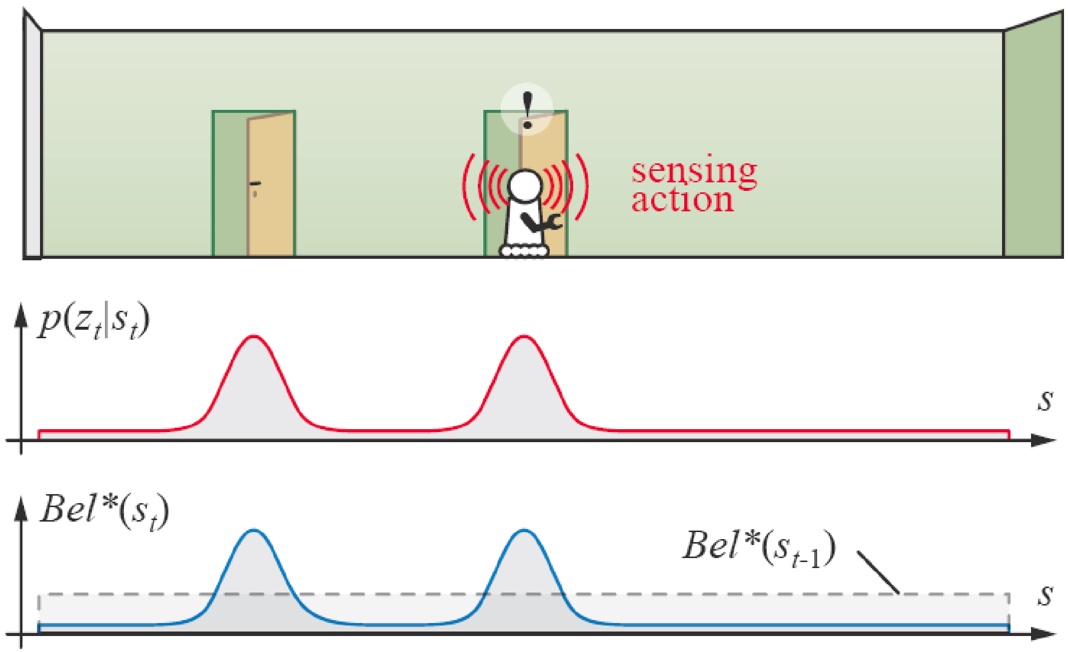


Fig. 1b. ($t = t_1$) The robot has moved down the hallway and now senses a door $p(z_t|s_t)$ which results in the shown belief $Bel^\star(s_t)$. It has two peaks since the robot could be standing in front of either door. The previous distribution is illustrated by the dashed line.

Making Use of Negative Information

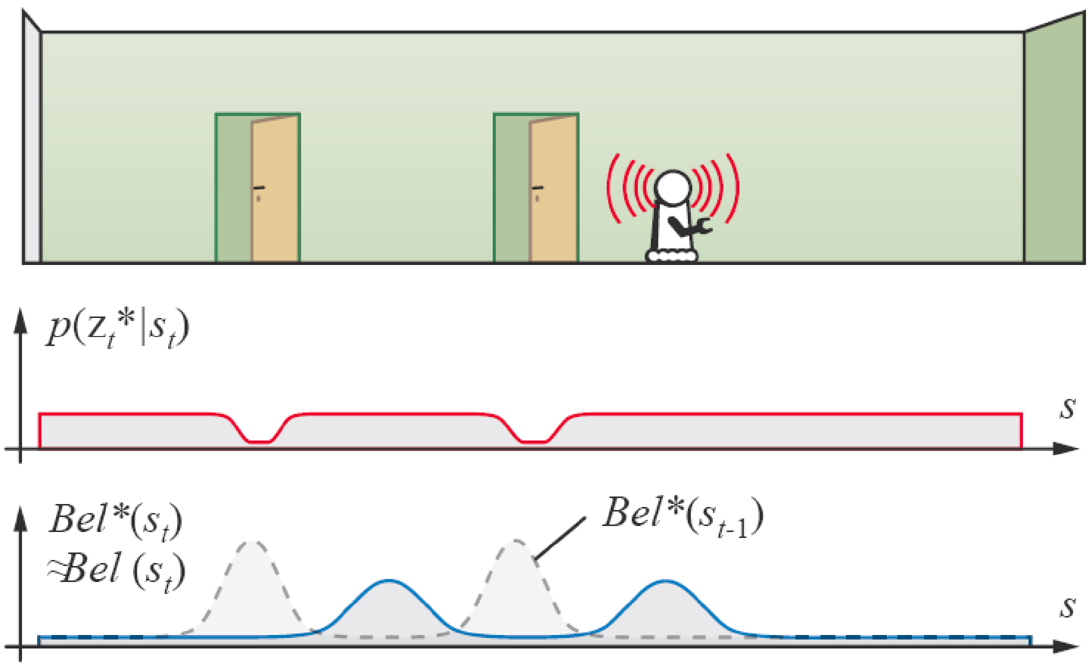


Fig. 1c. ($t = t_3$) The robot moves on. There are no doors nearby so the "door sensor" does not sense a door. The sensor update distribution is shown in $p(z_t^\star|s_t)$. This negative information is of negligible use at this position: it does not help differentiate between the peaks.

Making Use of Negative Information

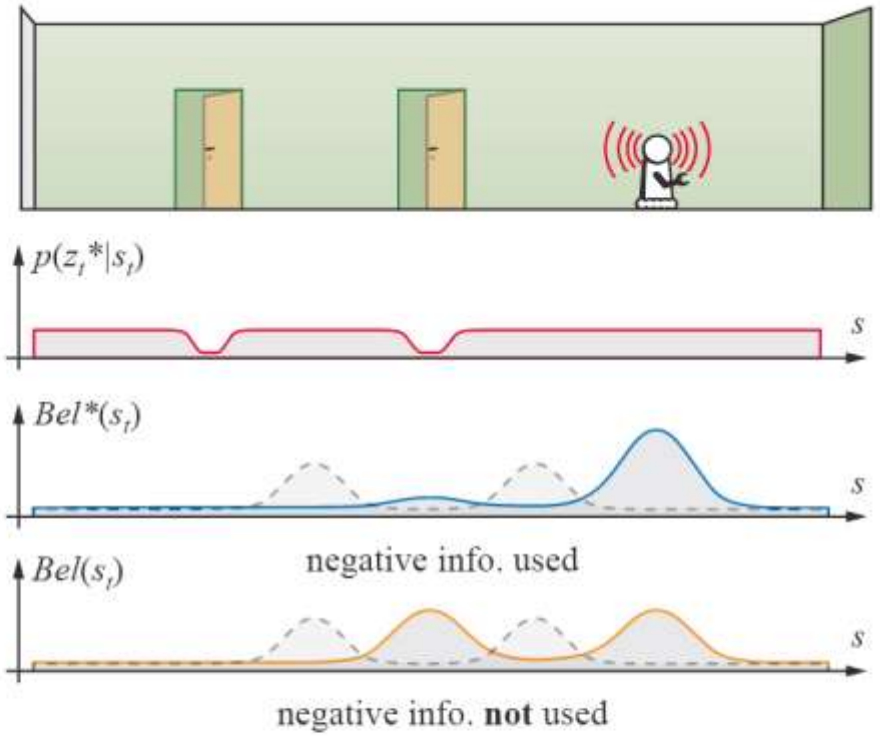


Fig. 1d. ($t = t_4$) The robot moves on and the door sensor still does not sense a door. $Bel^\star(s_t)$ shows the belief if negative information is taken into account, whereas $Bel(s_t)$ shows the belief without using negative information to better illustrate the case. As can be seen from the diagram, using negative information allows the robot to rule out the left peak.

Mathematical Modeling

$$Bel^{-}(s_t) \leftarrow \int p\left(st \mid s_{t-1,} u_{t-1}\right) Bel\left(s_{t-1}\right) ds_{t-1}$$

$$Bel(s_t) \leftarrow \eta p(z_t \mid s_t) Bel^{-}(s_t)$$

$$P(z^{*}_{l,t} \mid s_t)$$

$$P(z^{*}_{l,t} \mid s_t, r_{t,} o_t)$$

t : Time
l: Landmark
z: Observation
u: action
s: State
*: negative information
r: sensing range
o: possible occlusion

ALGORITHM

$$Bel^{-}(s_t) \leftarrow \int p\left(st \mid s_{t-1,} u_{t-1}\right) Bel\left(s_{t-1}\right) ds_{t-1}$$

if (landmark l detected) **then**

$$Bel(s_t) \leftarrow \eta p(z_t \mid s_t) Bel^{-}(s_t)$$

else

$$Bel(s_t) \leftarrow \eta p(z_{l,t}^{*} \mid s_t, r_{t,} o_t) Bel^{-}(s_t)$$

end if

EXPERIMENTS

- Particle Distribution
  - 100 Particles (MCL)
  - 2000 Particles to get better representation.
  - Not Using negative Information VS using negative information.
- Entropy H (information theoretical quality measure of the positon estimate.

$$H_p(s_t) = -\sum_{s_t} Bel(s_t) \log(Bel(s_t))$$

Results

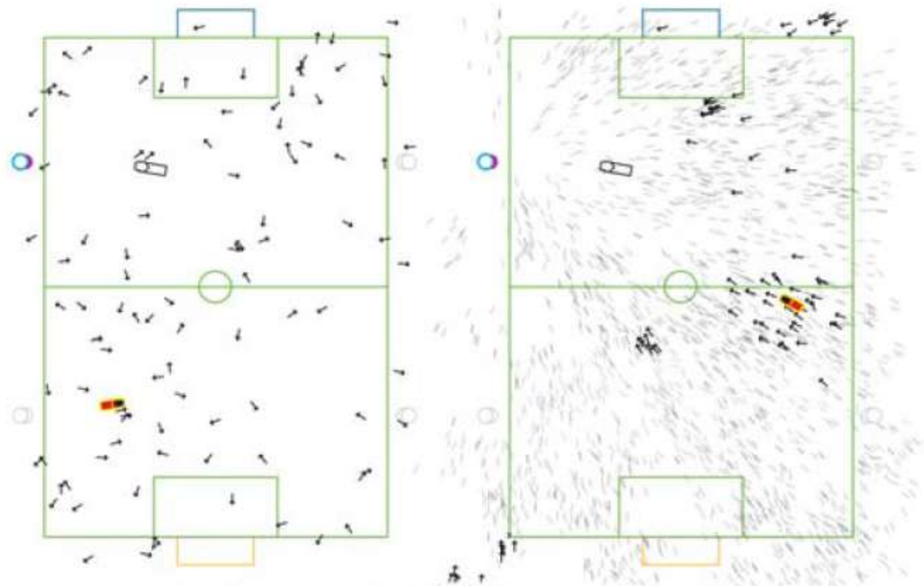


Fig. 6. Particle distribution not using negative information, initial uniform distribution and distribution after 10s. Solid arrows indicate Monte Carlo particles (100). The experiment was repeated using 2000 particles (shaded lines) to better represent the actual probability distribution. The actual robot position is indicated by the white symbol, the estimated robot pose by the solid symbol. Not using negative information and only using the bearing to the landmark, the robot is unable to localize. Some clusters of particles form but they do not converge. As one would expect, the position distribution is almost uniform but the relative angle is quite distinct.

RESULTS

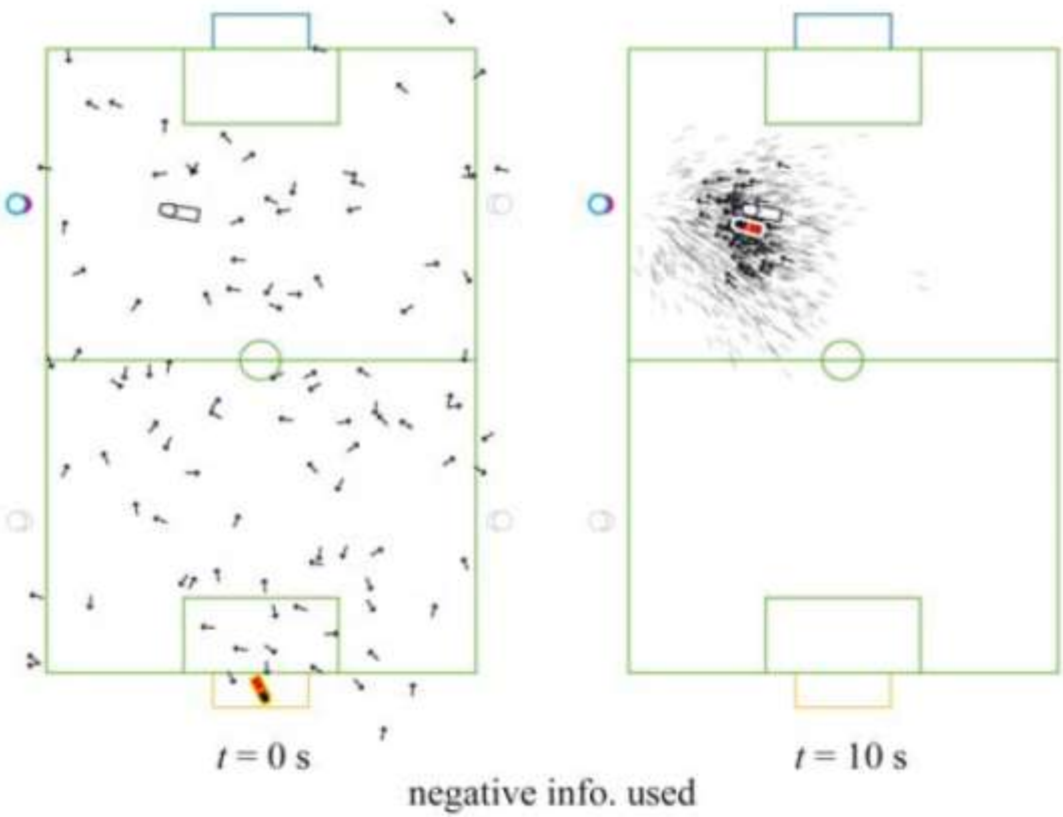


Fig. 7. Particle distribution when negative information is incorporated, initial uniform distribution and distribution after 10s. When incorporating negative information, the robot is able to localize quickly.

RESULTS

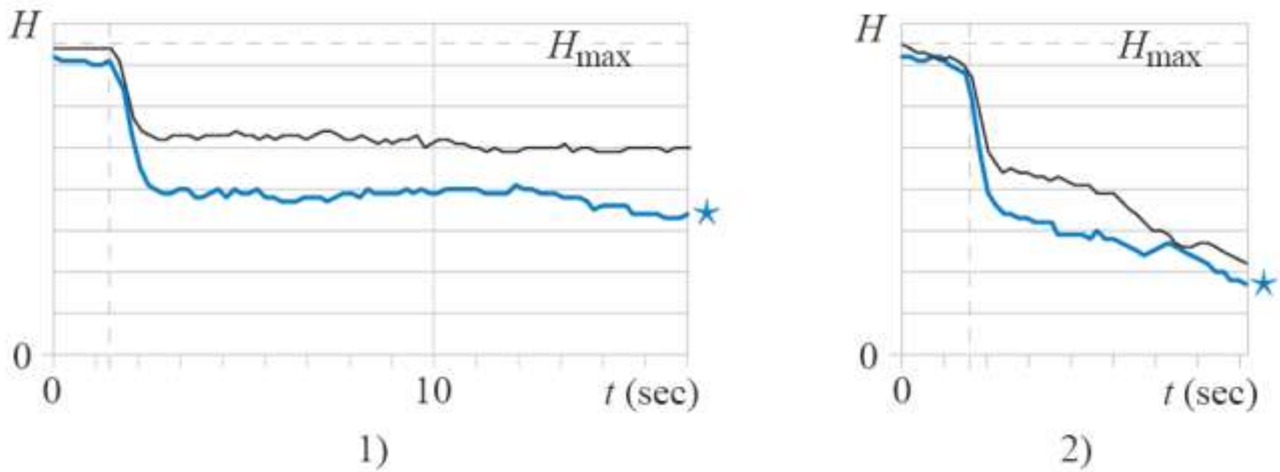


Fig. 8. Expected entropy of the belief in the localization task with (*) and without (thin line) using negative information. 1) At first the robot does not see the landmark. As soon as the landmark comes into the robot's view (indicated by the dashed vertical line), the entropy drops. Using negative information, the quality of the localization is greatly improved and the entropy continues to decrease over time. 2) Additionally using field lines for localization enables the robot to localize even without negative information. Incorporating negative information, however, yields a higher rate of convergence and the entropy is significantly lowered.

GERMAN TEAM LOCALIZATION ARCHITECTURE

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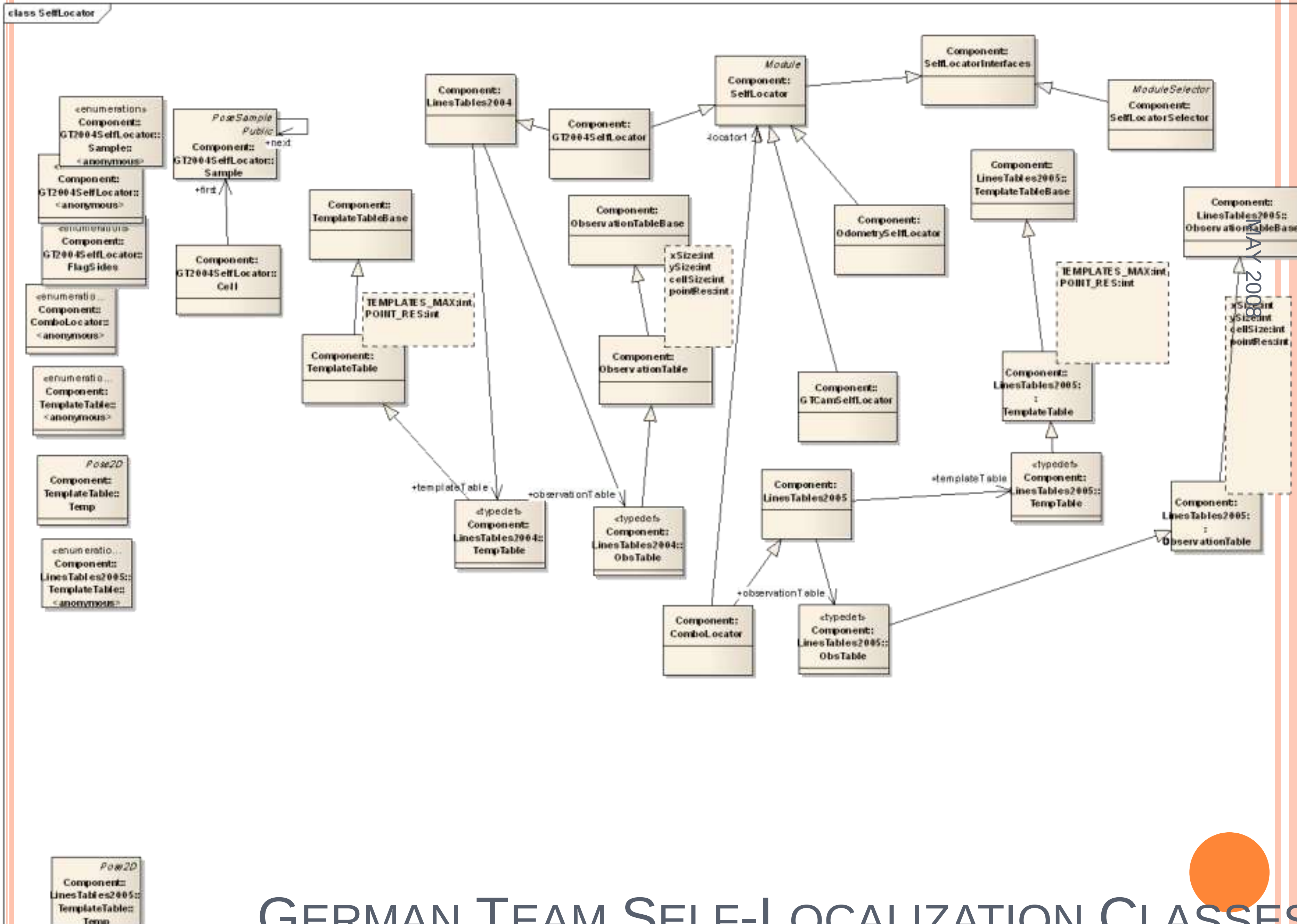

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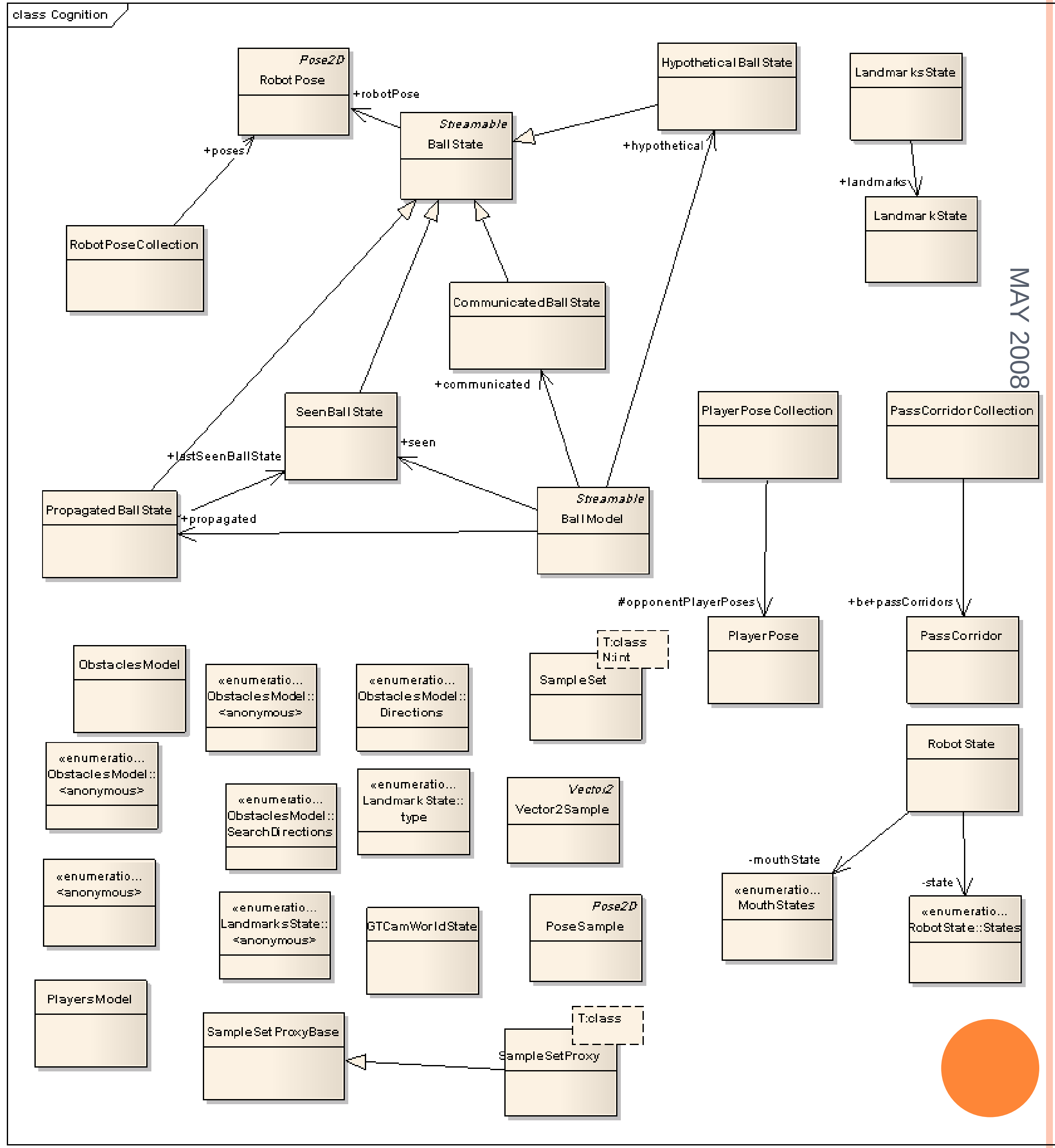
German Team Self-Localization Classes

COGNITION



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What Next?

- Monte Carlo is bad for accurate sensors??!
- There are different types of localization techniques: Kalman, Multihypothesis tracking, Grid, Topology, in addition to particle…
  - What is the difference between them? And which one is better?
- All These issues will be discussed with a lot more in our next presentation (next week) Inshallah.

Future

GUIDENCE

Holding our Bags

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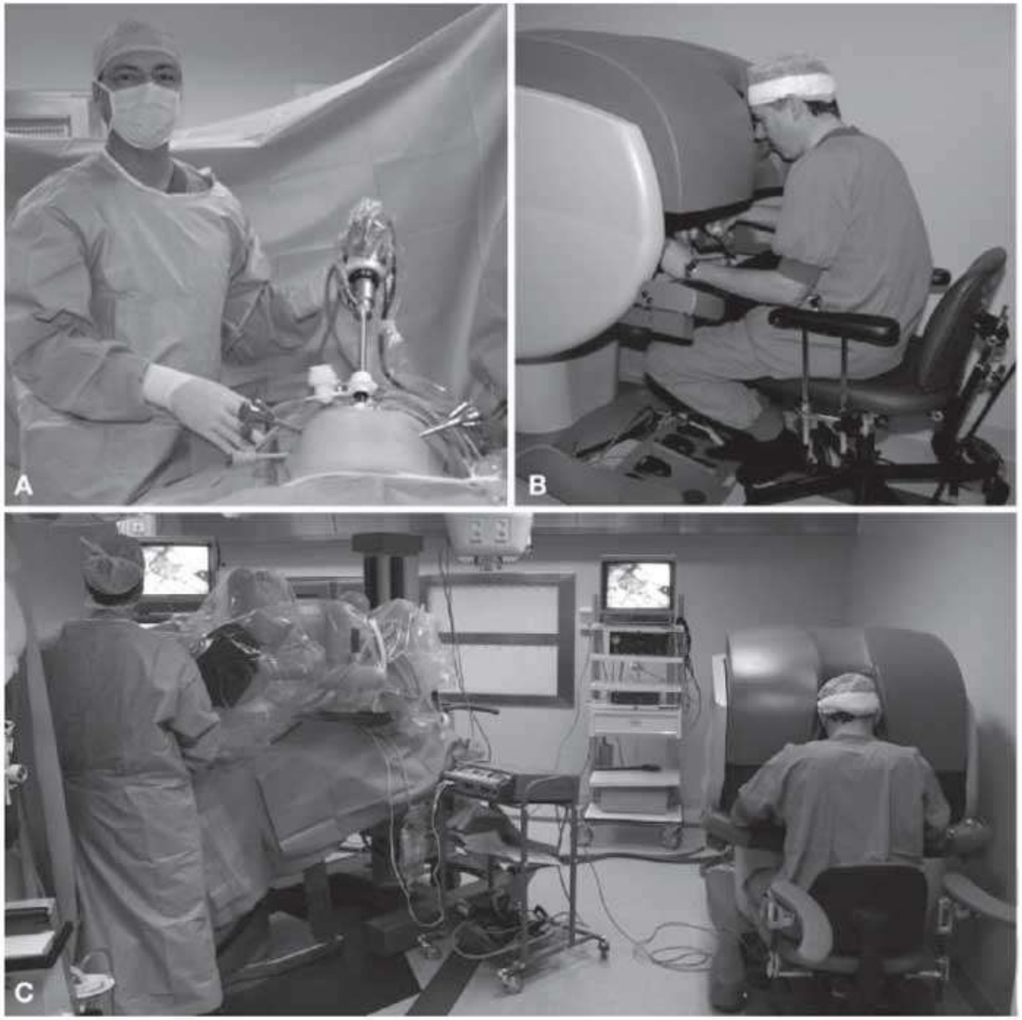
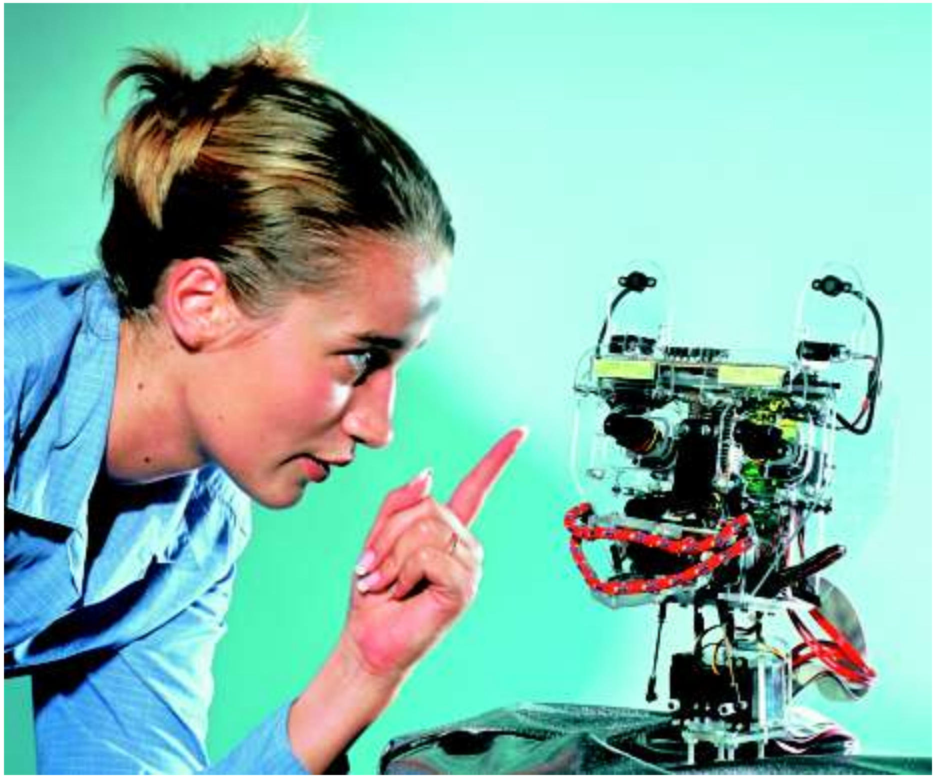
MEDICINE



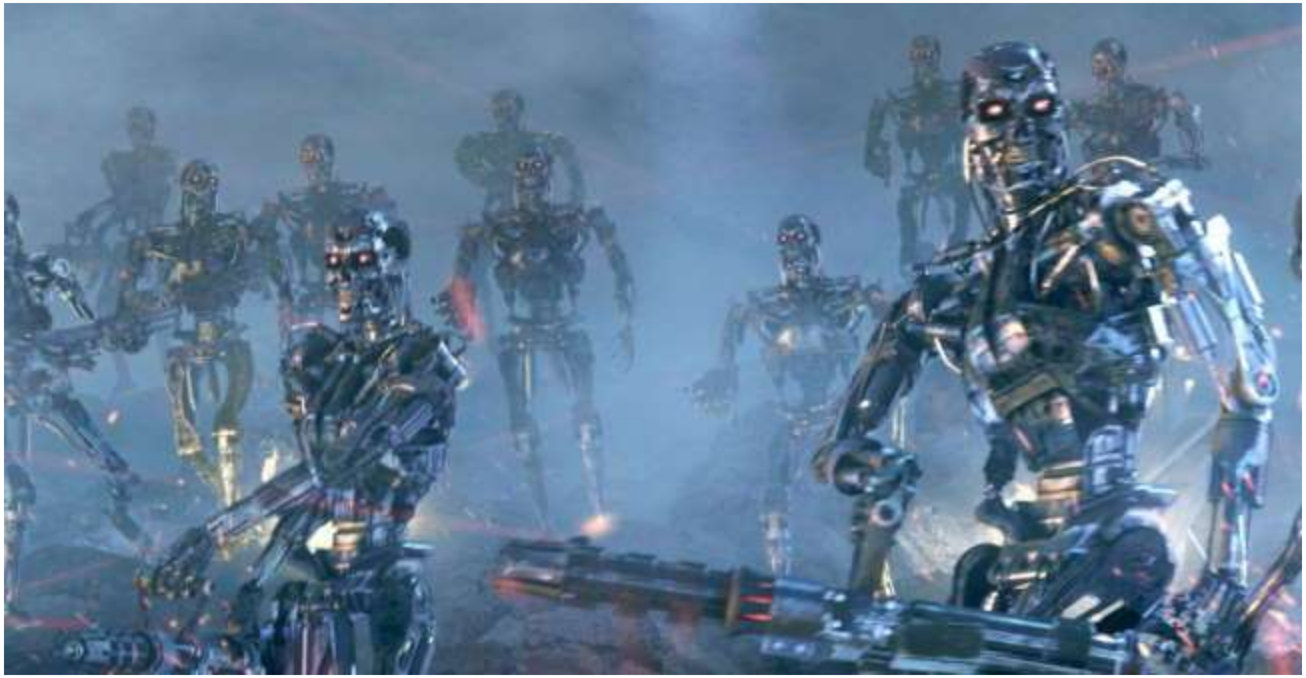
DANCING…

UNDERSTAND AND FEAL



PLAY WITH

Or Maybe…



QUESTIONS