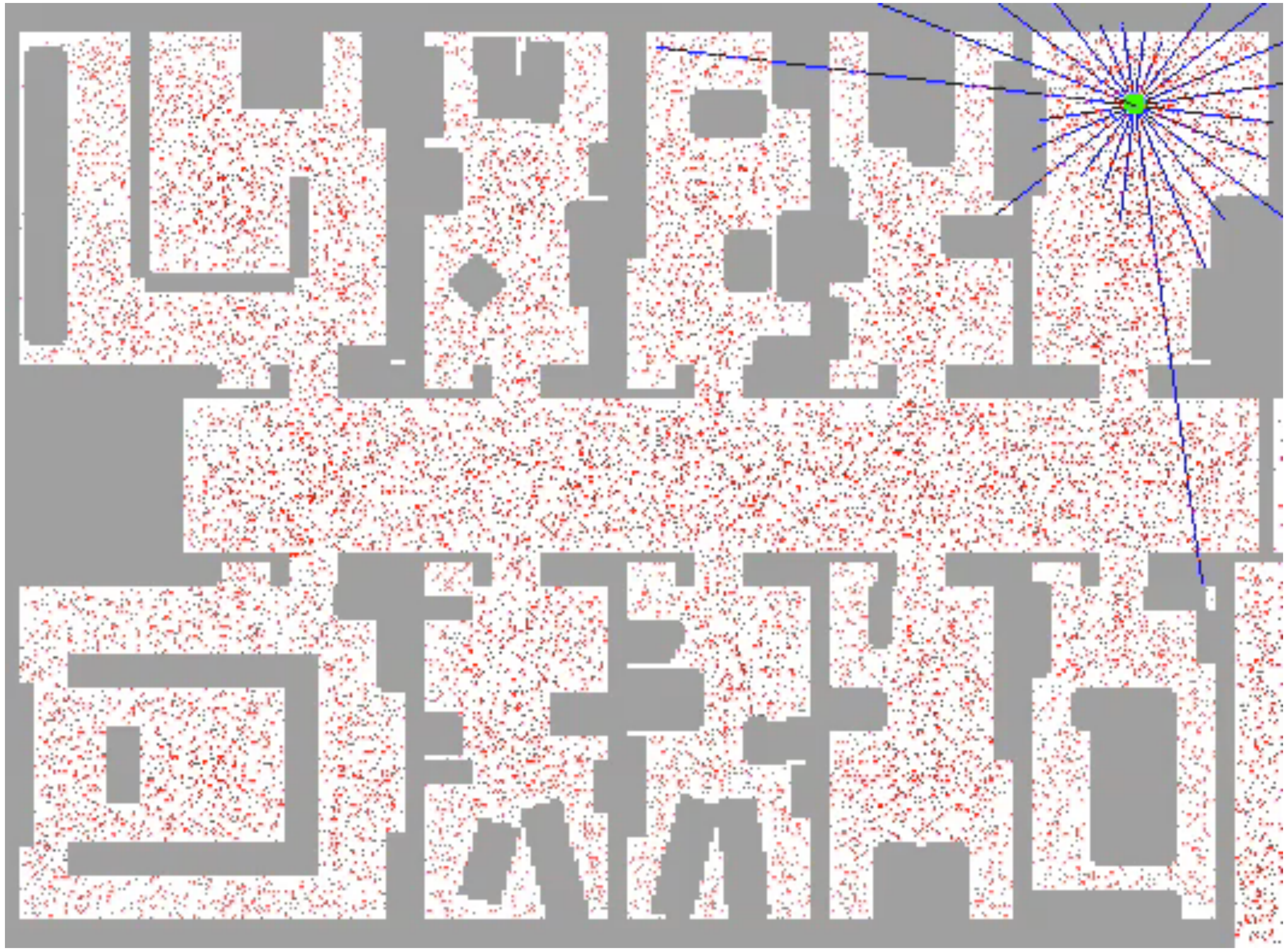
Lecture 21

Mobile Robotics - V - Localization



from Probabilistic Robotics

Course logistics

- **No class on Wed 11/22**
- **There will be quiz released tomorrow and due on 11/22 by 1pm.**
- Project 5 is posted on 11/15 and will be due **11/29.**
  - Start early!
- Updated Project points as we removed P6:
  - P0 5 points
  - P1-5 12 points
  - Final (Open) Project 15

Final (Open) Project timeline

Sun	Mon	Tue	Wed	Thu	Fri	Sat
19	Today 20	21	22	23	24	25
26	27	28	29	30	1	2
3	4	5	6	7	8	9
10	11	12	13	14	15	16
17	18	19	20	21	22	23

In-class proposal presentation

Proposal Slides Due

Poster for printing due

Poster Presentation

Final video due

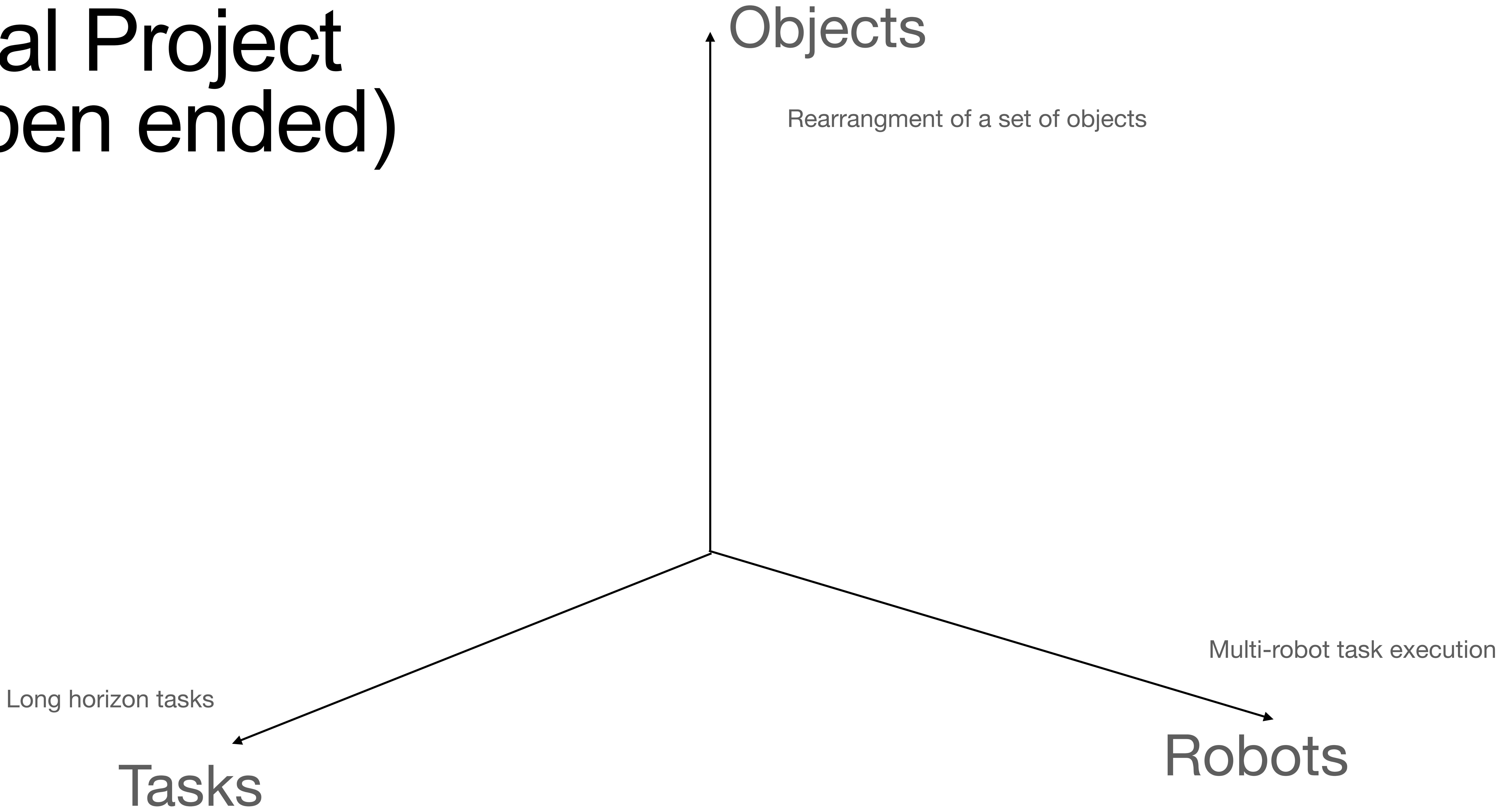
Final (Open) Project timeline

- Form your groups: Use the excel sheet in the Ed post.
- Proposal Slides: (template will be provided)
  - 1-4 Slides
  - Title, Motivation, Input - Output, Deliverables, Timeline, Who is doing what?
  - Where does your project stand not the 3-axes (robots, objects, tasks)?
  - Backup plan
- In-class proposal presentation (<8mins) :
  - Teams will get feedback from the class
- Final video:
  - Describing the project idea and the outcome.
- Poster presentation: (template will be provided)
  - Presenting the project idea and the outcome to audience.

Final Project: 15%

- Project proposal slides + presentation: 3%
- Final project video: 6%
- Poster presentation (evaluation by judges): 6%

Final Project (Open ended)



Continuing previous Lecture
PF and localization

Particle Filter

Particle_filter($\mathcal{X}_{t-1}, u_t, z_t$):

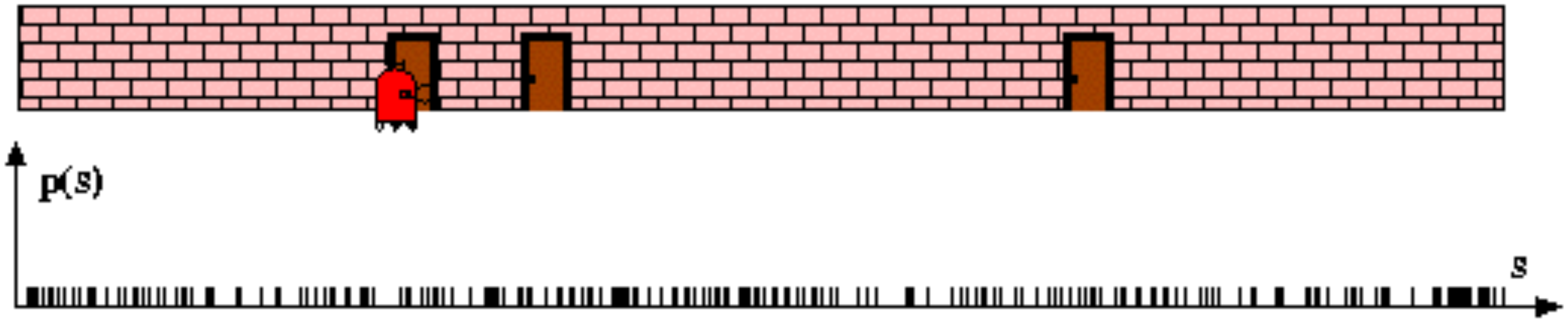
$\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
for $j = 1$ *to* J *do*
    sample $x_t^{[j]} \sim \pi(x_t)$
    $w_t^{[j]} = \frac{p(x_t^{[j]})}{\pi(x_t^{[j]})}$
    $\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[j]}, w_t^{[j]} \rangle$
endfor
for $j = 1$ *to* J *do*
    draw $i \in 1, \ldots, J$ *with probability* $\propto w_t^{[i]}$
    add $x_t^{[i]}$ *to* $\mathcal{X}_t$
endfor
return $\mathcal{X}_t$

Particle Filter for Localization

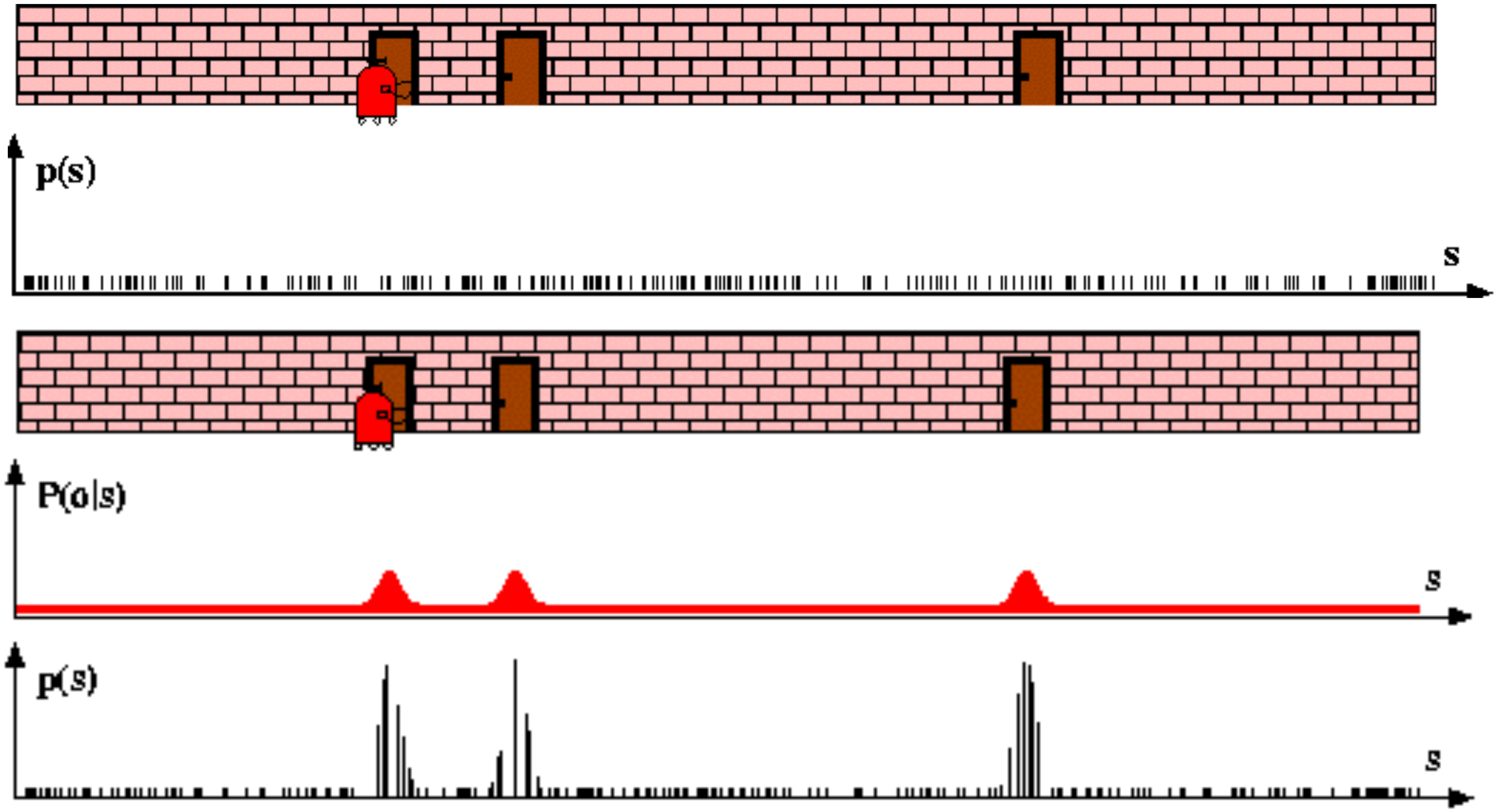
Particle_filter($\mathcal{X}_{t-1}, u_t, z_t$):

$\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$
for $j = 1$ *to* J *do*
    sample $x_t^{[j]} \sim p(x_t \mid u_t, x_{t-1}^{[j]})$
    $w_t^{[j]} = p(z_t \mid x_t^{[j]})$
    $\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[j]}, w_t^{[j]} \rangle$
endfor
for $j = 1$ *to* J *do*
    draw $i \in 1, \ldots, J$ *with probability* $\propto w_t^{[i]}$
    add $x_t^{[i]}$ *to* $\mathcal{X}_t$
endfor
return $\mathcal{X}_t$

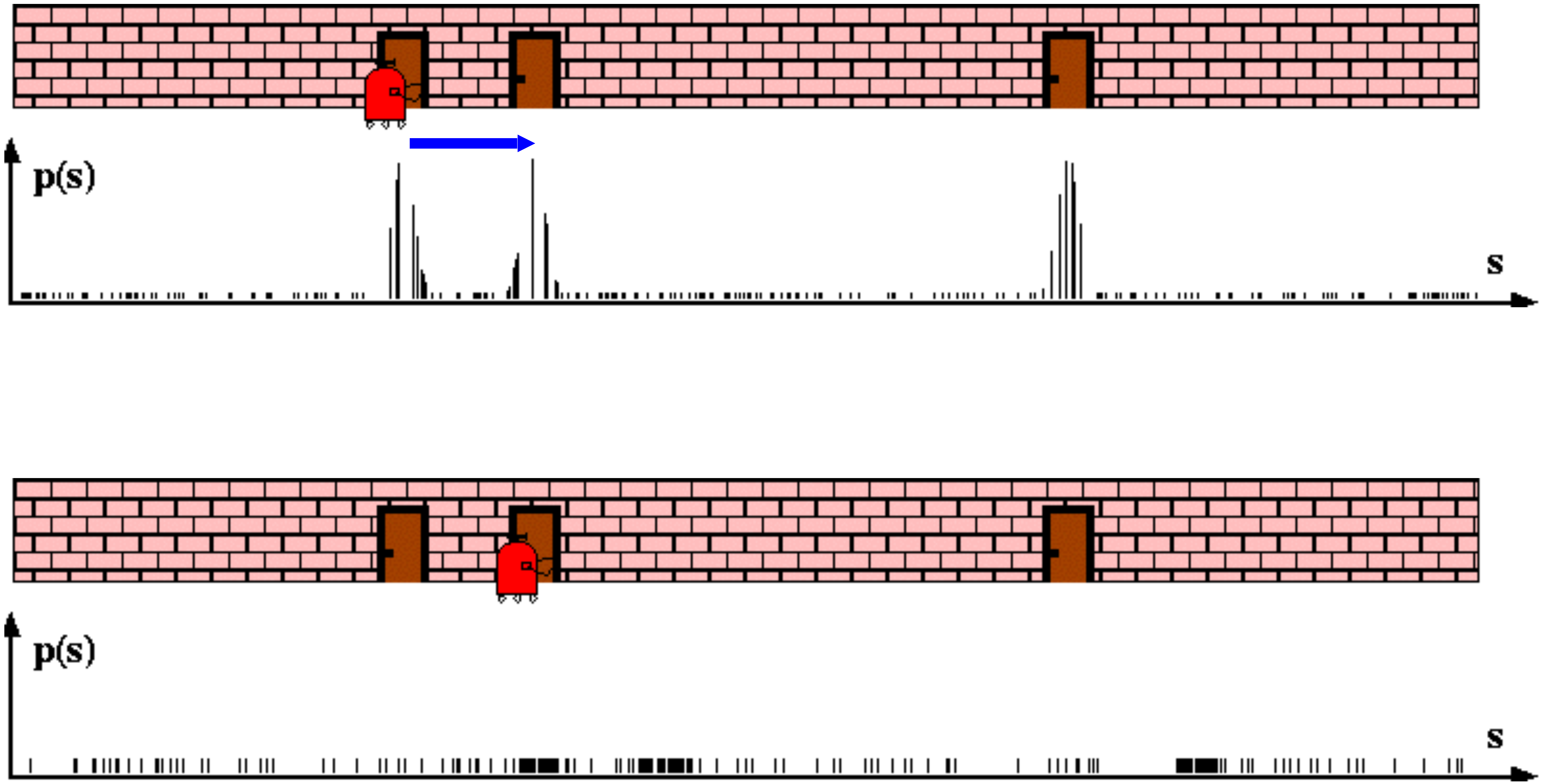
Particle Filters



Sensor Information: Importance Sampling

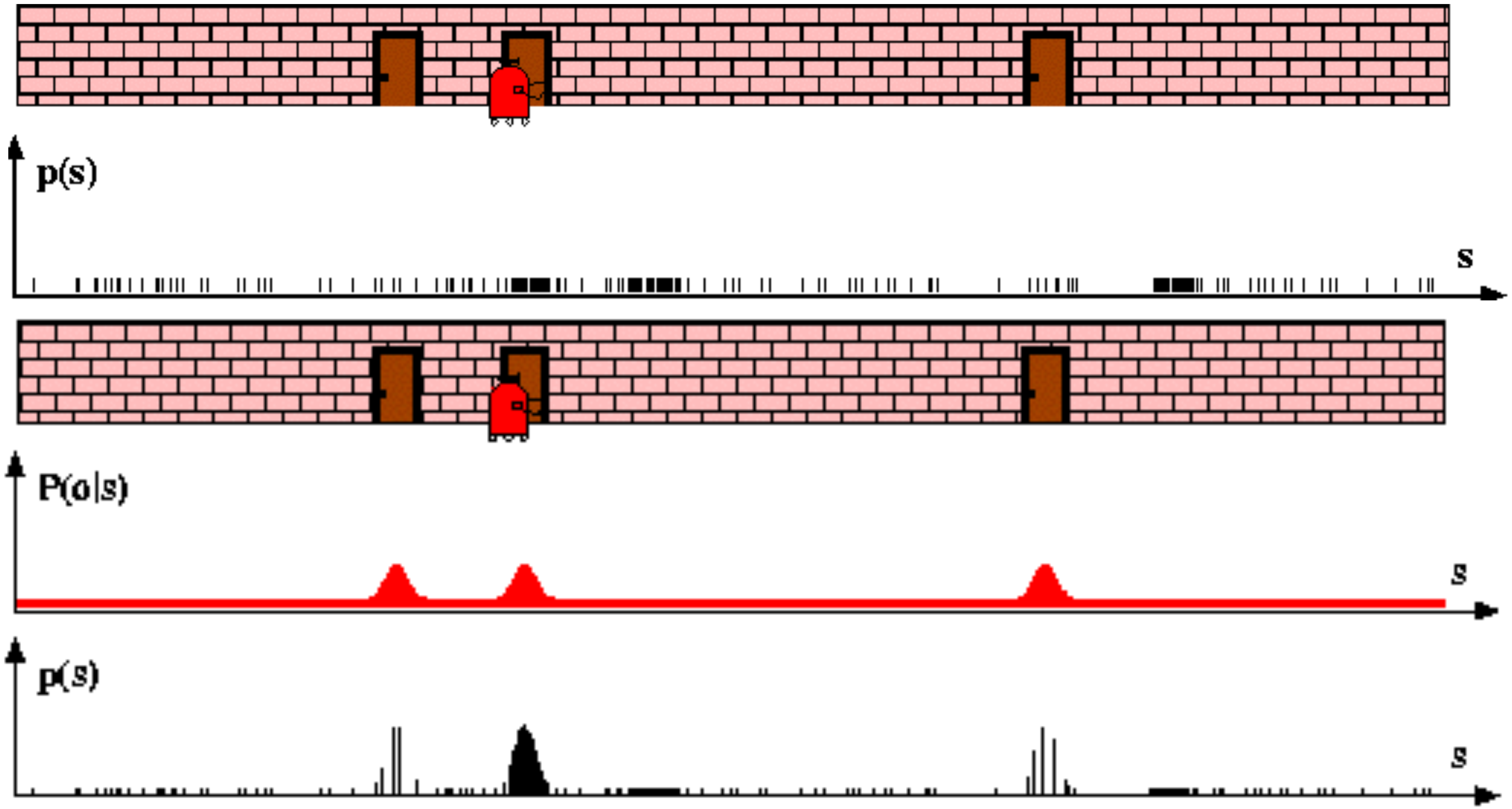


Robot Motion



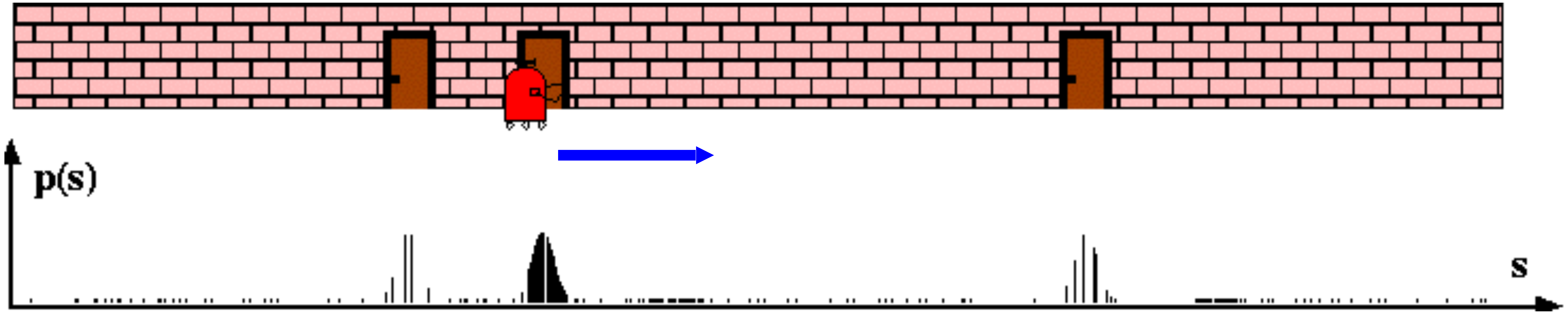
Slide borrowed from Dieter Fox

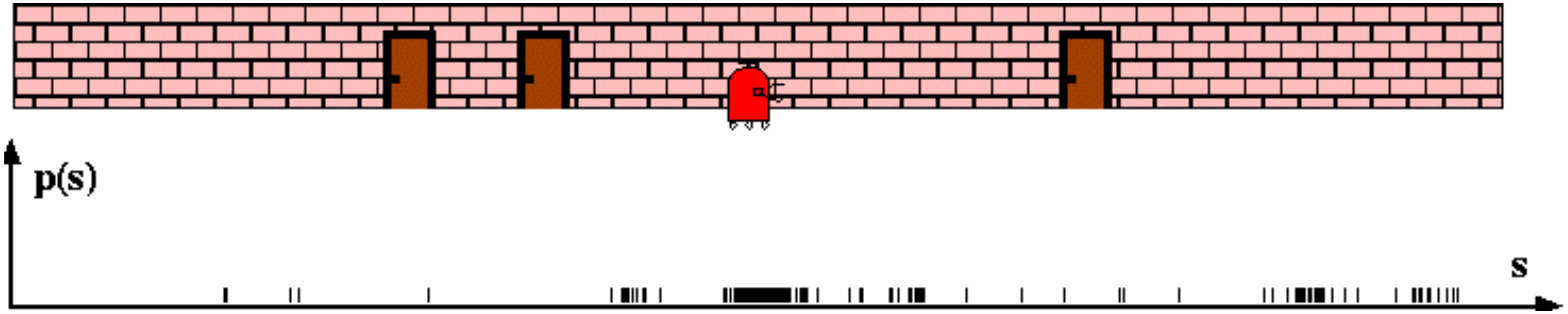
Sensor Information: Importance Sampling



Slide borrowed from Dieter Fox

Robot Motion





Slide borrowed from Dieter Fox

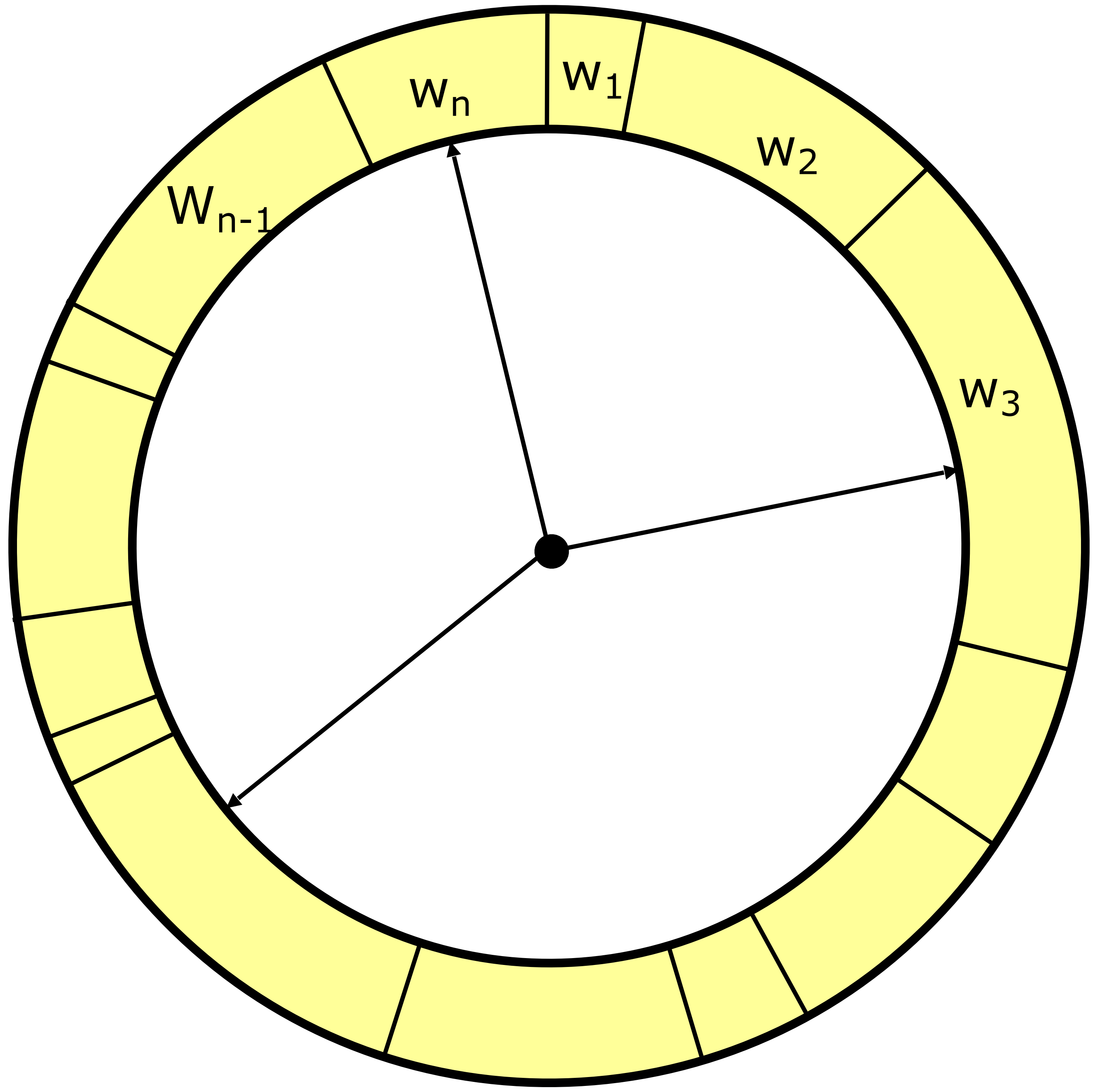
Resampling

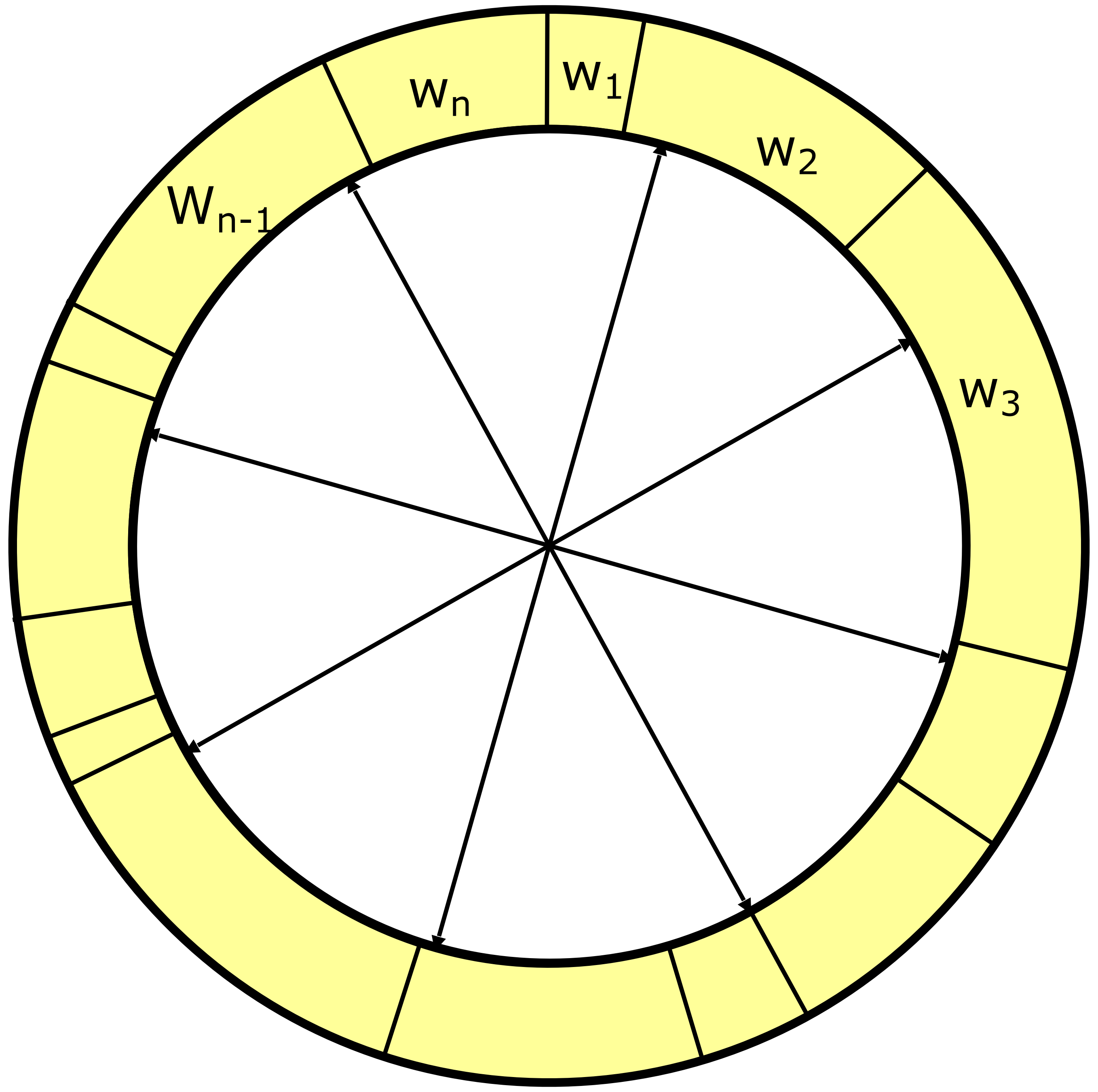
- **Given**: Set S of weighted samples.

- **Wanted** : Random sample, where the probability of drawing x_i is given by w_i.

- Typically done n times with replacement to generate new sample set S'.

Resampling

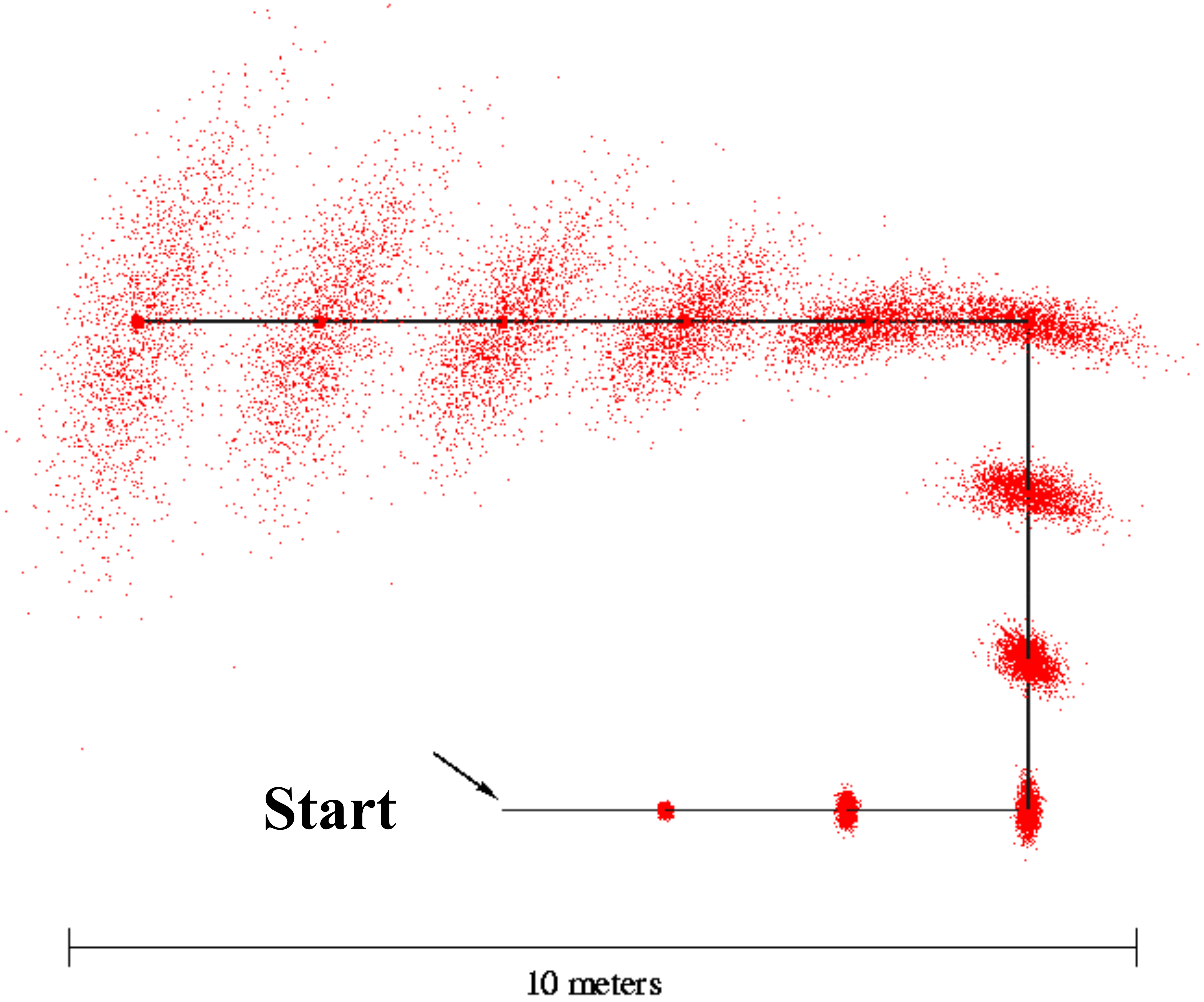




- Roulette wheel
- Binary search, n log n

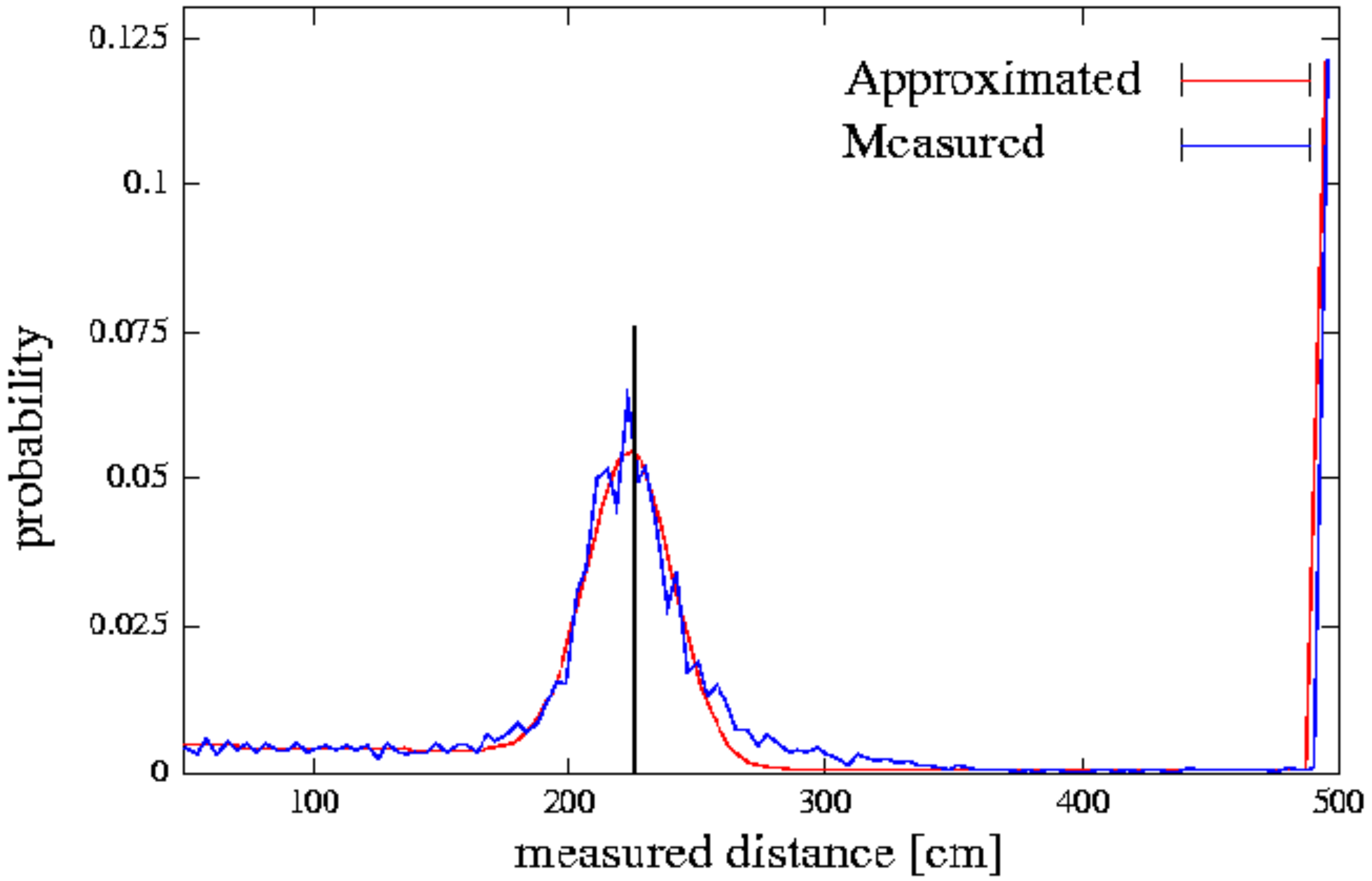
- Stochastic universal sampling
- Systematic resampling
- Linear time complexity
- Easy to implement, low variance

Motion Model Reminder

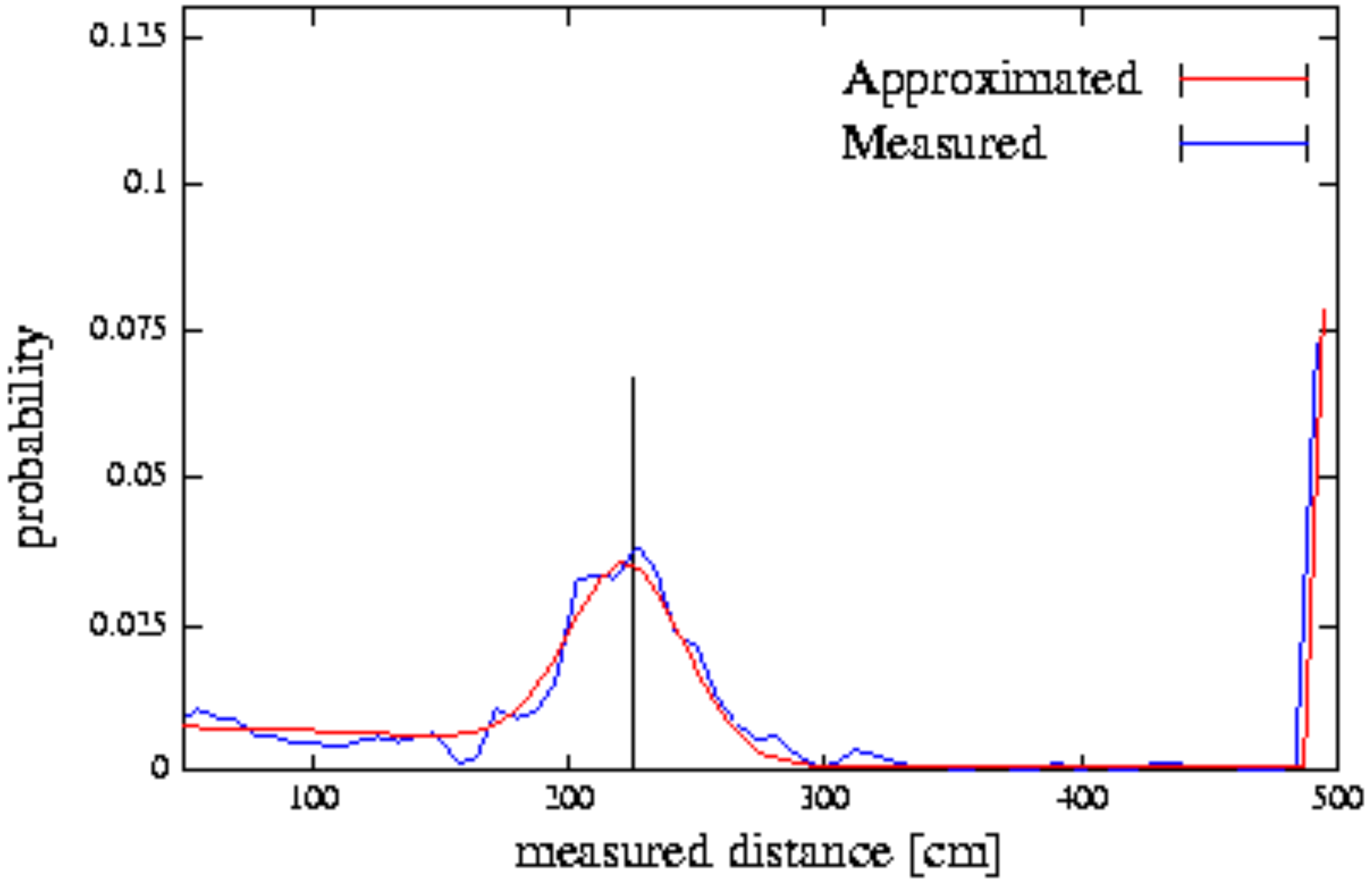


Slide borrowed from Dieter Fox

Proximity Sensor Model Reminder



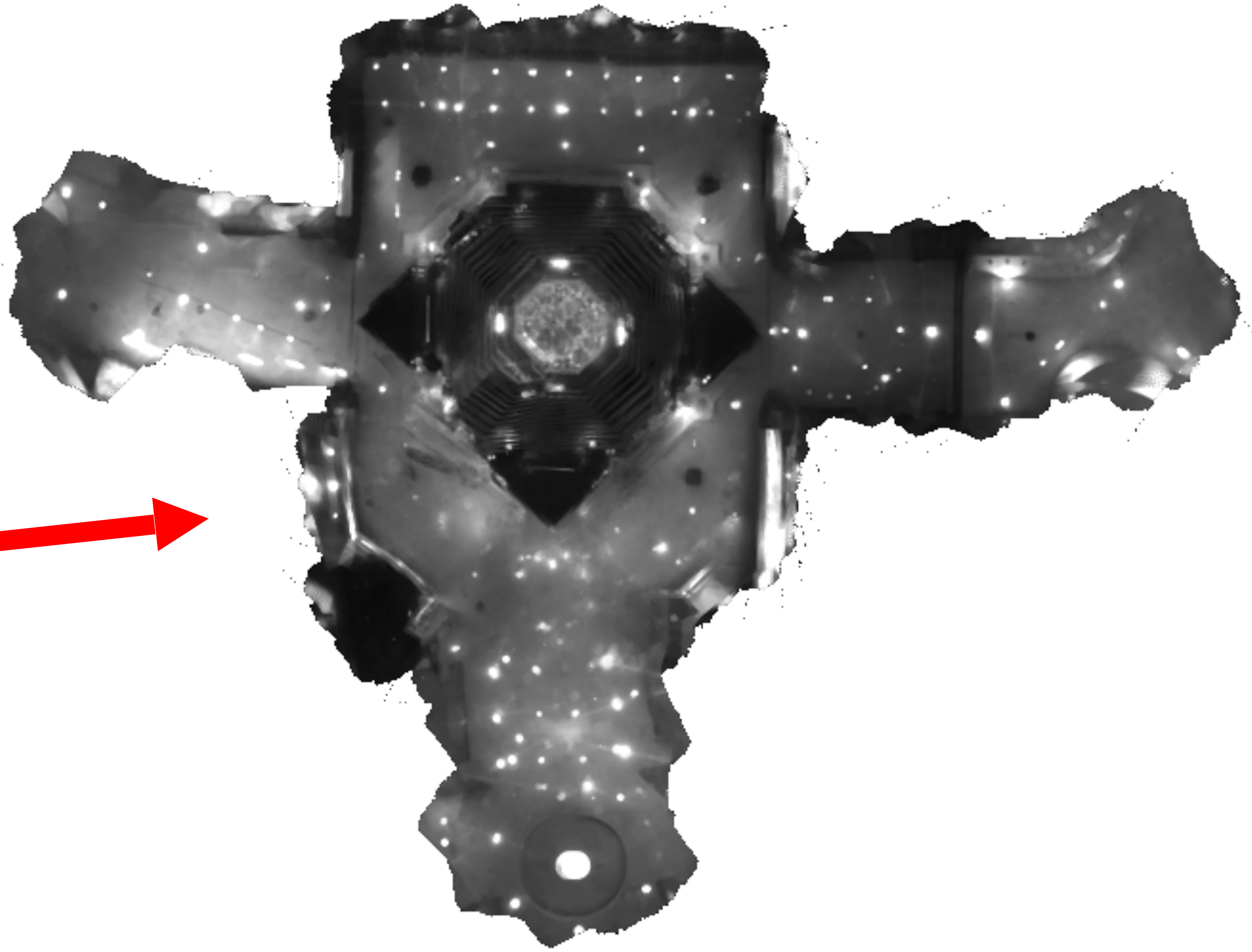
Laser sensor



Sonar sensor

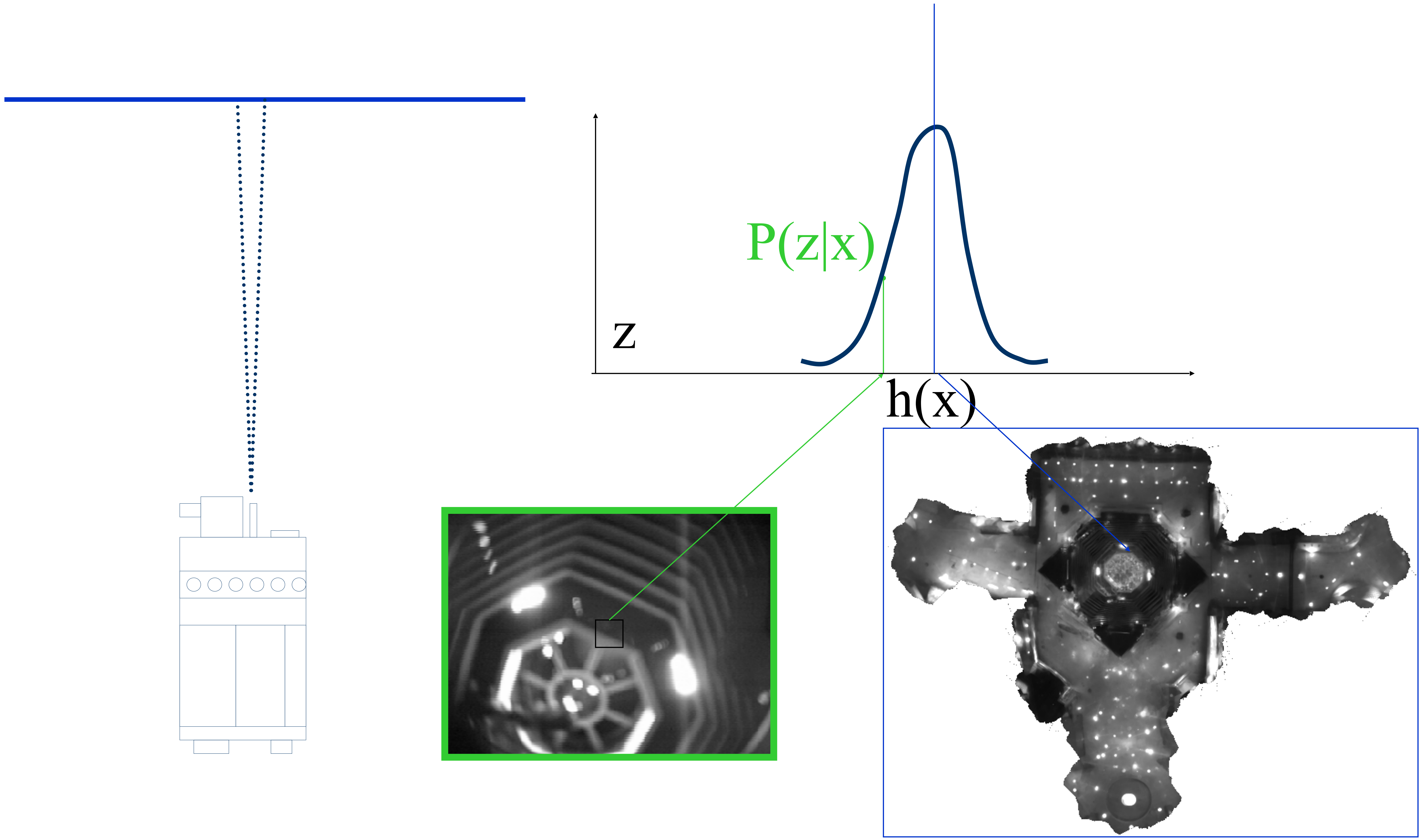
Slide borrowed from Dieter Fox

Using Ceiling Maps for Localization



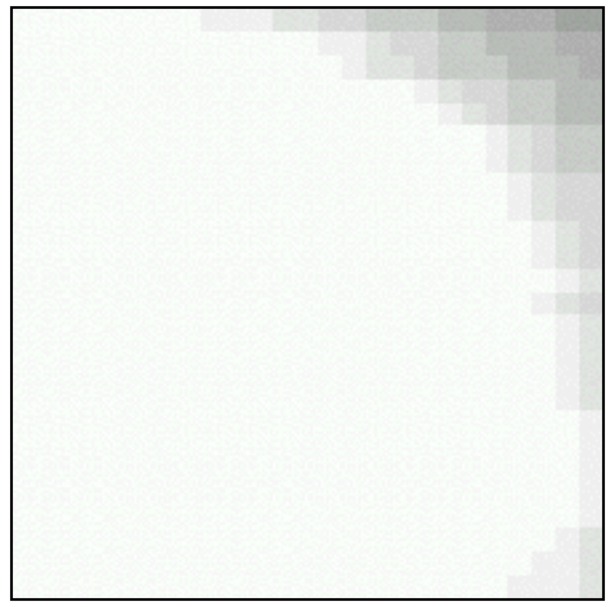
Slide borrowed from Dieter Fox

Vision-based Localization

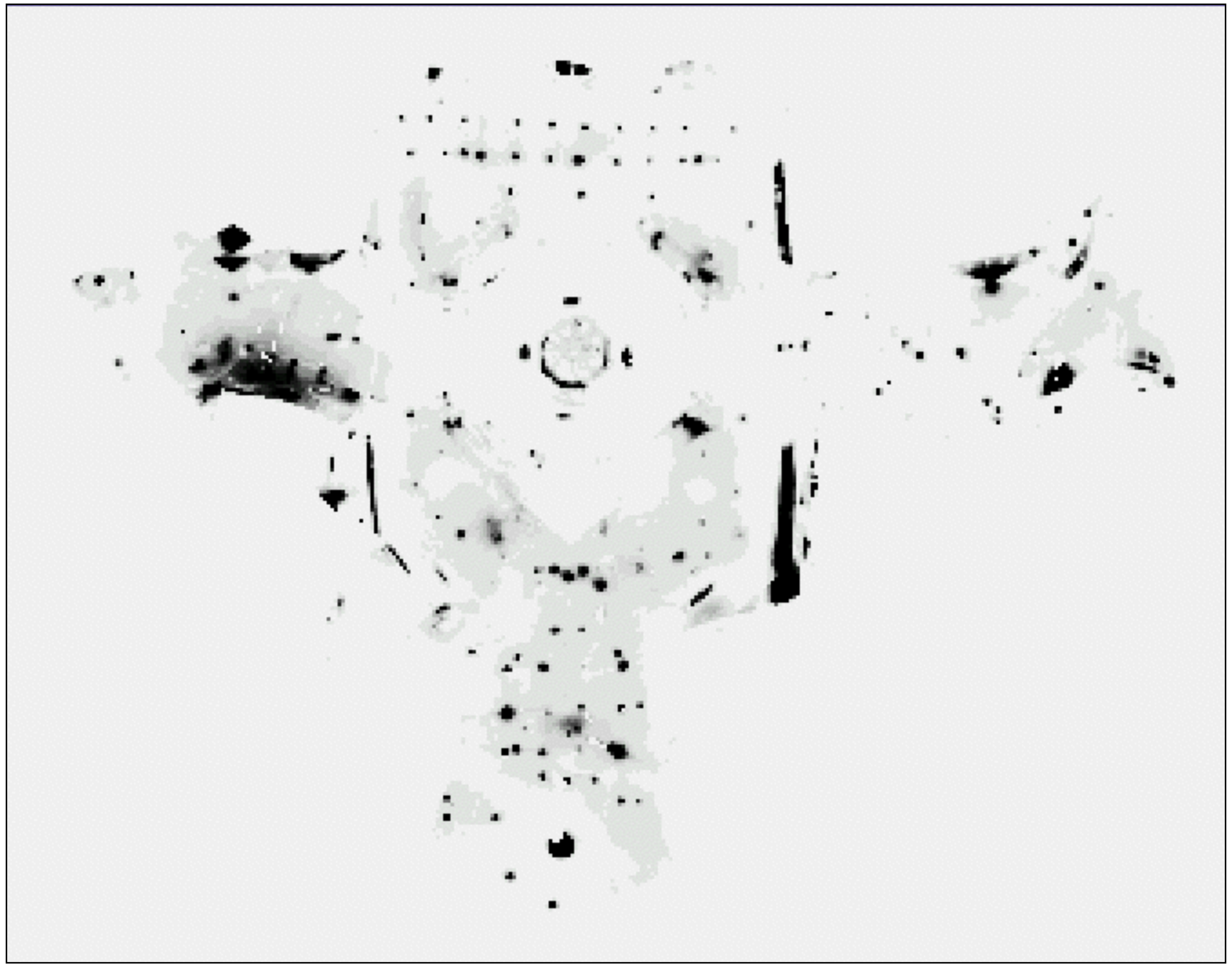


Under a Light

Measurement z:

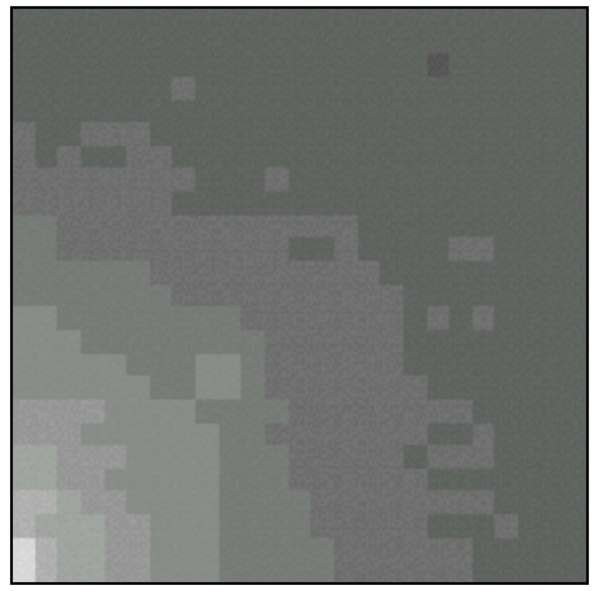


***P(z|x)*:**

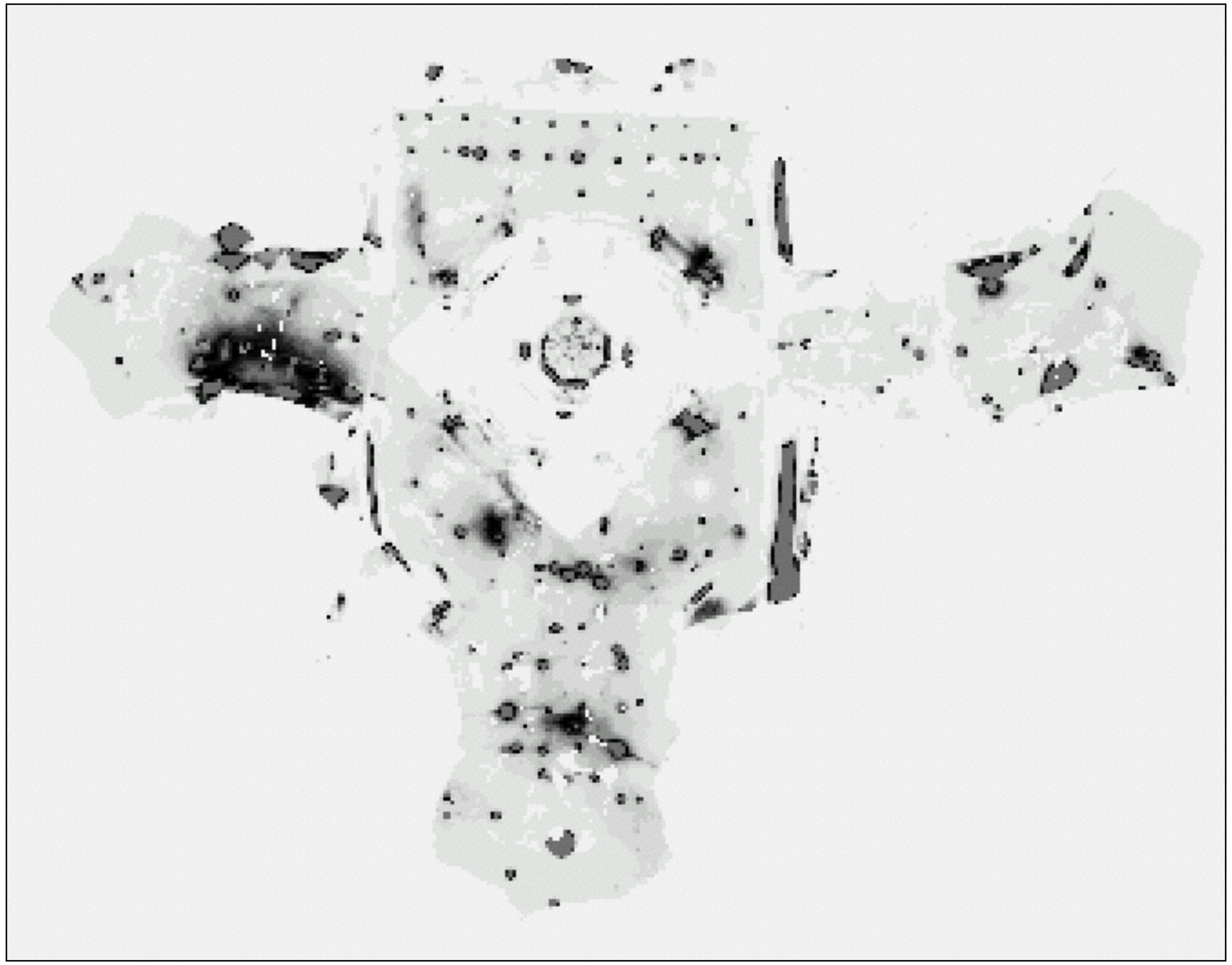


Next to a Light

Measurement z:



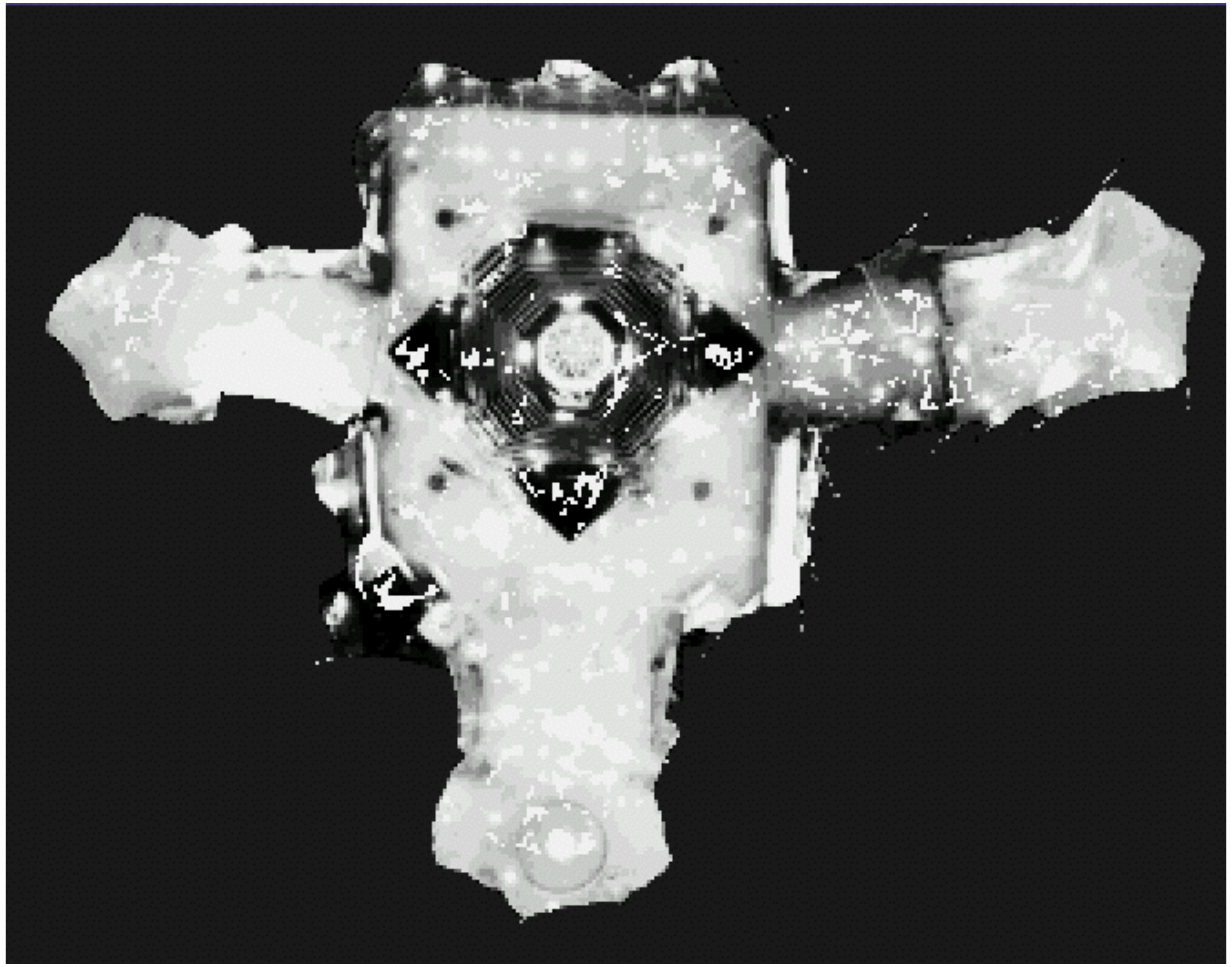
$P(z|x)$:



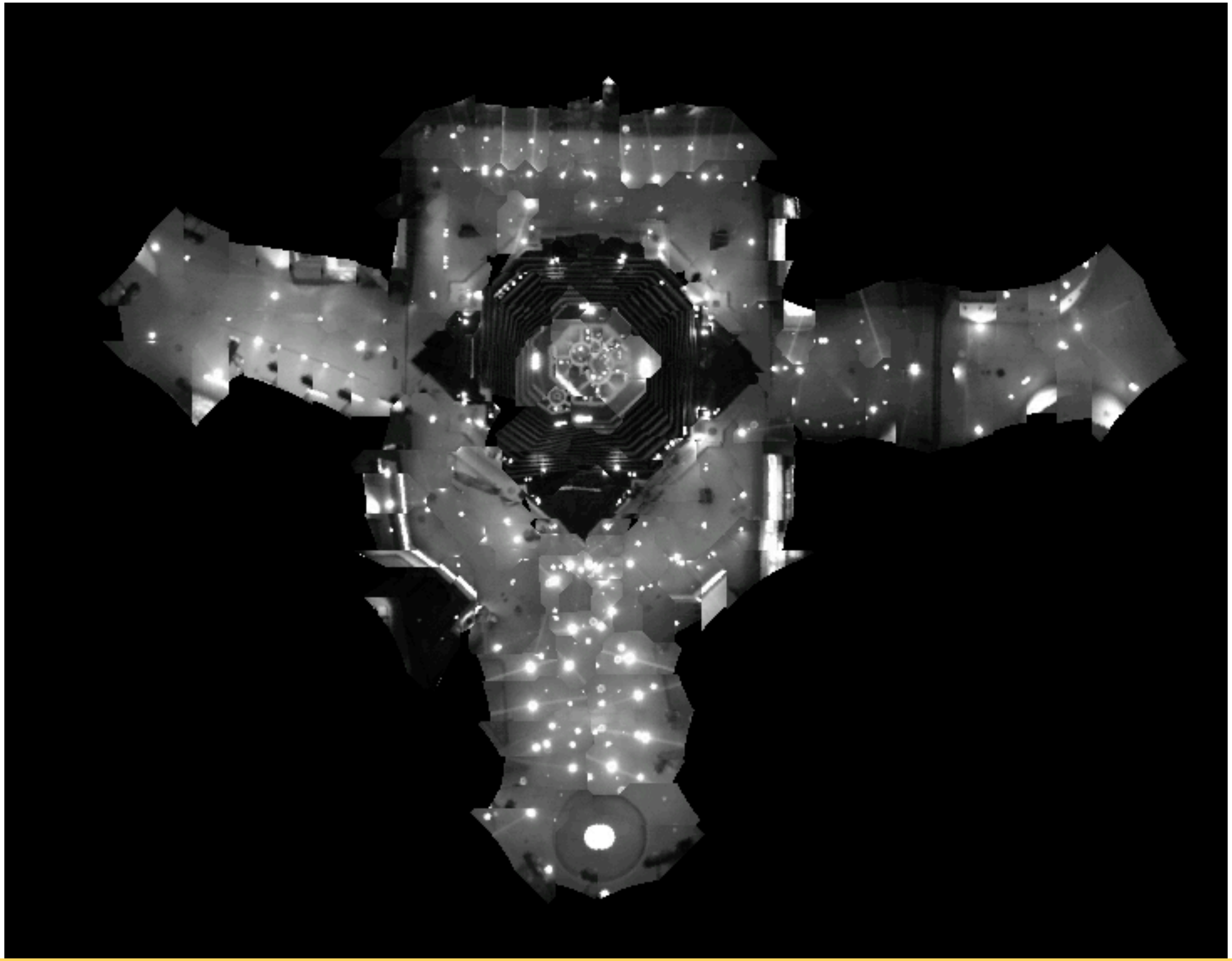
Elsewhere

Measurement z:

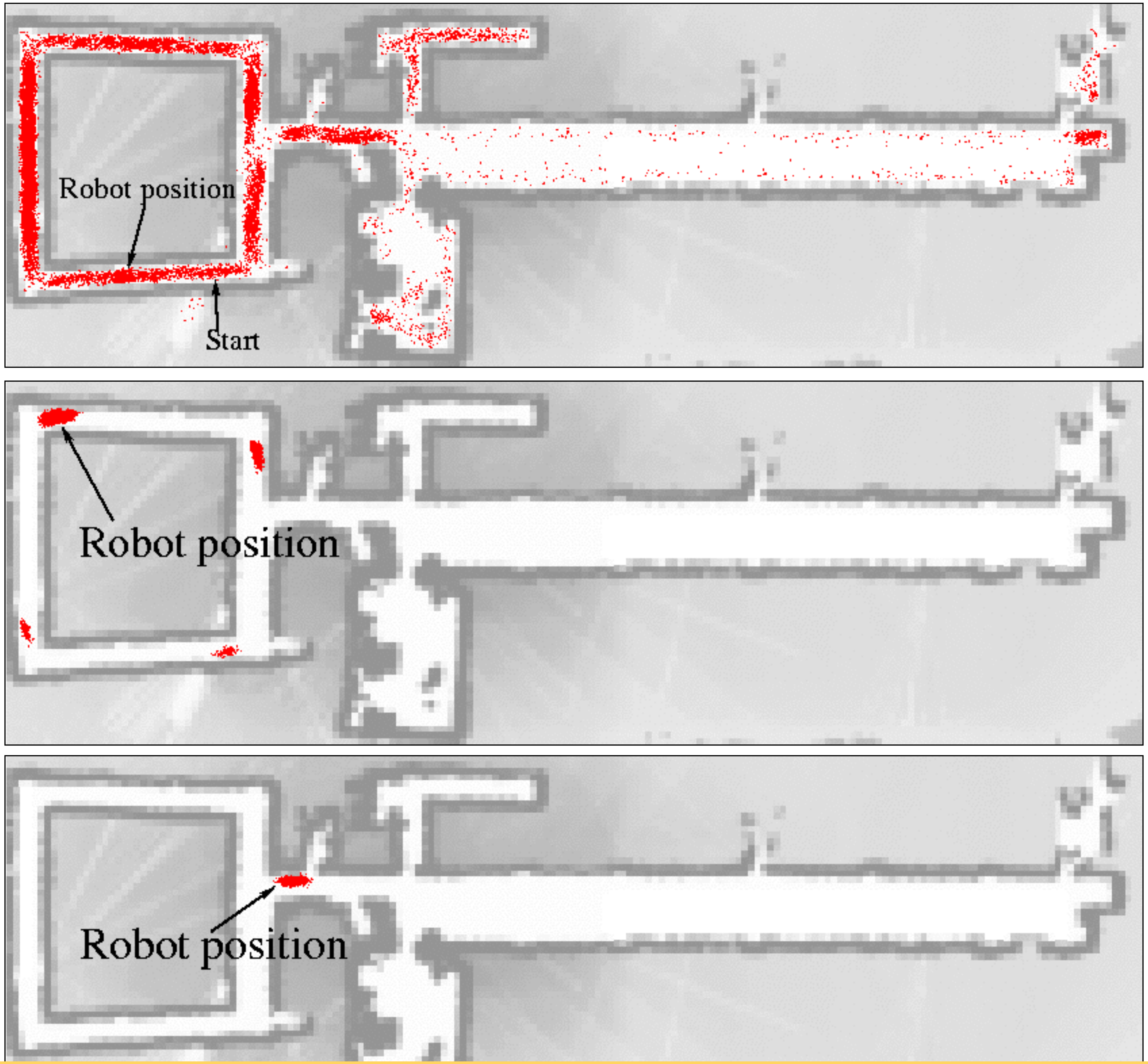
$P(z|x)$:



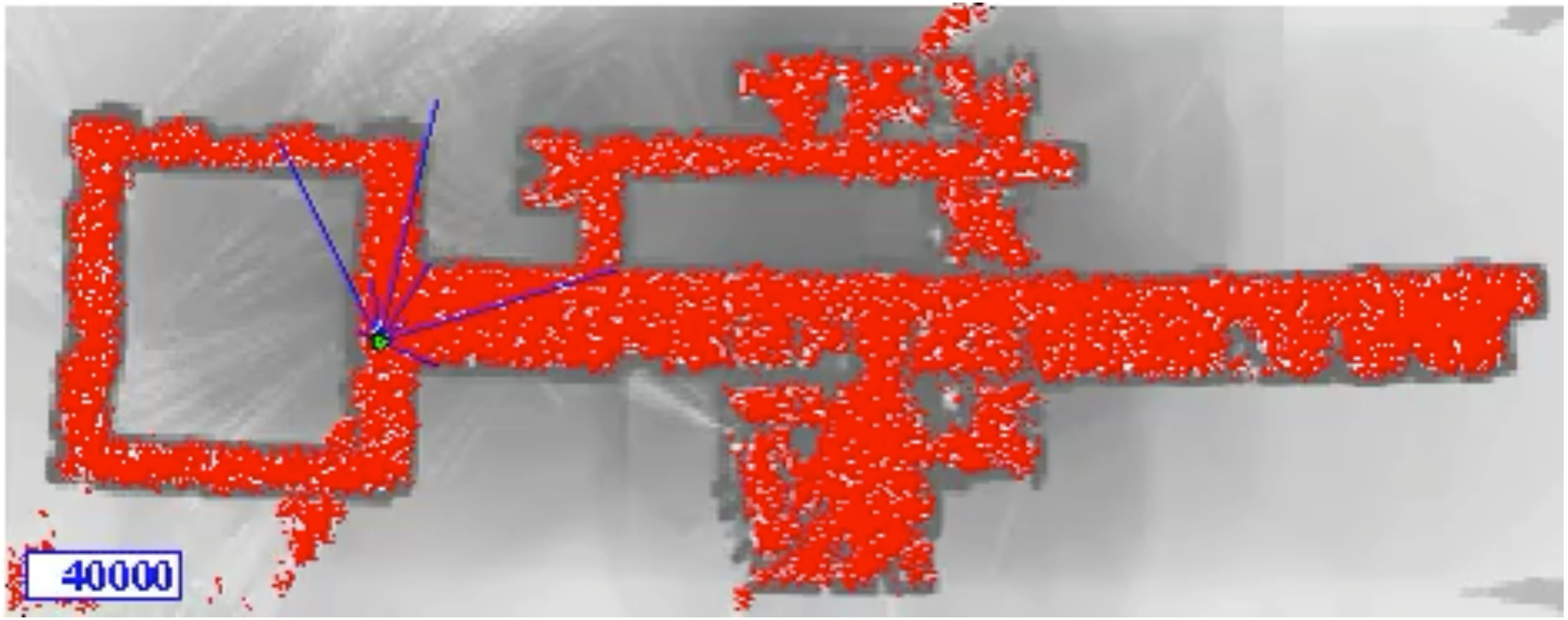
Global Localization Using Vision



Adaptive Sampling

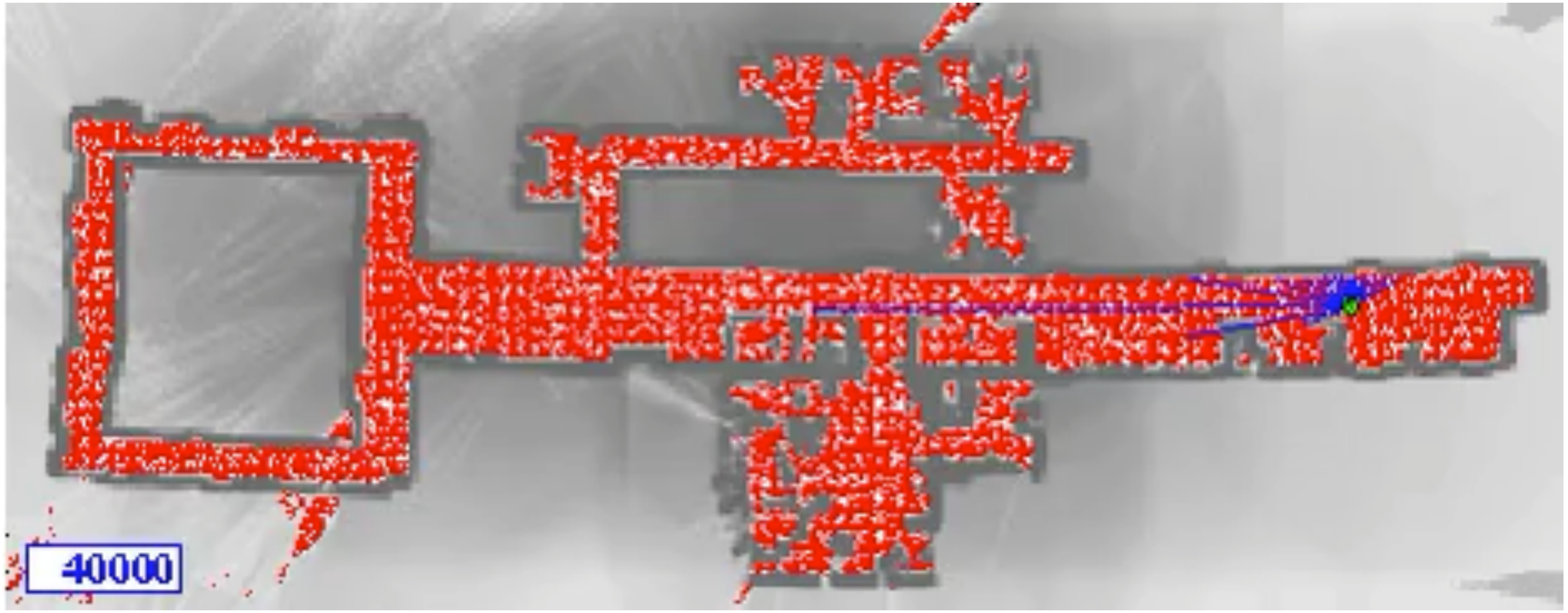


KLD-Sampling Sonar

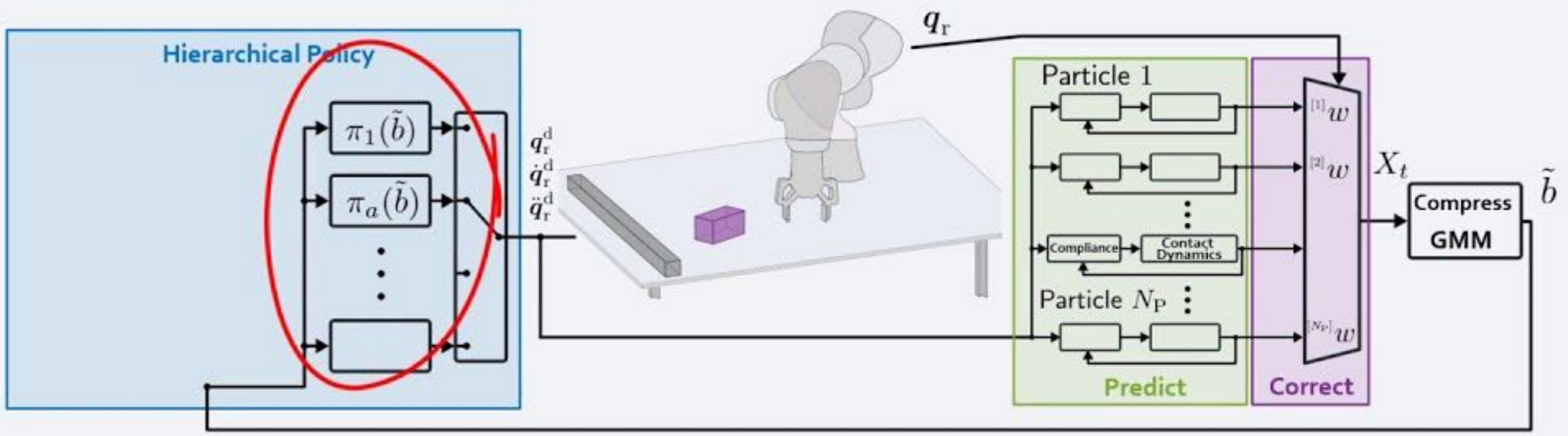


Adapt number of particles on the fly based on statistical approximation measure

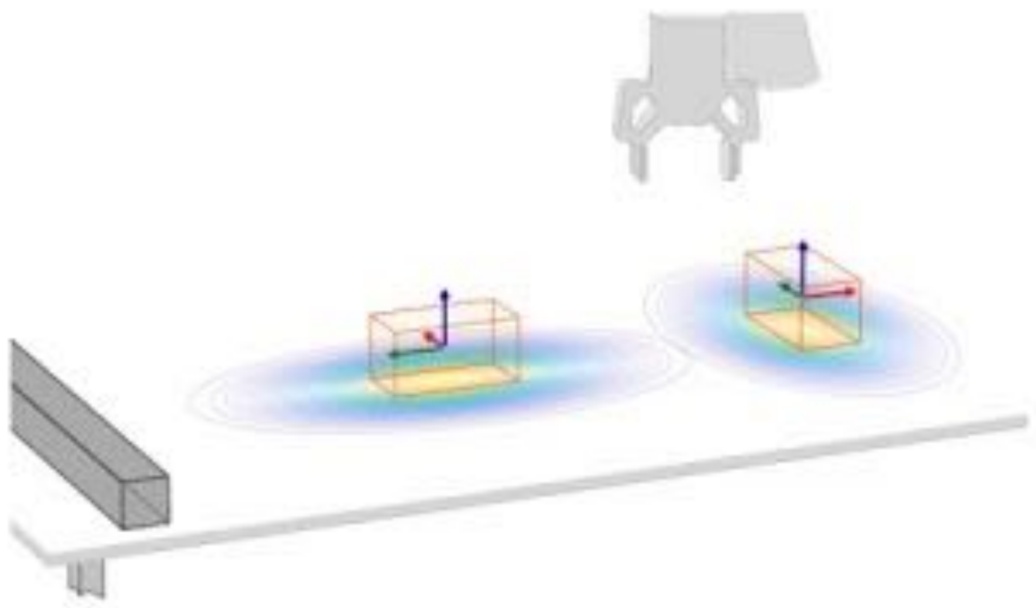
KLD-Sampling Laser



What if the localization is not about the robot?



Hierarchical Policy – Goal-Directed Low-Level Controllers



"Controlling Contact-Rich Manipulation Under Partial Observability"

Florian Wirnshofer (Siemens AG)*; Philipp Sebastian Schmitt (Siemens AG); Georg von Wichert (Siemens AG); Wolfram Burgard (University of Freiburg)

RSS 2020

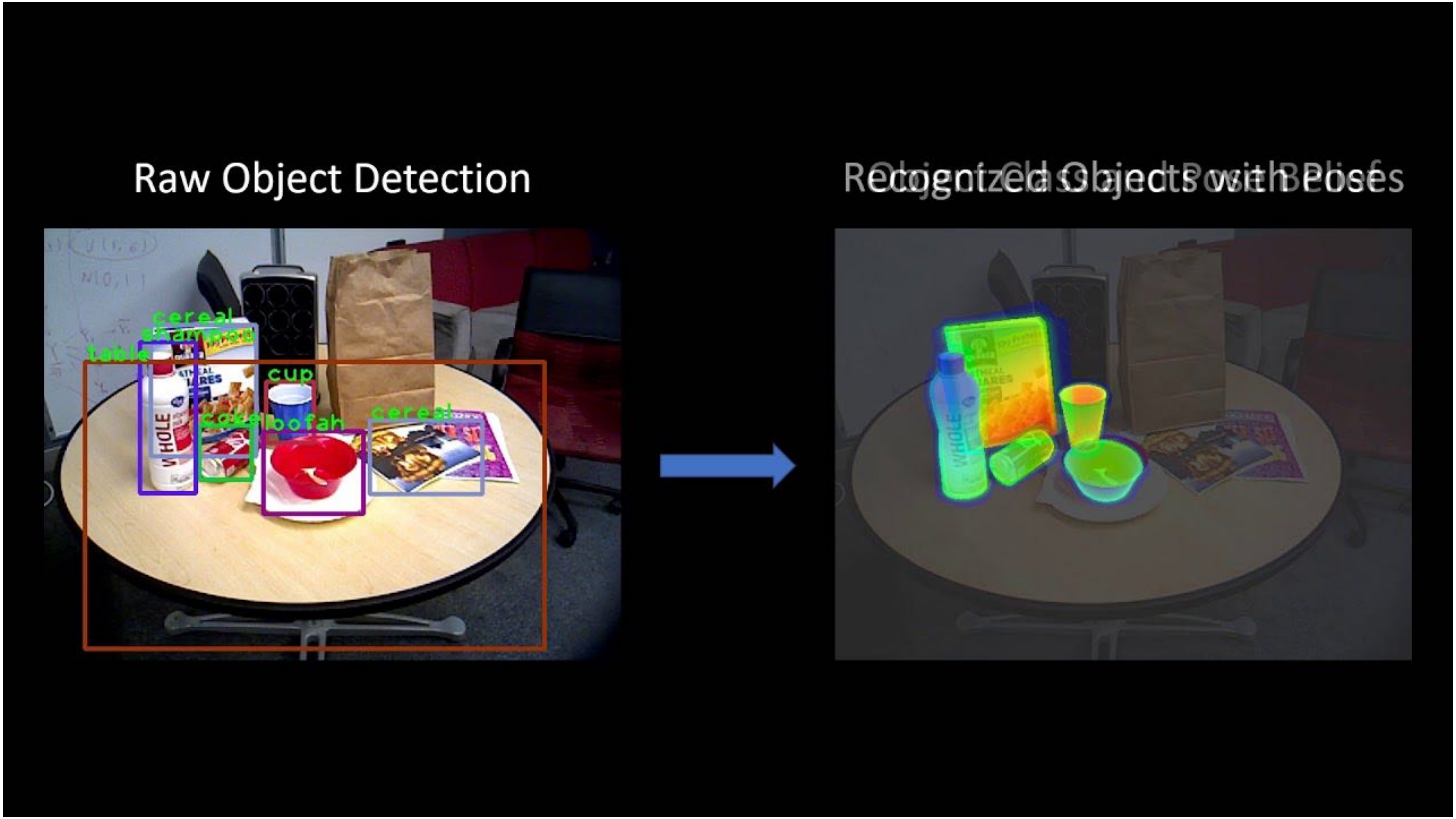
Zhiqiang Sui, Lingzhu Xiang, Odest Chadwicke Jenkins, Karthik Desingh,
"Goal-directed Robot Manipulation through Axiomatic Scene Estimation," IJRR 2017.

Physically Plausible Scene Estimation for Manipulation in Clutter

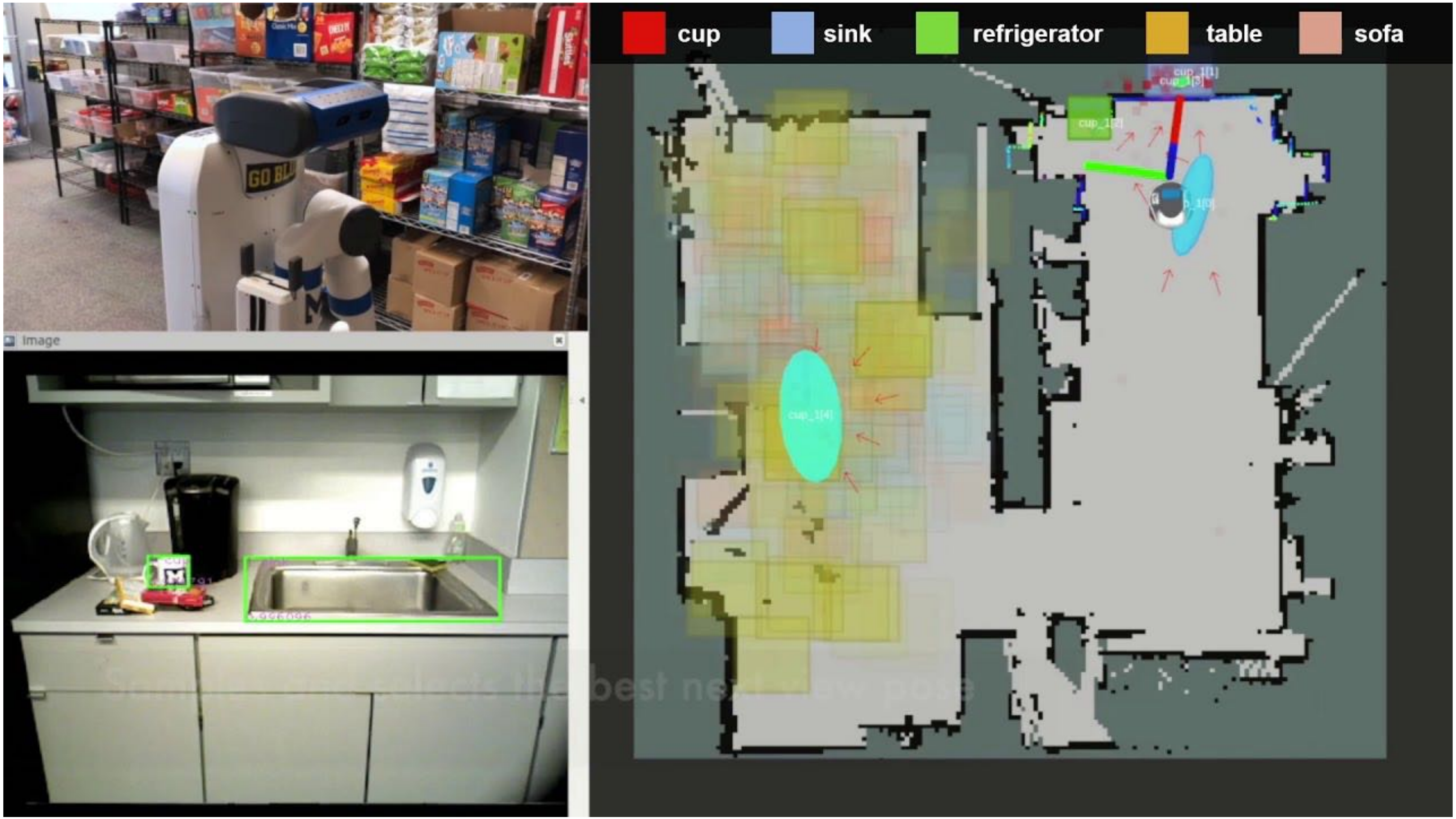
Karthik Desingh[1], Odest Chadwicke Jenkins[1], Lionel Reveret[2], Zhiqiang Sui[1]

[1]University of Michigan, Ann Arbor, USA
[2]INRIA RhÔne-Alpes, Saint Ismier, France

Karthik Desingh, Odest Chadwicke Jenkins, Lionel Reveret, Zhiqiang Sui, "Physically Plausible Scene Estimation for Manipulation in Clutter," Humanoids 2016.



Zhen Zeng, Yunwen Zhou, Odest Chadwicke Jenkins, Karthik Desingh, "Semantic Mapping with Simultaneous Object Detection and Localization," IROS 2018



Zhen Zeng, Adrian Röfer, Odest Chadwicke Jenkins, "SLiM: Semantic Linking Maps for Active Visual Object Search.," ICRA 2020

Pipeline

From RGB-D observations ...

Zhiqiang Sui, Haonan Chang, Ning Xu, Odest Chadwicke Jenkins, "Geofusion: Geometric consistency informed scene estimation in dense clutter", *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 5913-5920, Oct. 2020, doi: 10.1109/LRA.2020.3010443.

Next Lecture:
Mapping