Introduction to Mobile Robotics

Bayes Filter – Particle Filter and Monte Carlo Localization

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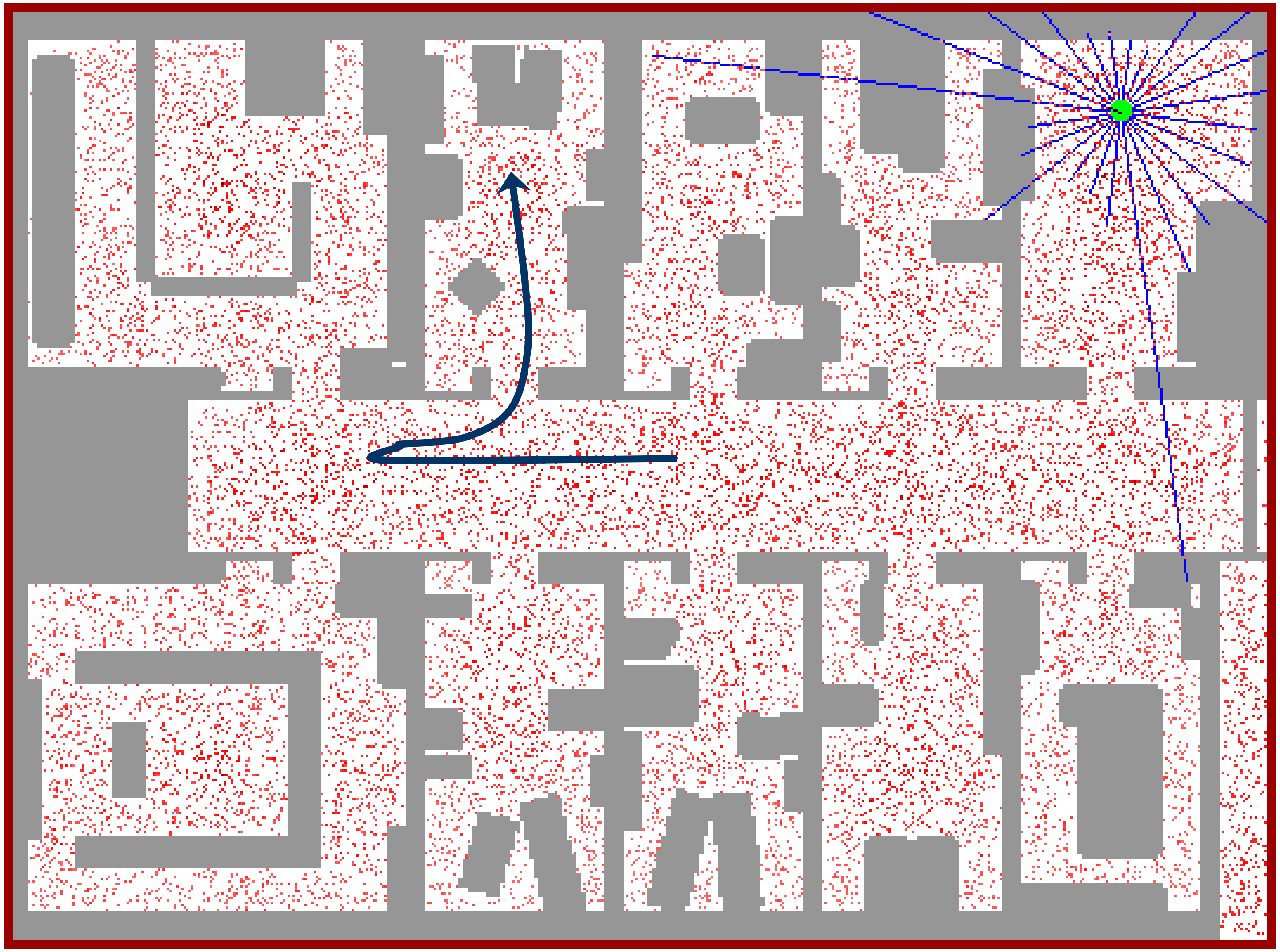
Motivation

- Recall: Discrete filter
  - Discretize the continuous state space
  - High memory complexity
  - Fixed resolution (does not adapt to the belief)

- Particle filters are a way to **efficiently** represent **non-Gaussian distribution**

- Basic principle
  - Set of state hypotheses (“particles”)
  - Survival-of-the-fittest

Sample-based Localization (sonar)



Mathematical Description

- Set of weighted samples

$$S = \left\{ \left\langle s^{[i]}, w^{[i]} \right\rangle \mid i = 1, \ldots, N \right\}$$

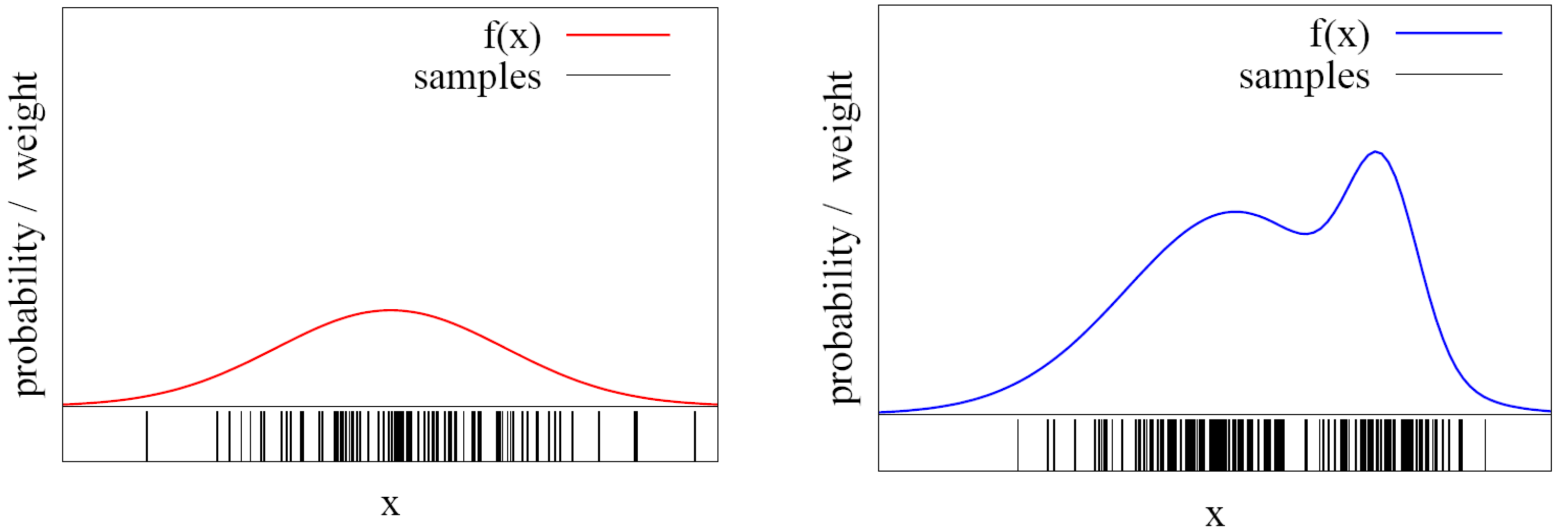
State hypothesis   Importance weight

- The samples represent the posterior

$$p(x) = \sum_{i=1}^{N} w_i \cdot \delta_{s^{[i]}}(x)$$

Function Approximation

- Particle sets can be used to approximate functions

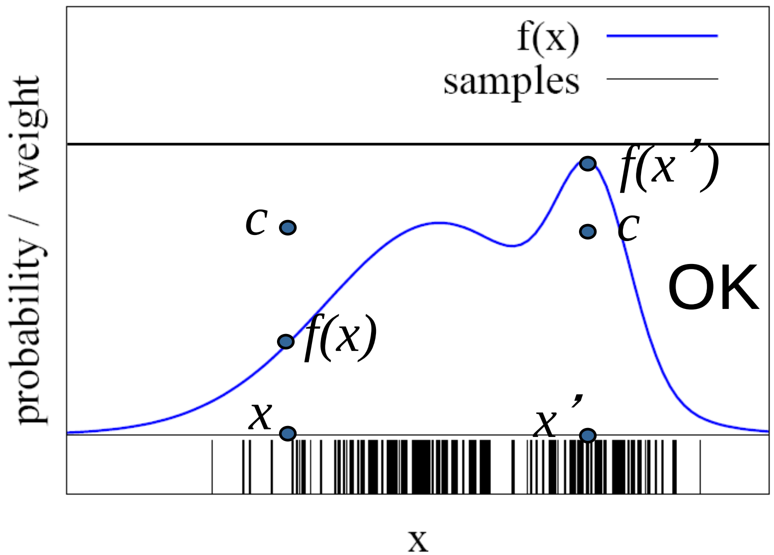


- The more particles fall into an interval, the higher the probability of that interval

- How to draw samples from a function/distribution?

Rejection Sampling

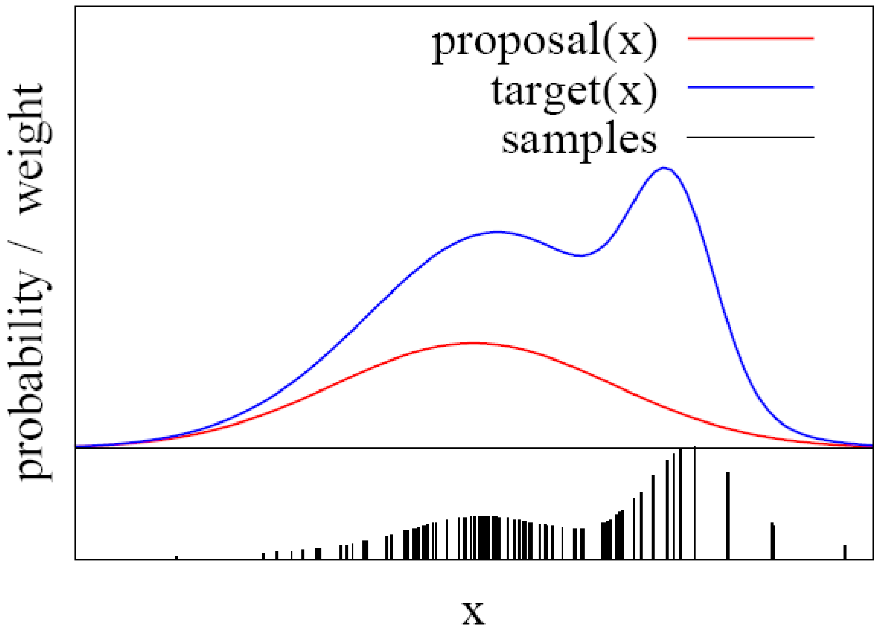
- Let us assume that $f(x)<1$ for all x
- Sample x from a uniform distribution
- Sample c from [0,1]
- if $f(x) > c$ keep the sample
  otherwise reject the sample



Importance Sampling Principle

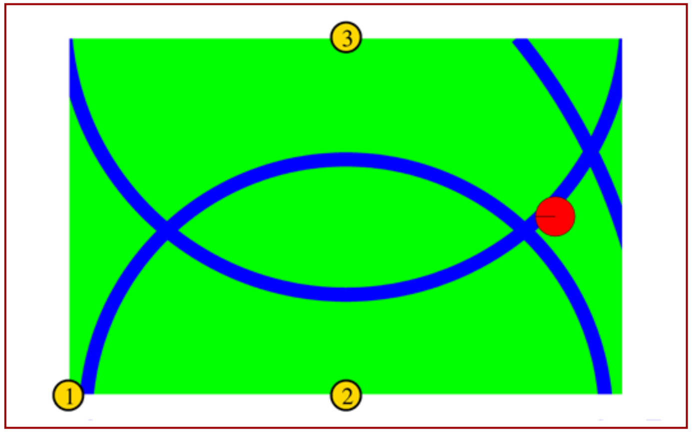
- We can even use a different distribution g to generate samples from f
- By introducing an importance weight w, we can account for the "differences between g and f"
- $w = f / g$
- f is called target
- g is called proposal
- Pre-condition:

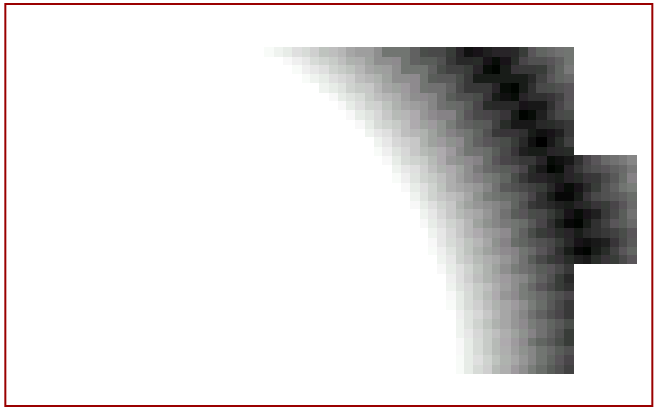
  $f(x)>0 \rightarrow g(x)>0$
- Derivation: See webpage

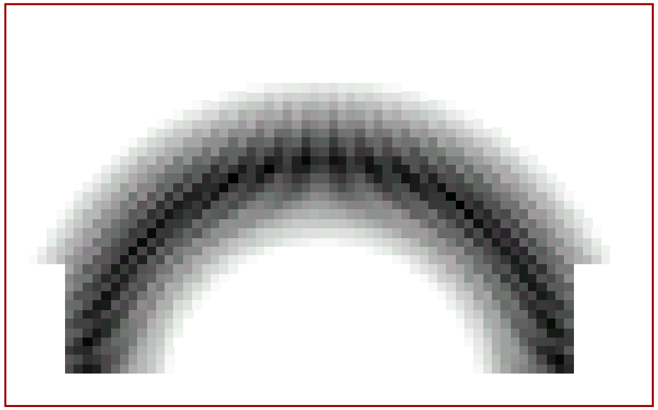


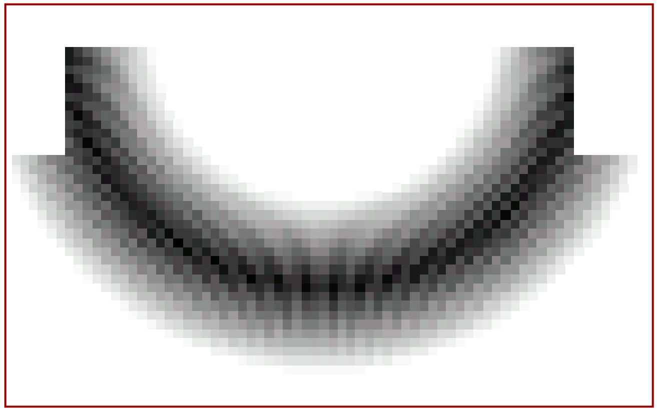
Importance Sampling with Resampling: Landmark Detection Example

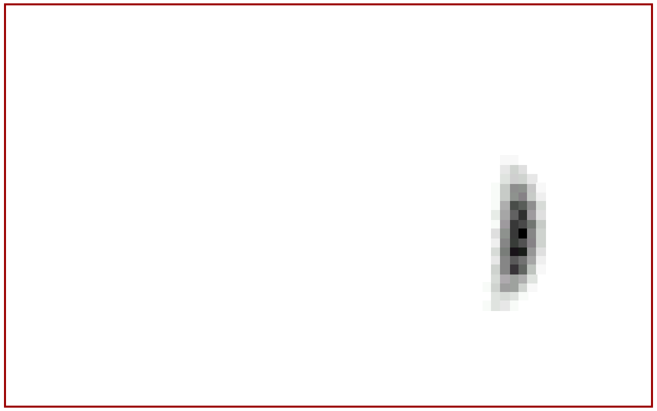
Distributions



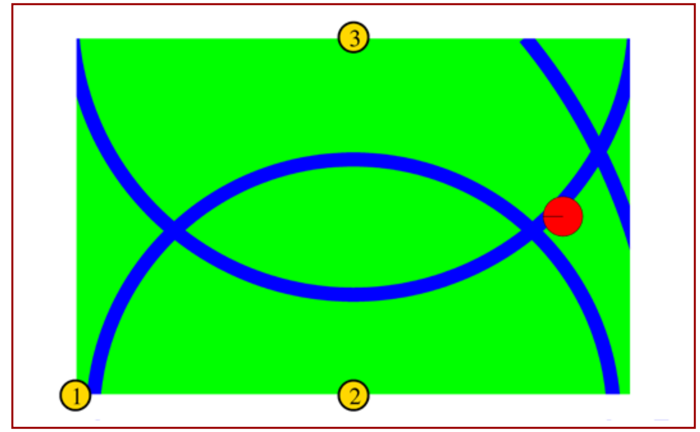


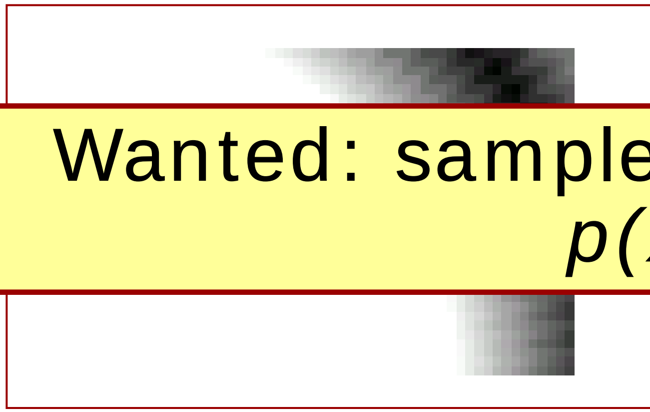


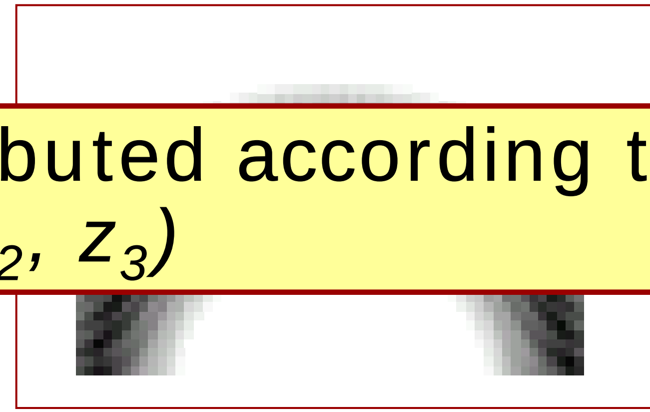




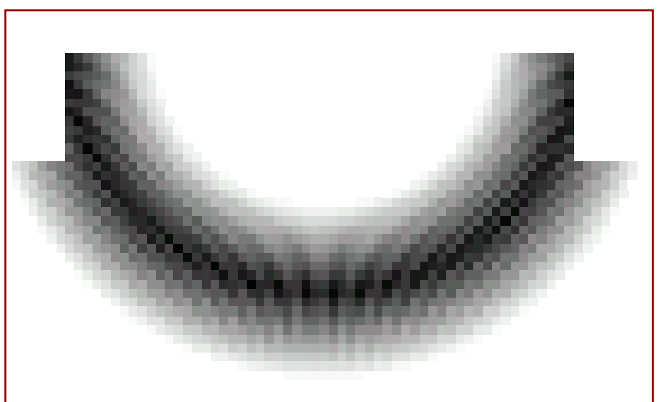
Distributions

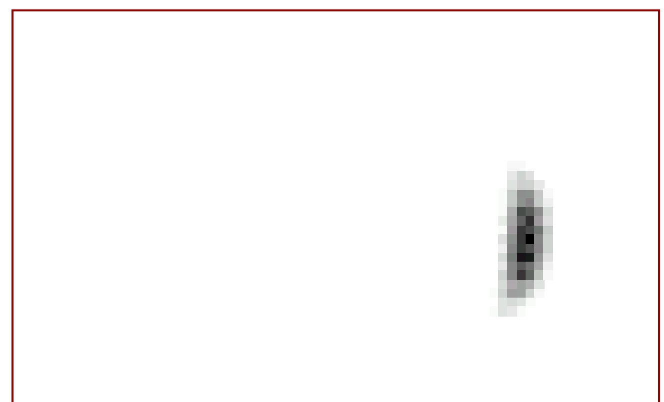






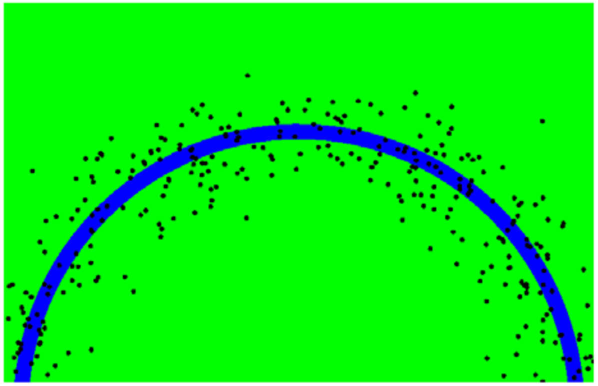
Wanted: samples distributed according to $p(x|\ z_1, z_2, z_3)$

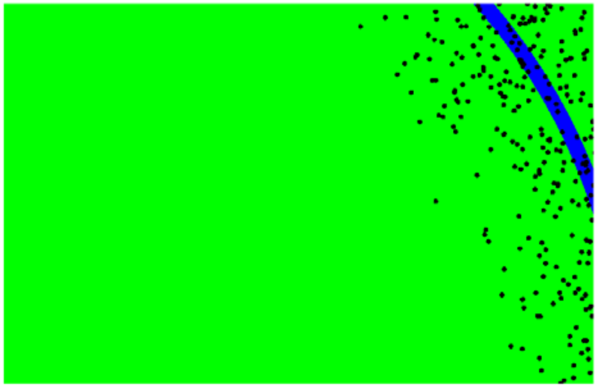


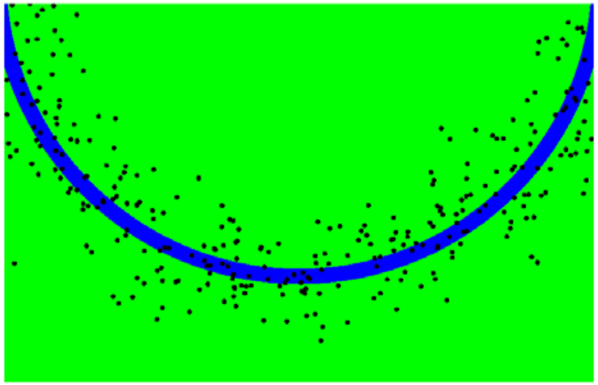


This is Easy!

We can draw samples from $p(x|z_l)$ by adding noise to the detection parameters.







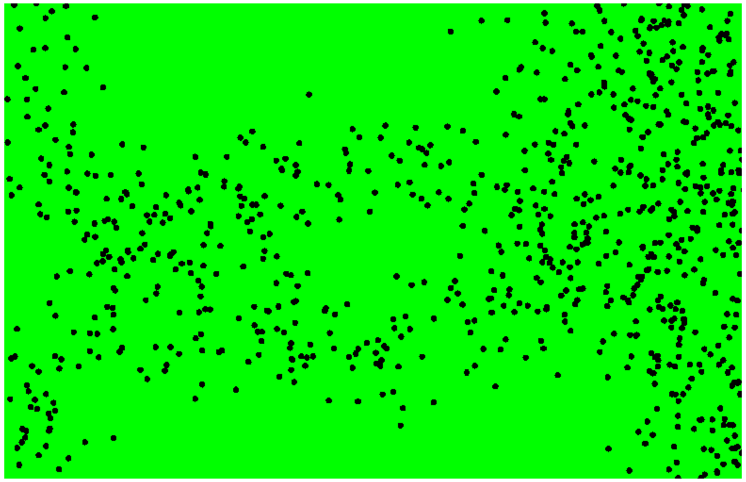
Importance Sampling

$$\text{Target distribution f: } p(x \mid z_1, z_2, \ldots, z_n) = \frac{\prod_k p(z_k \mid x) \quad p(x)}{p(z_1, z_2, \ldots, z_n)}$$

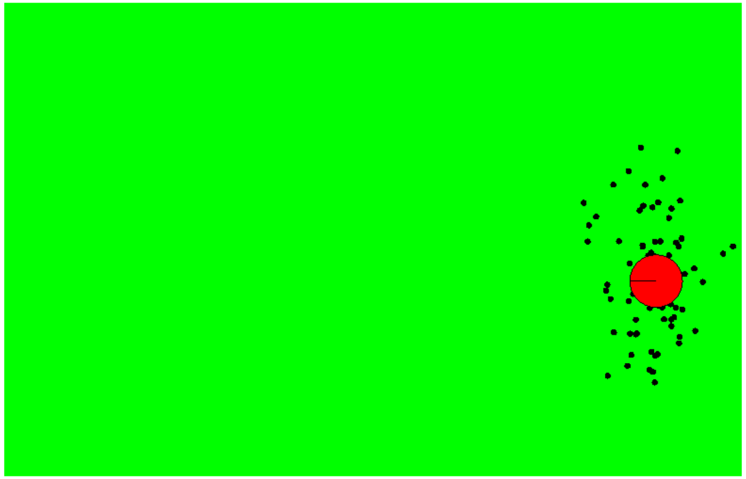
$$\text{Sampling distribution g: } p(x \mid z_l) = \frac{p(z_l \mid x) p(x)}{p(z_l)}$$

$$\text{Importance weights w: } \frac{f}{g} = \frac{p(x \mid z_1, z_2, \ldots, z_n)}{p(x \mid z_l)} = \frac{p(z_l) \prod_{k \neq l} p(z_k \mid x)}{p(z_1, z_2, \ldots, z_n)}$$

Importance Sampling with Resampling

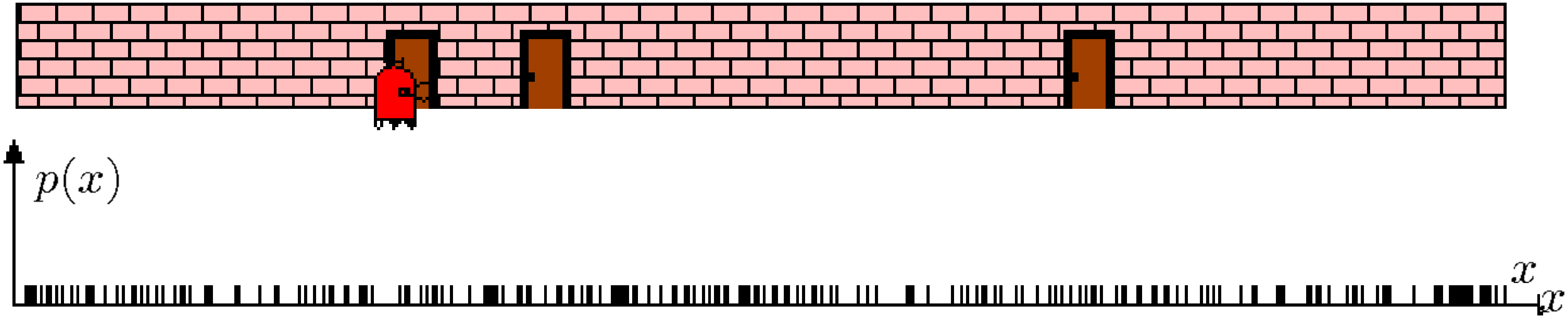


Weighted samples



After resampling

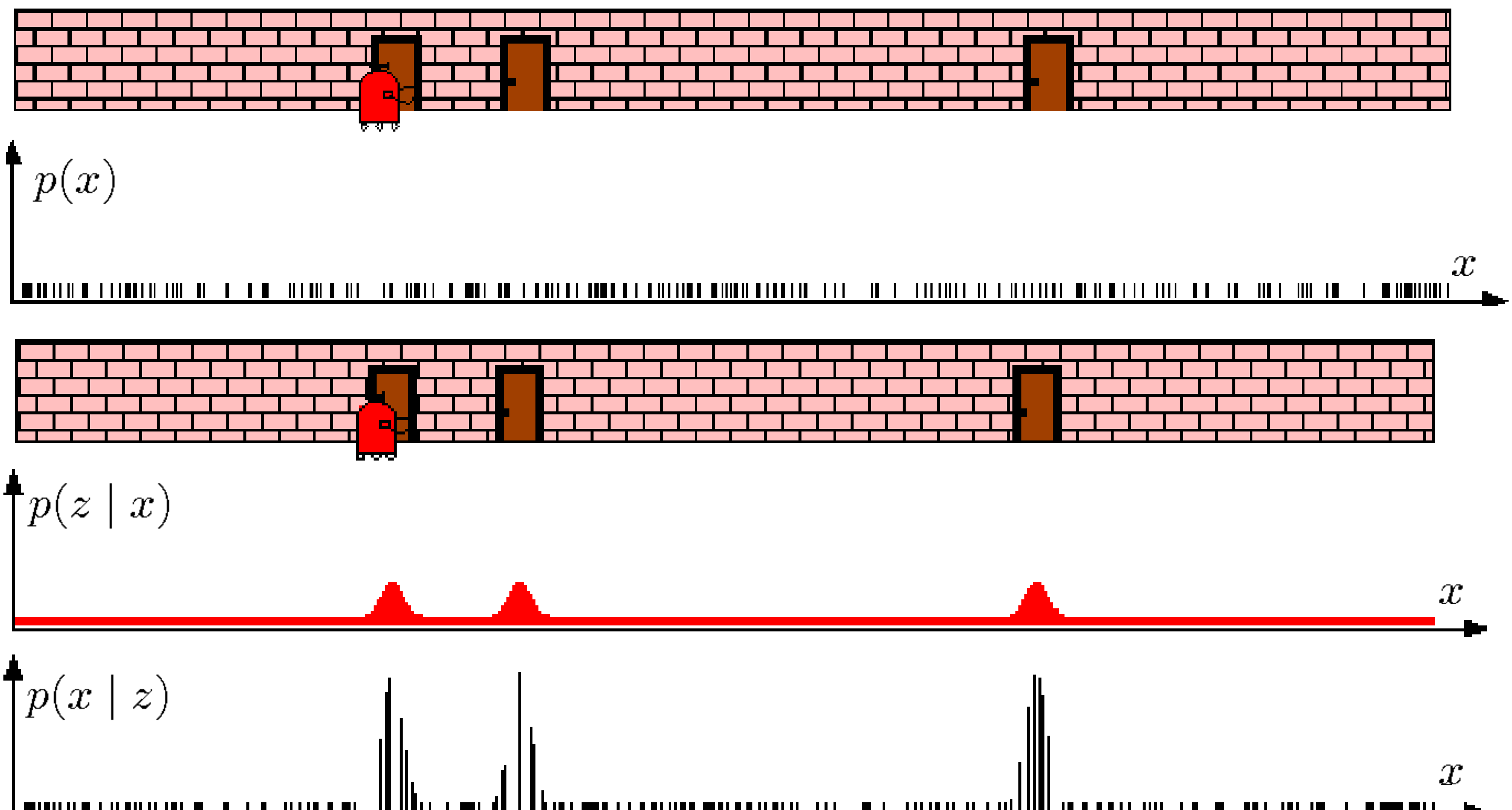
Particle Filters



Sensor Information: Importance Sampling

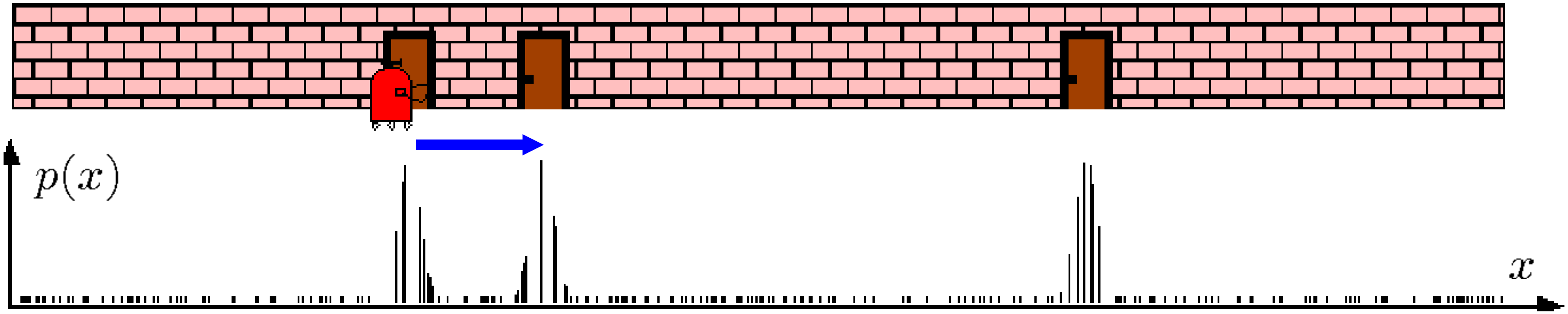
$$Bel(x) \leftarrow \alpha\, p(z \mid x)\, Bel^{-}(x)$$

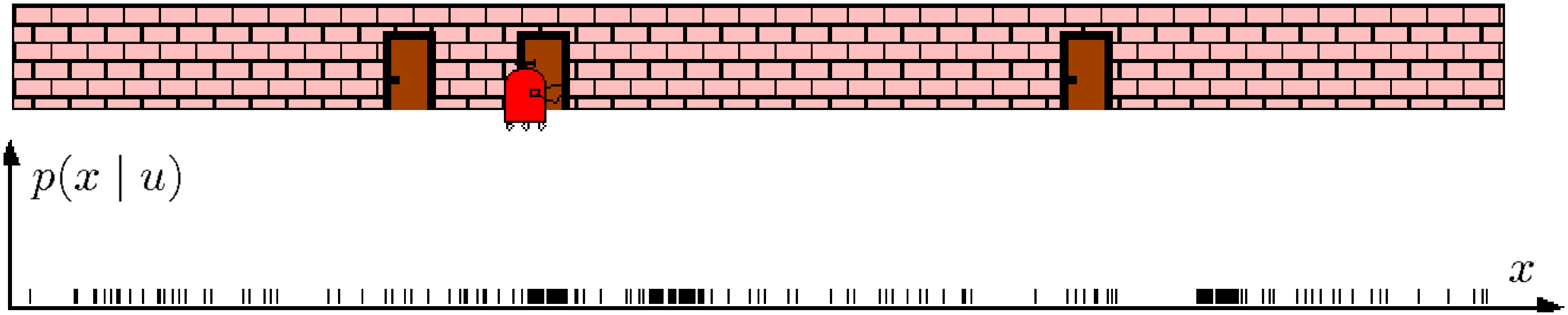
$$w \leftarrow \frac{\alpha\, p(z \mid x)\, Bel^{-}(x)}{Bel^{-}(x)} = \alpha\, p(z \mid x)$$



Robot Motion

$$Bel^{-}(x) \leftarrow \int p(x \mid u, x')\, Bel(x')\, \mathrm{d}x'$$





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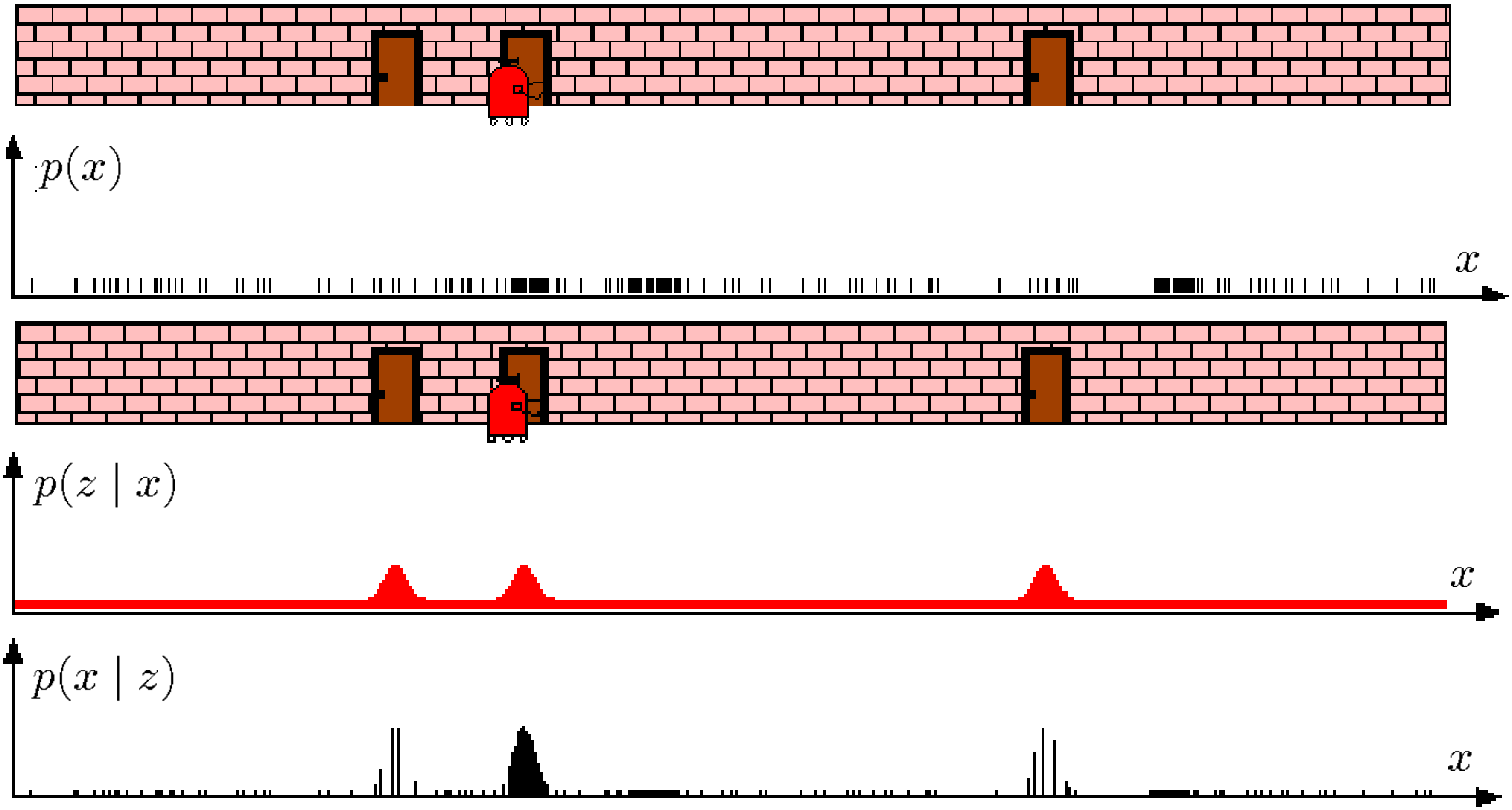

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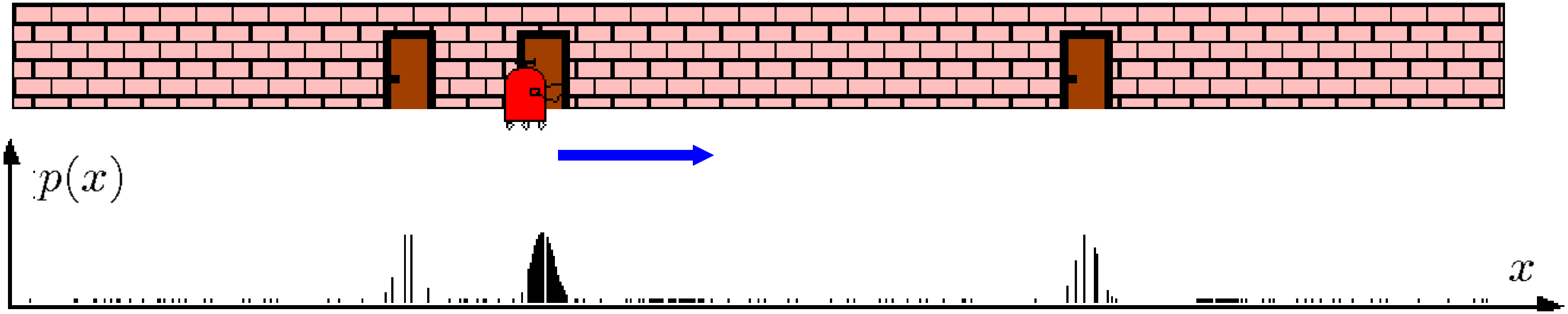
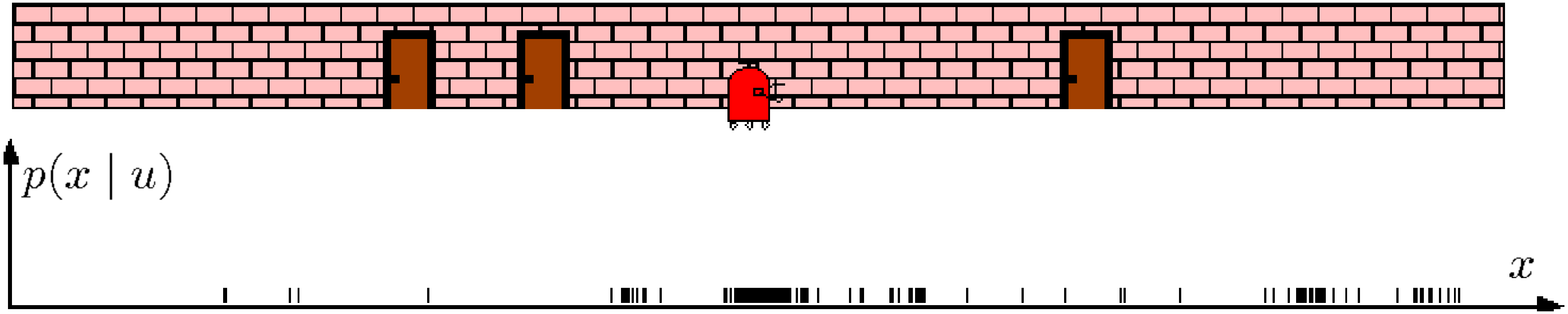




Particle Filter Algorithm

- Sample the next generation for particles using the proposal distribution

- Compute the importance weights :

  weight = target distribution / proposal distribution

- Resampling: "Replace unlikely samples by more likely ones"

Particle Filter Algorithm

1. Algorithm **particle_filter**(S_{t-1}, u_t, z_t):
2. $S_t = \emptyset, \quad \eta = 0$
3. **For** $i = 1, \ldots, n$ — ***Generate new samples***
4. Sample index *j(i)* from the discrete distribution given by w_{t-1}
5. Sample x_t^i from $p(x_t \mid x_{t-1}, u_t)$ using $x_{t-1}^{j(i)}$ and u_t
6. $w_t^i = p(z_t \mid x_t^i)$ — ***Compute importance weight***
7. $\eta = \eta + w_t^i$ — ***Update normalization factor***

   $S_t = S_t \cup \{< x_t^i, w_t^i >\}$

8. $i = 1, \ldots, n$ — ***Add to new particle set***
9. **For** $w_t^i = w_t^i / \eta$
10. S_t — ***Normalize weights***
11. return

Particle Filter Algorithm

$$Bel(x_t) = \eta\, p(z_t \mid x_t) \int p(x_t \mid x_{t-1}, u_t)\, Bel(x_{t-1})\, dx_{t-1}$$

draw x^i_{t-1} from $Bel(x_{t-1})$

draw x^i_t from $p(x_t \mid x^i_{t-1}, u_t)$

Importance factor for x^i_t:

$$w^i_t = \frac{\text{target distribution}}{\text{proposal distribution}}$$

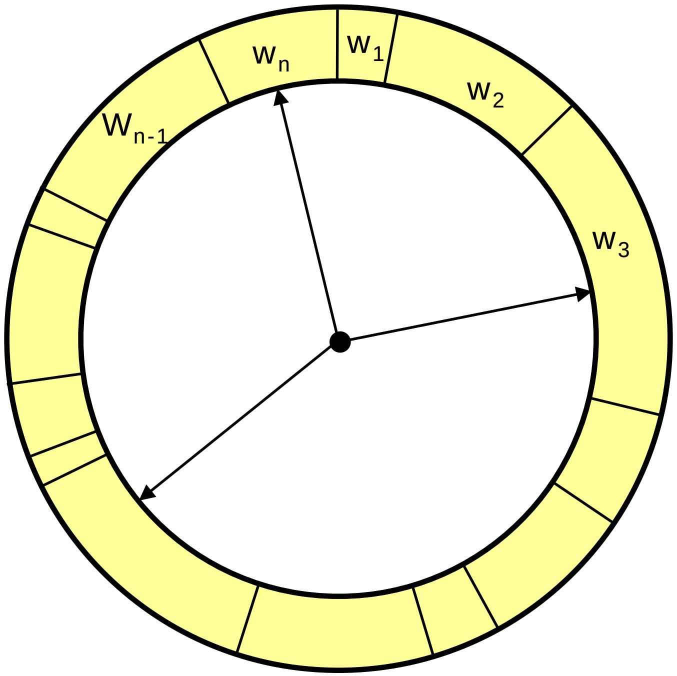
$$= \frac{\eta\, p(z_t \mid x_t)\, p(x_t \mid x_{t-1}, u_t)\, Bel(x_{t-1})}{p(x_t \mid x_{t-1}, u_t)\, Bel(x_{t-1})}$$

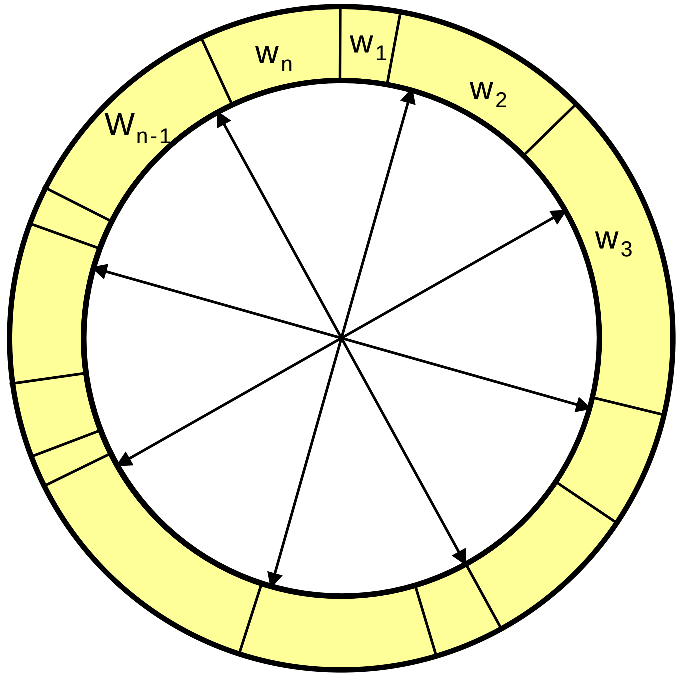
$$\propto p(z_t \mid x_t)$$

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

Resampling Algorithm

1. Algorithm **systematic_resampling**(S,n):

2. $S' = \emptyset, c_1 = w^1$
3. **For** $i = 2 \ldots n$ *Generate cdf*
4. $c_i = c_{i-1} + w^i$
5. $u_1 \sim U\,]0, n^{-1}], i = 1$ *Initialize threshold*

6. **For** $j = 1 \ldots n$ *Draw samples …*
7. **While** ($u_j > c_i$) *Skip until next threshold reached*
8. $i = i + 1$
9. $S' = S' \cup \left\{ < x^i, n^{-1} > \right\}$ *Insert*
10. $u_{j+1} = u_j + n^{-1}$ *Increment threshold*

11. **Return** S'

Also called **stochastic universal sampling**

Mobile Robot Localization

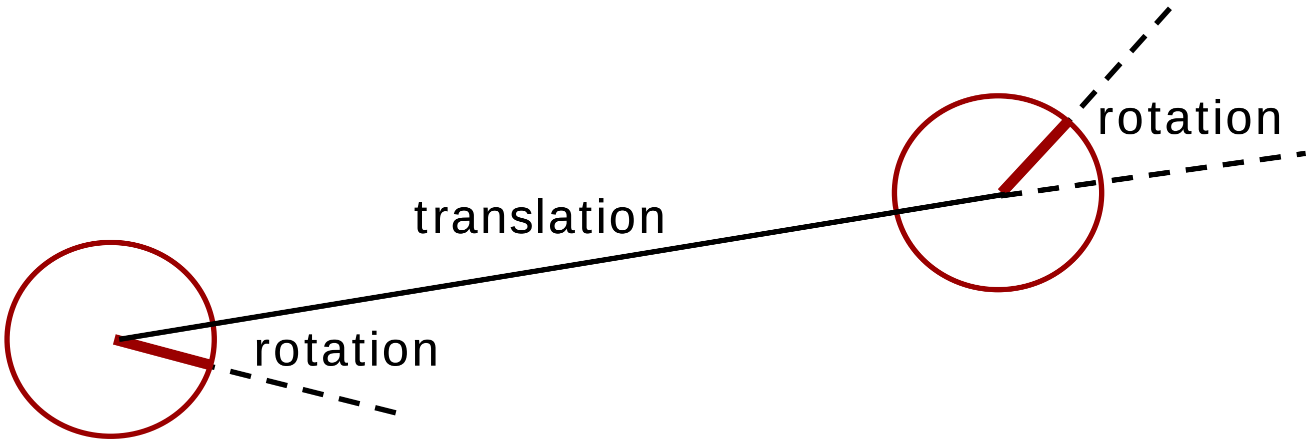
- Each particle is a potential pose of the robot
- Proposal distribution is the motion model of the robot (prediction step)
- The observation model is used to compute the importance weight (correction step)

[For details, see PDF file on the lecture web page]

Motion Model Reminder

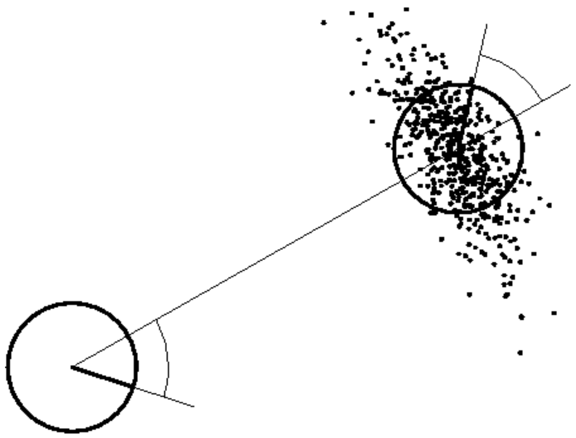
According to the estimated motion

Motion Model Reminder



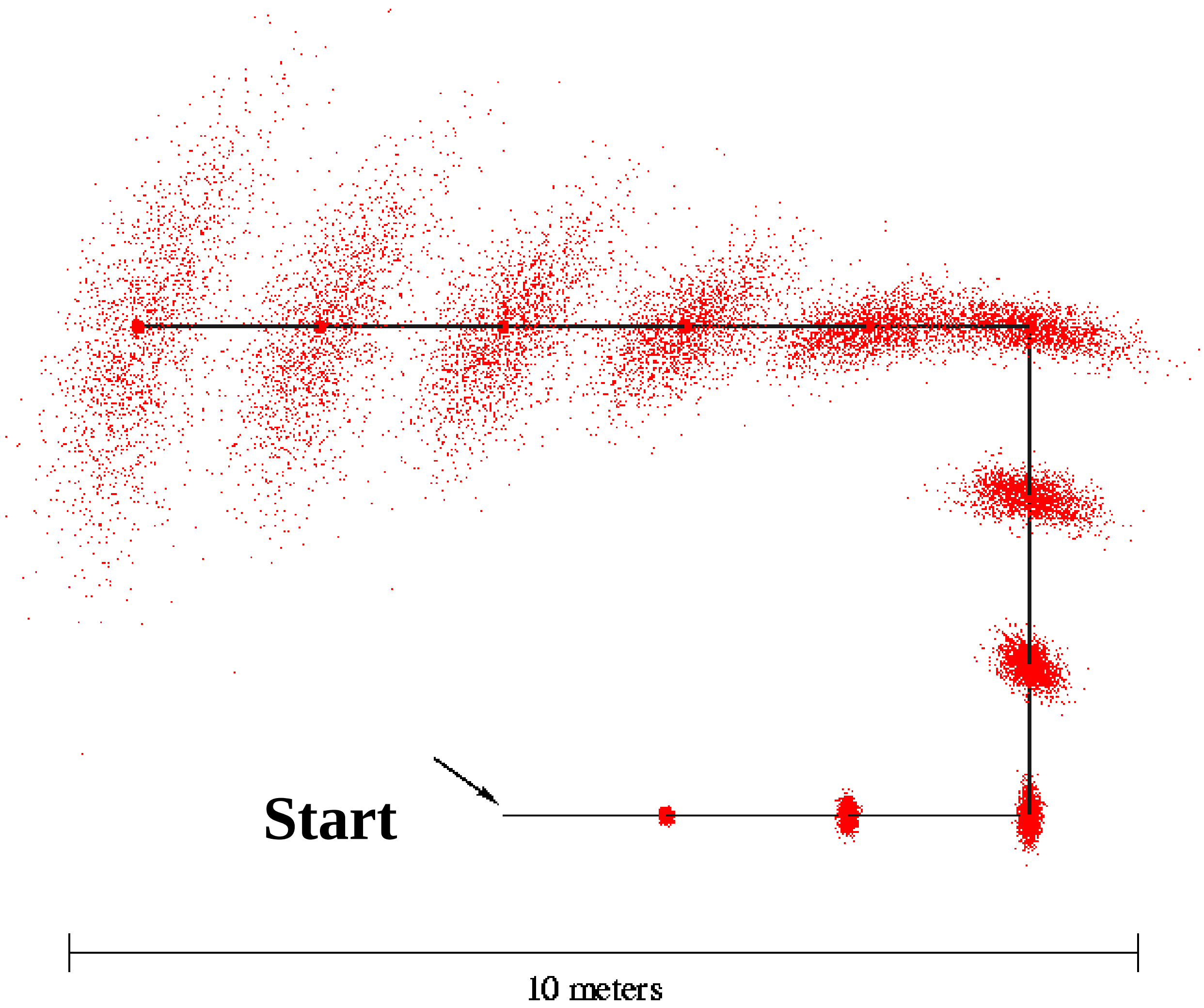
- Decompose the motion into
  - Traveled distance
  - Start rotation
  - End rotation

Motion Model Reminder

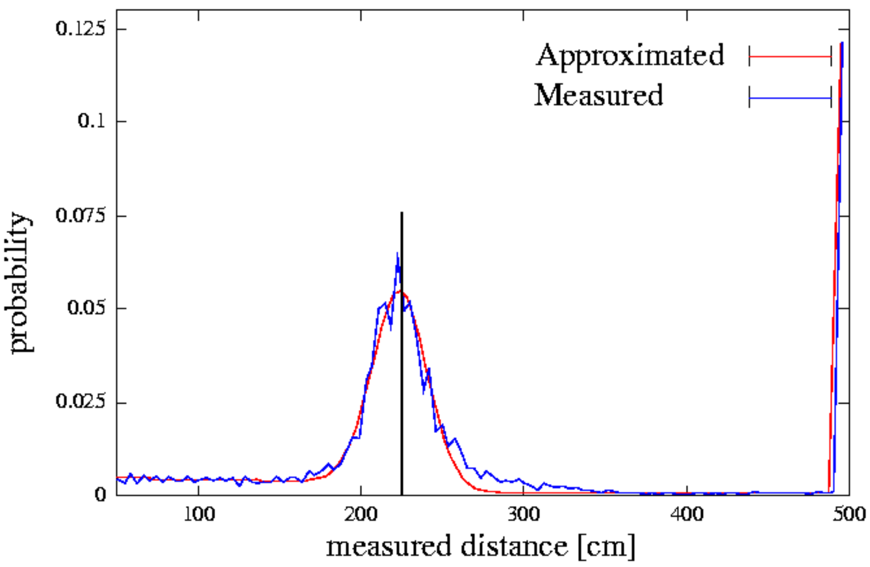


- Uncertainty in the translation of the robot: Gaussian over the traveled distance
- Uncertainty in the rotation of the robot: Gaussians over start and end rotation
- For each particle, draw a new pose by sampling from these three individual normal distributions

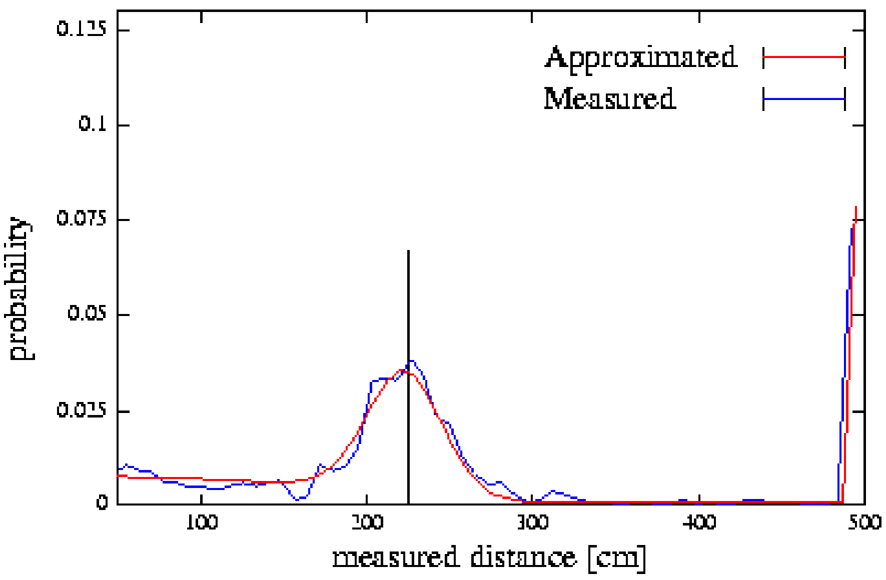
Motion Model Reminder



Proximity Sensor Model Reminder



Laser sensor



Sonar sensor

Mobile Robot Localization Using Particle Filters (1)

- Each particle is a potential pose of the robot

- The set of weighted particles approximates the posterior belief about the robot’s pose (target distribution)

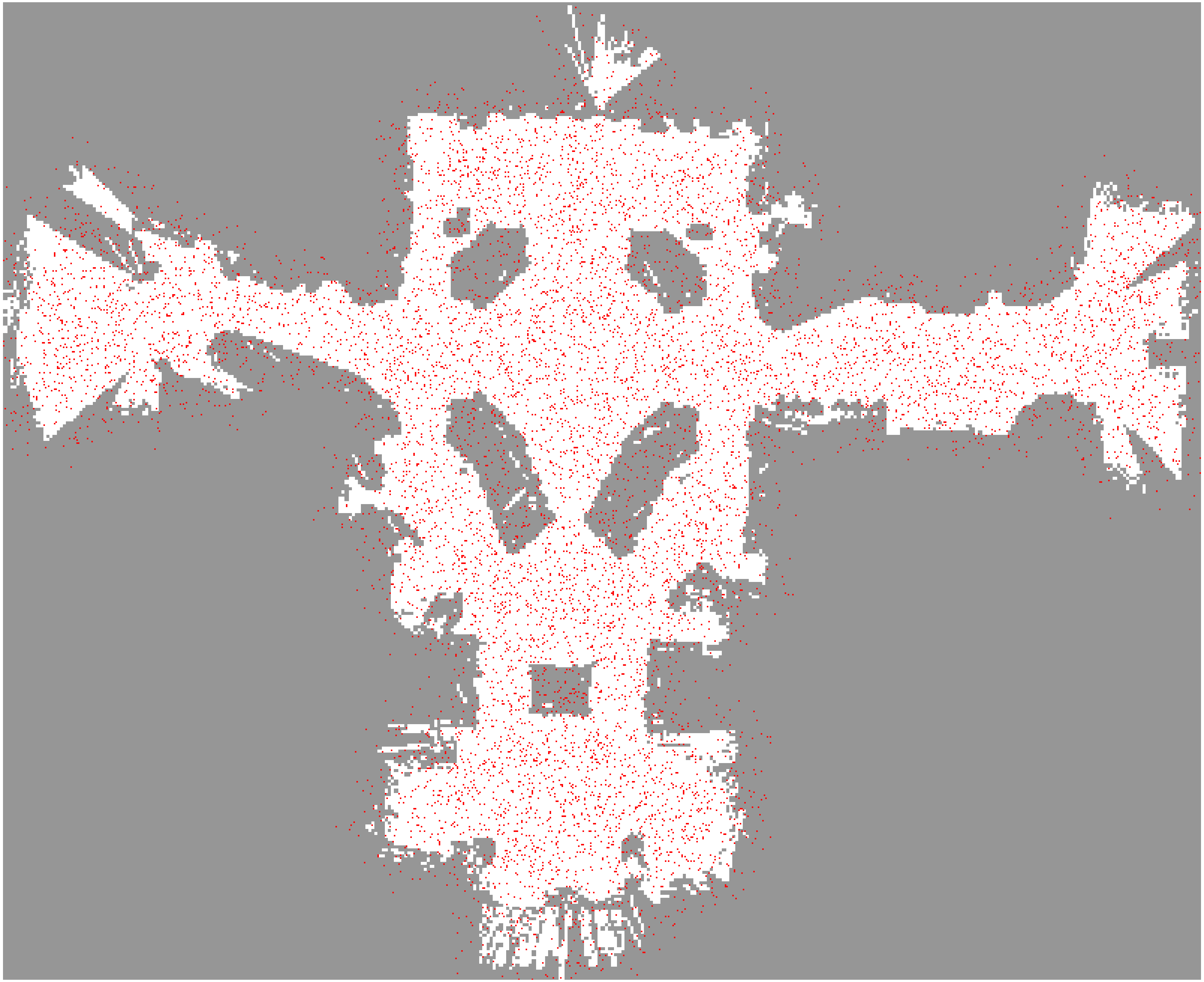
Mobile Robot Localization Using Particle Filters (2)

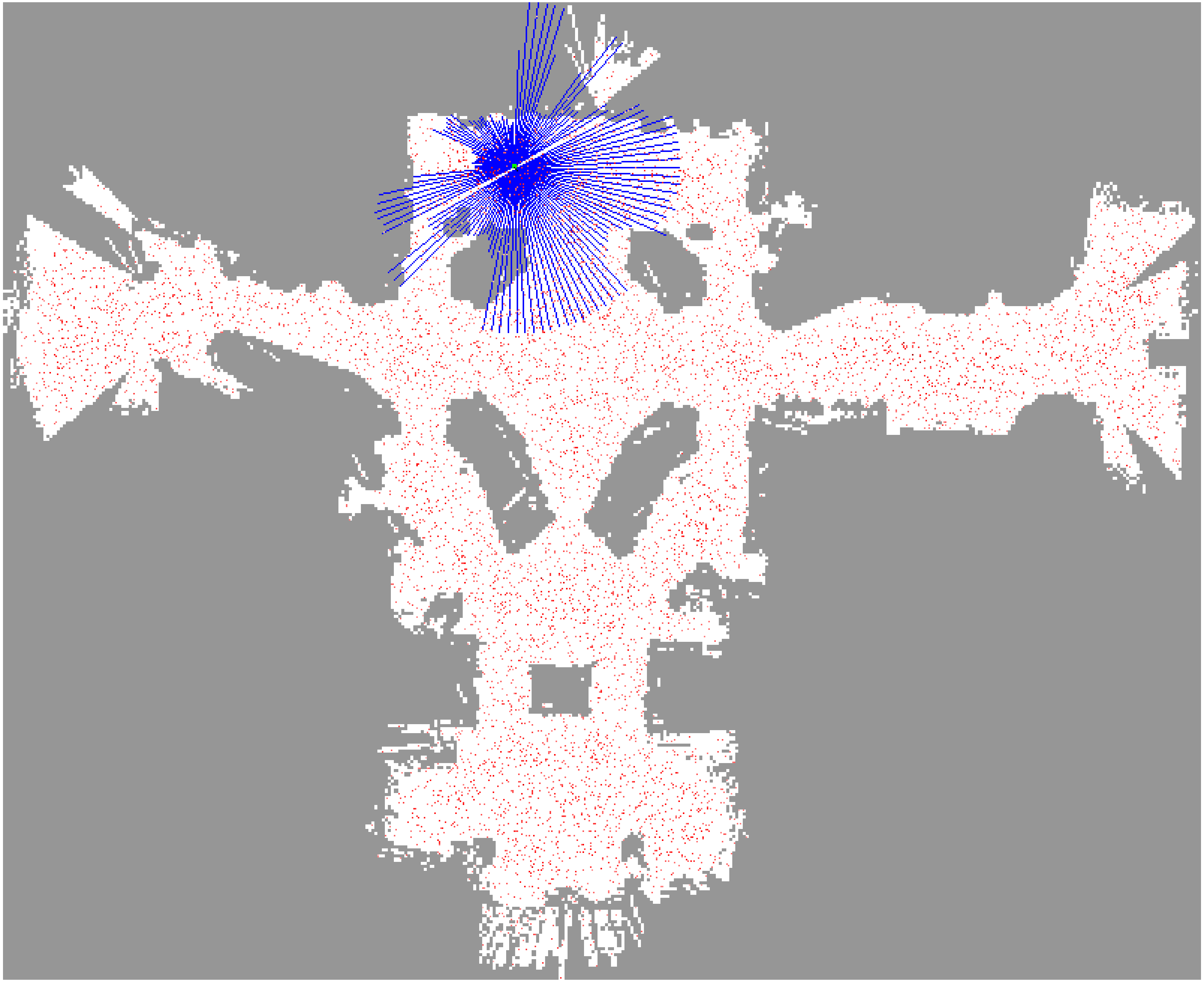
- Particles are drawn from the motion model (proposal distribution)
- Particles are weighted according to the observation model (sensor model)
- Particles are resampled according to the particle weights

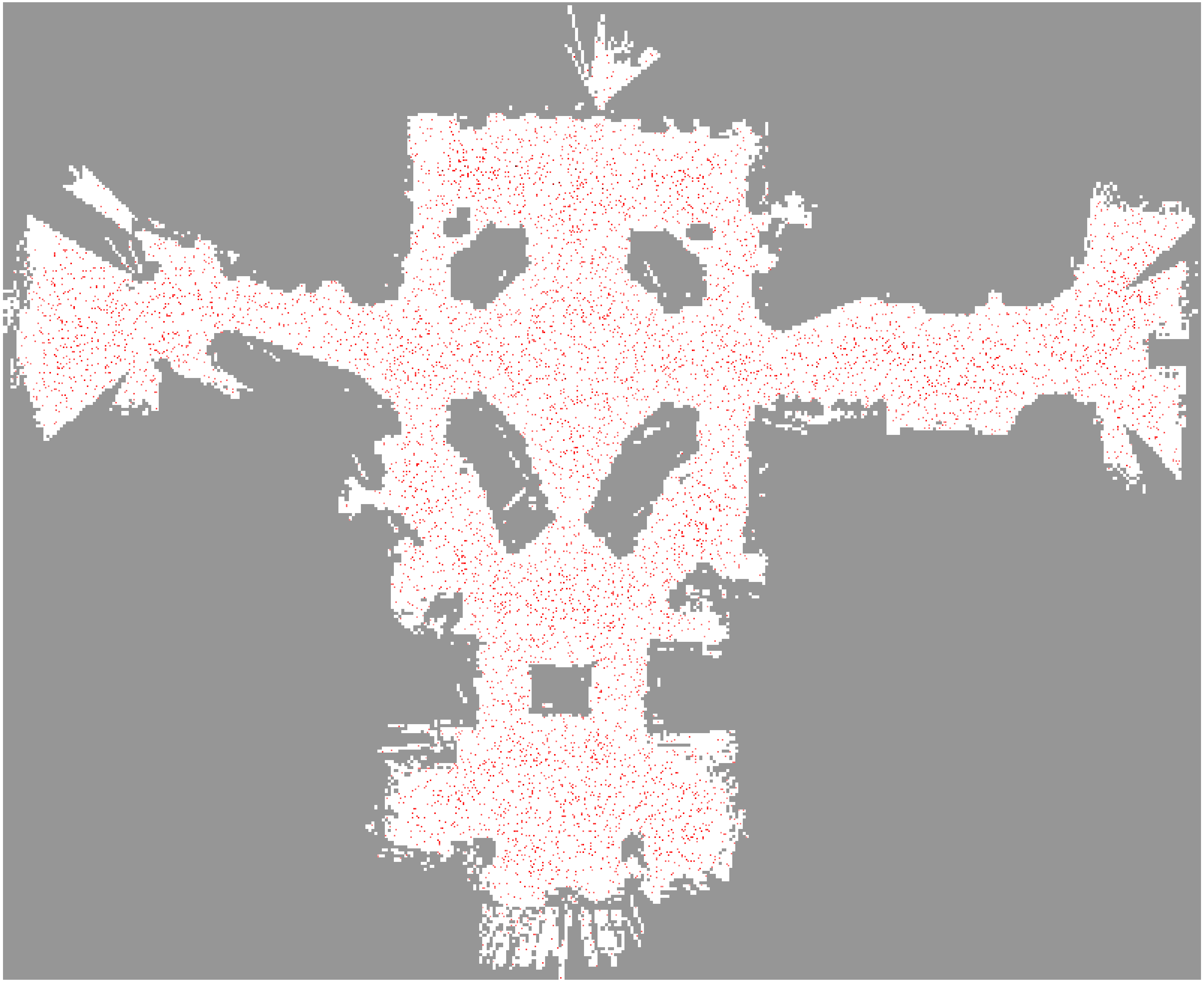
Mobile Robot Localization Using Particle Filters (3)

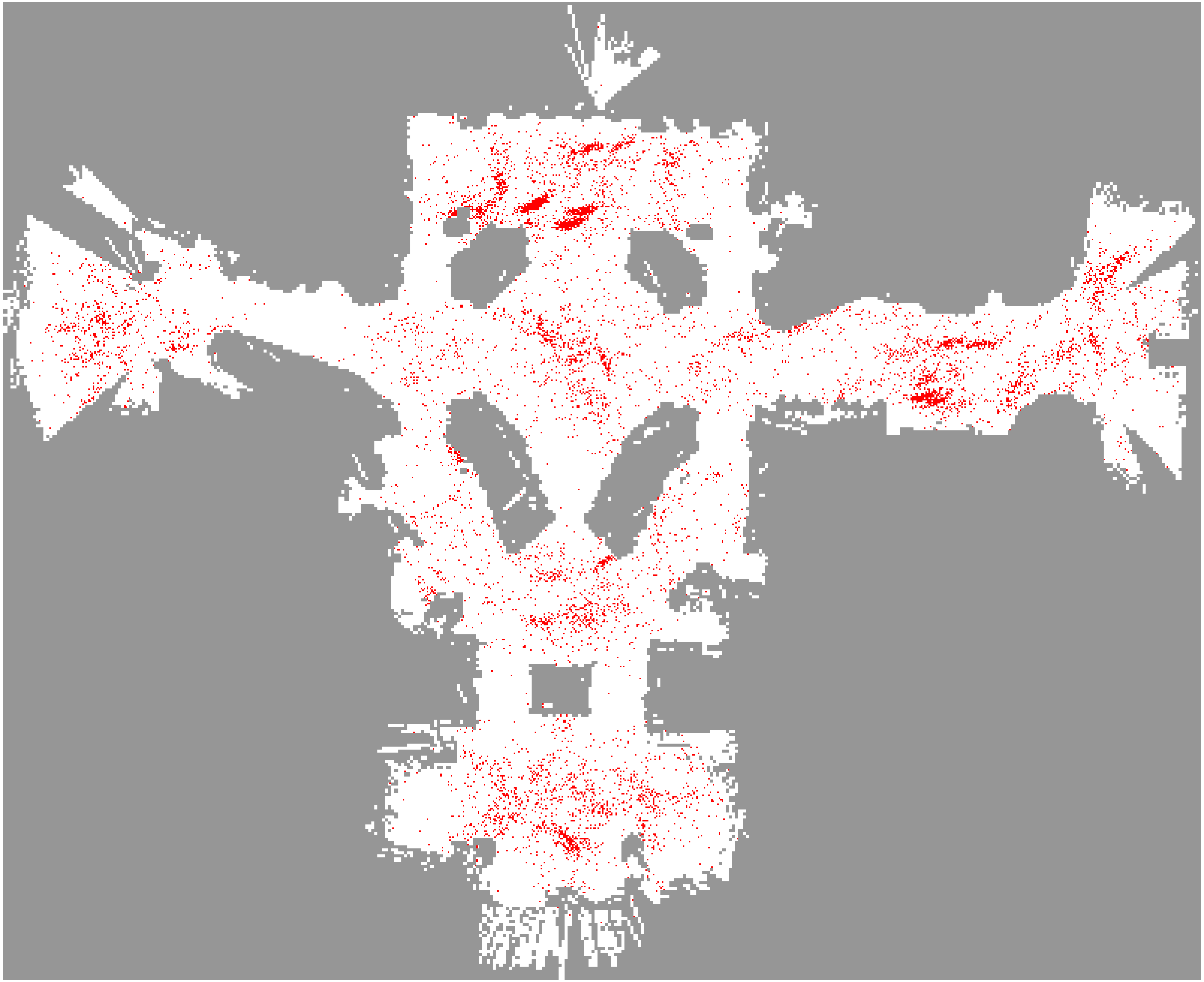
Why is resampling needed?

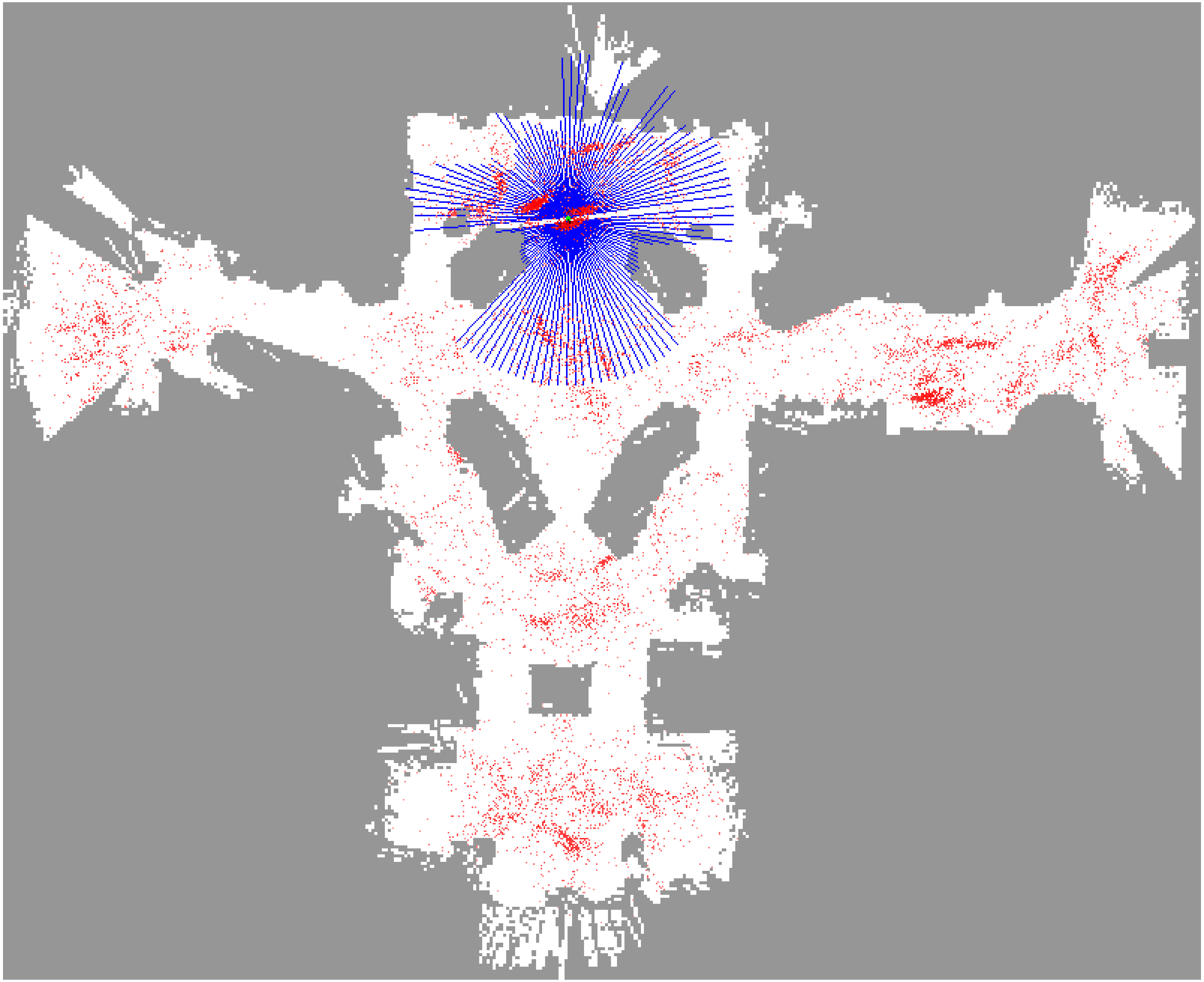
- We only have a finite number of particles
- Without resampling: The filter is likely to loose track of the “good” hypotheses
- Resampling ensures that particles stay in the meaningful area of the state space

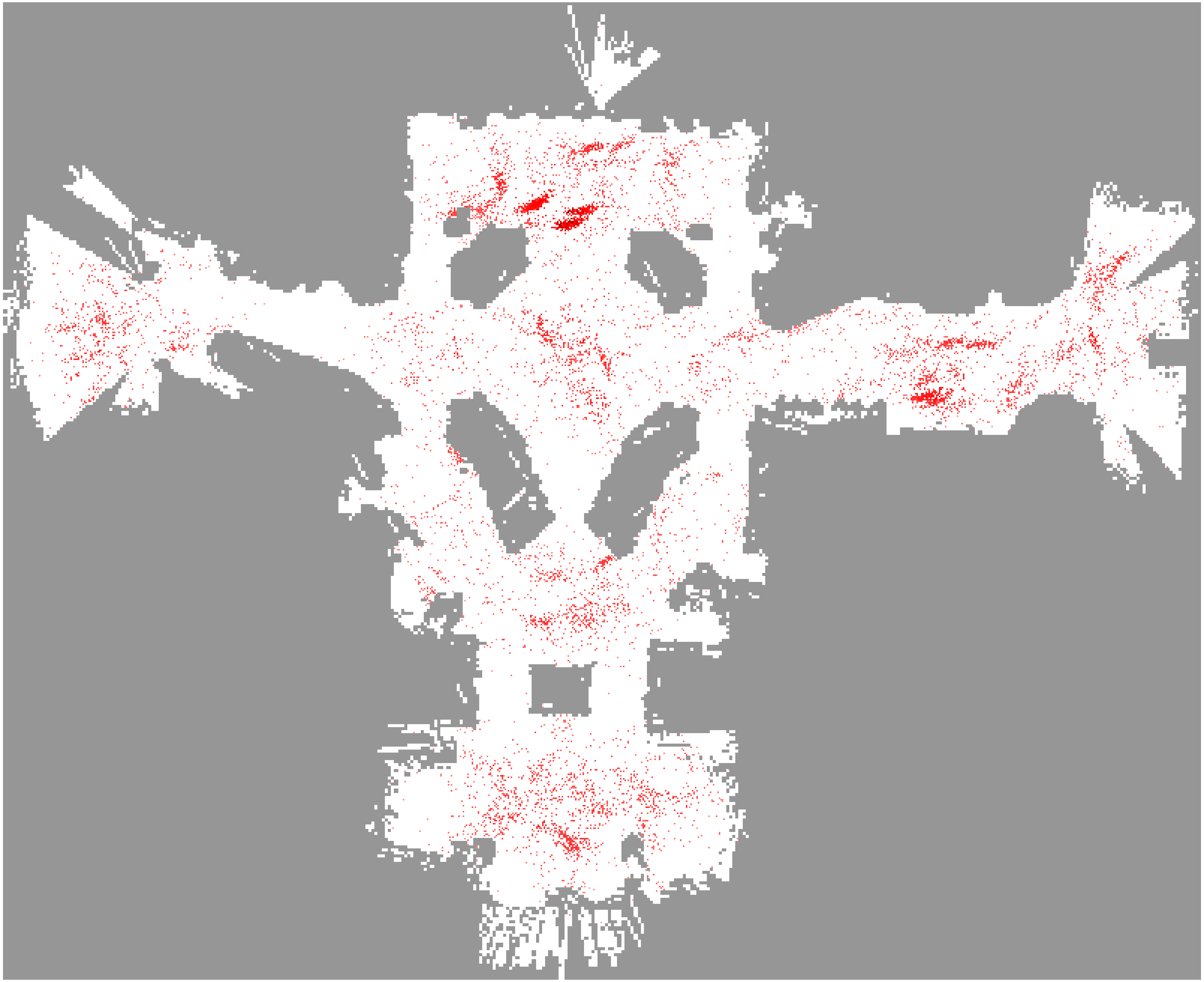


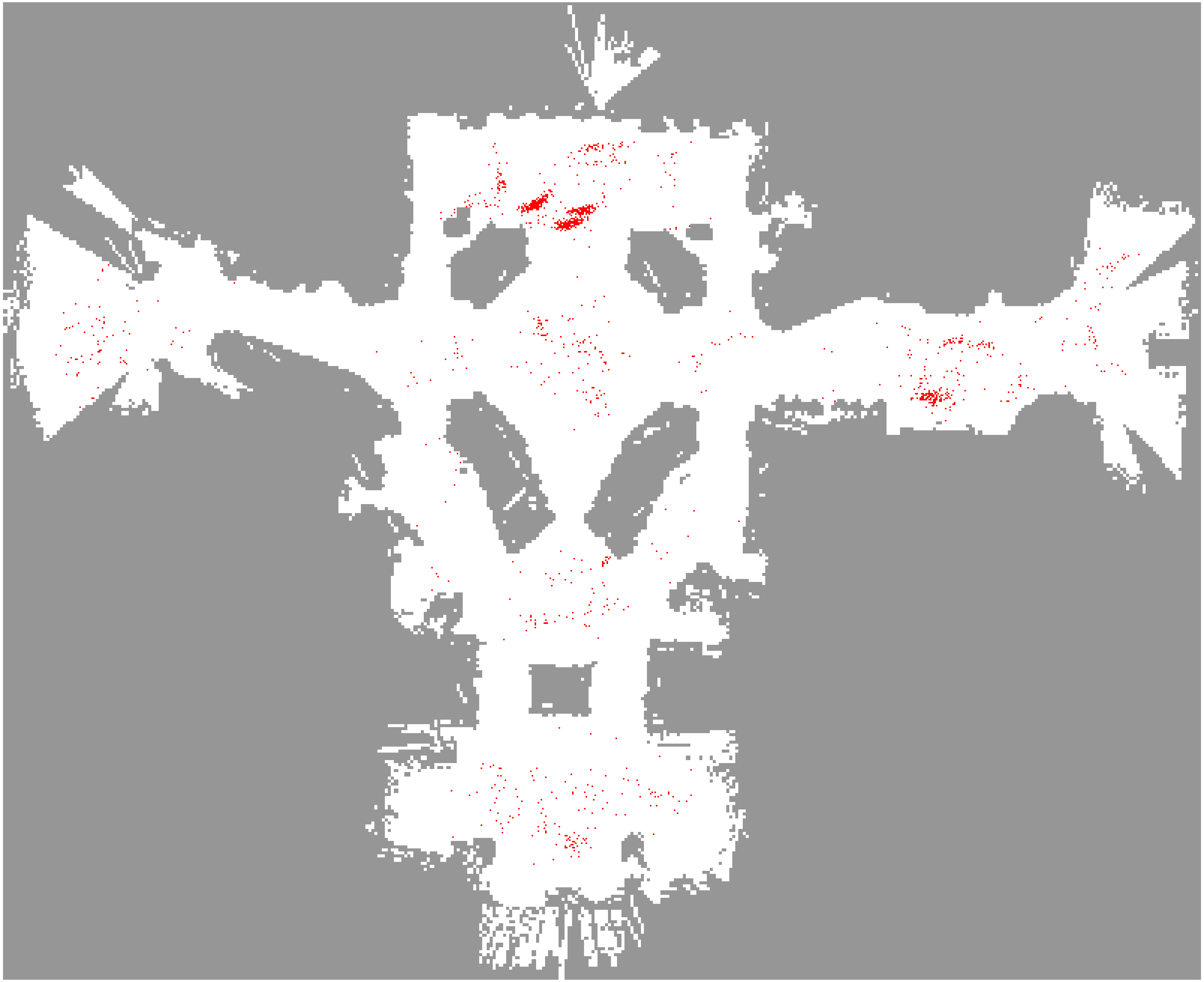


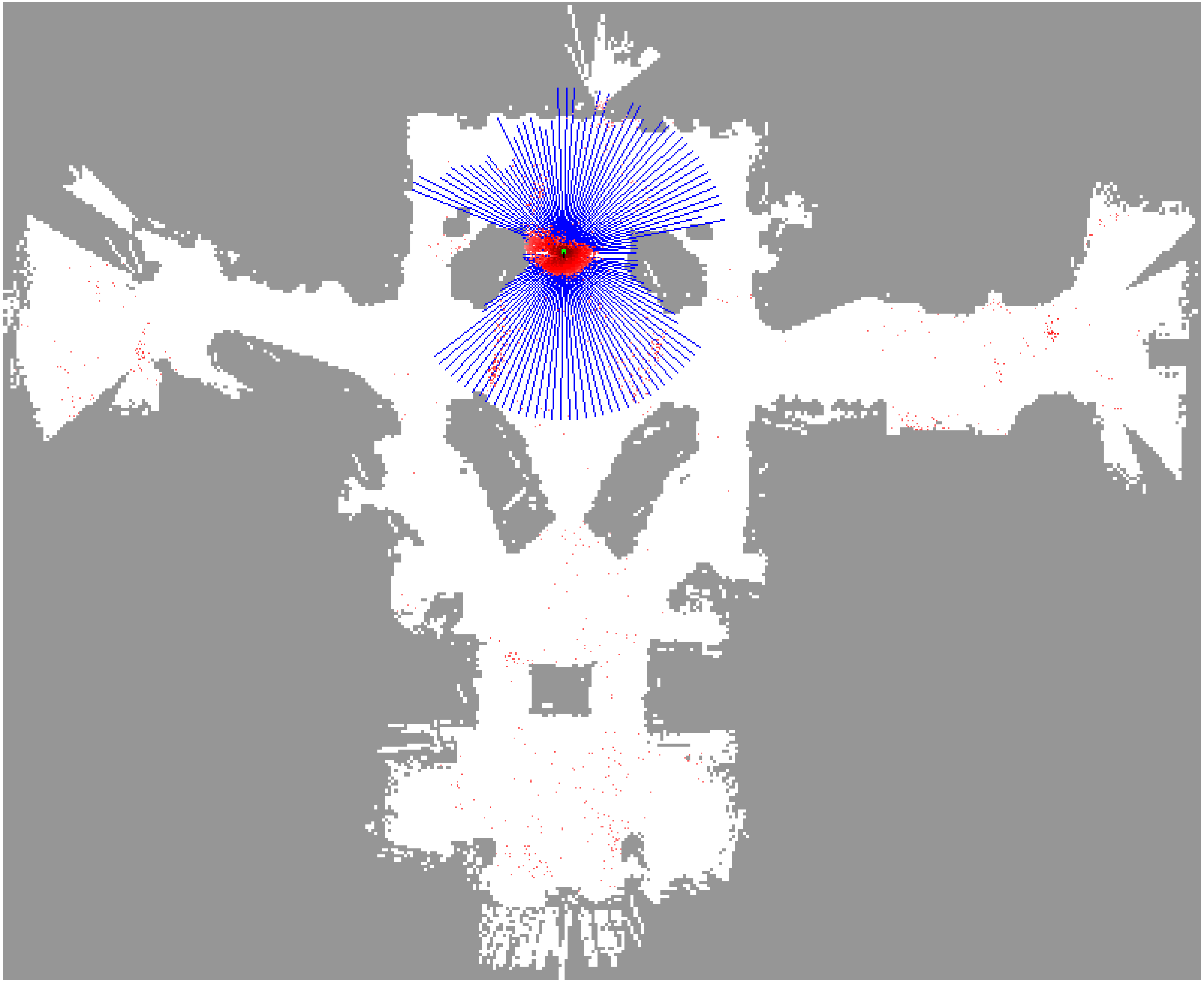


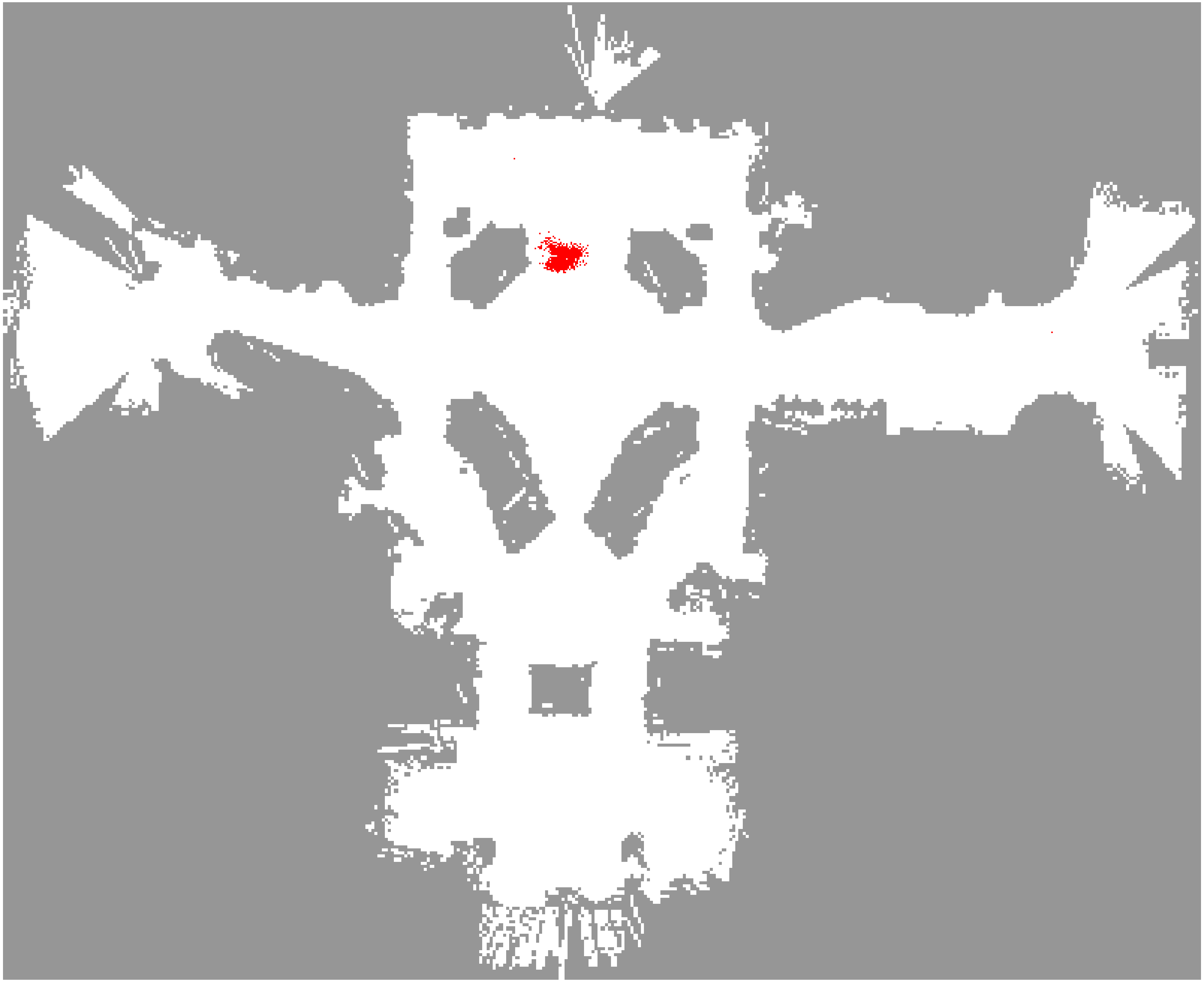


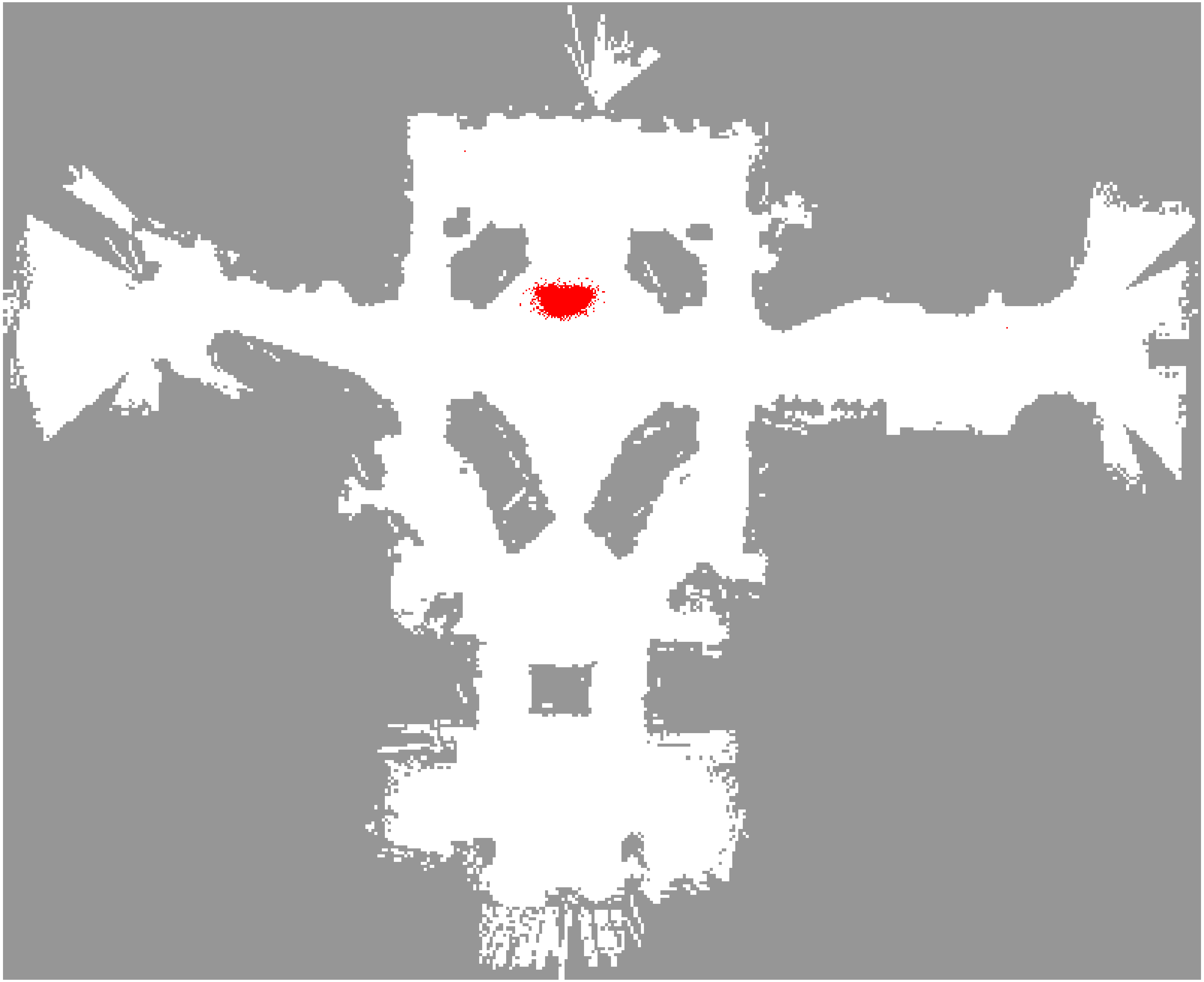


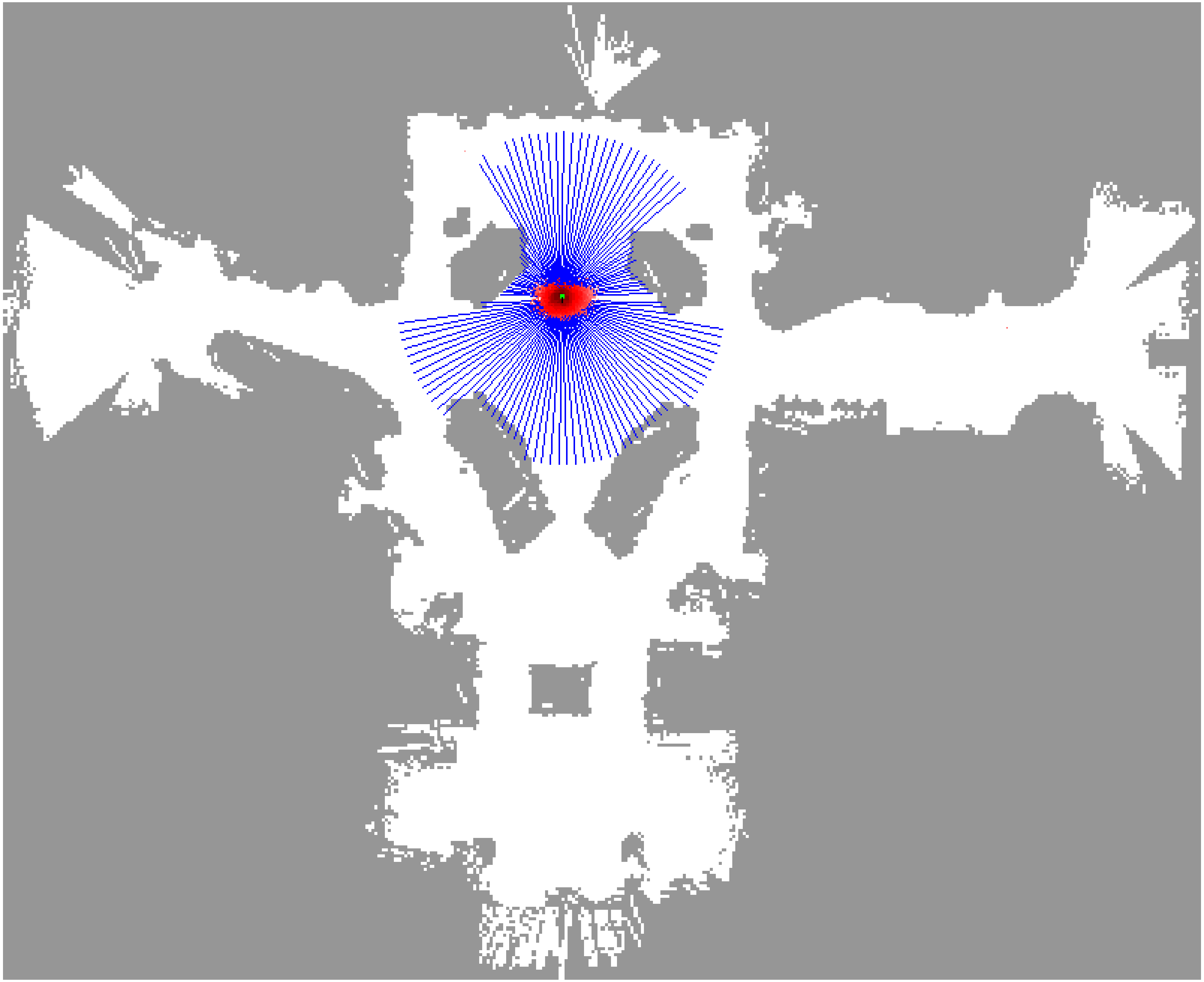


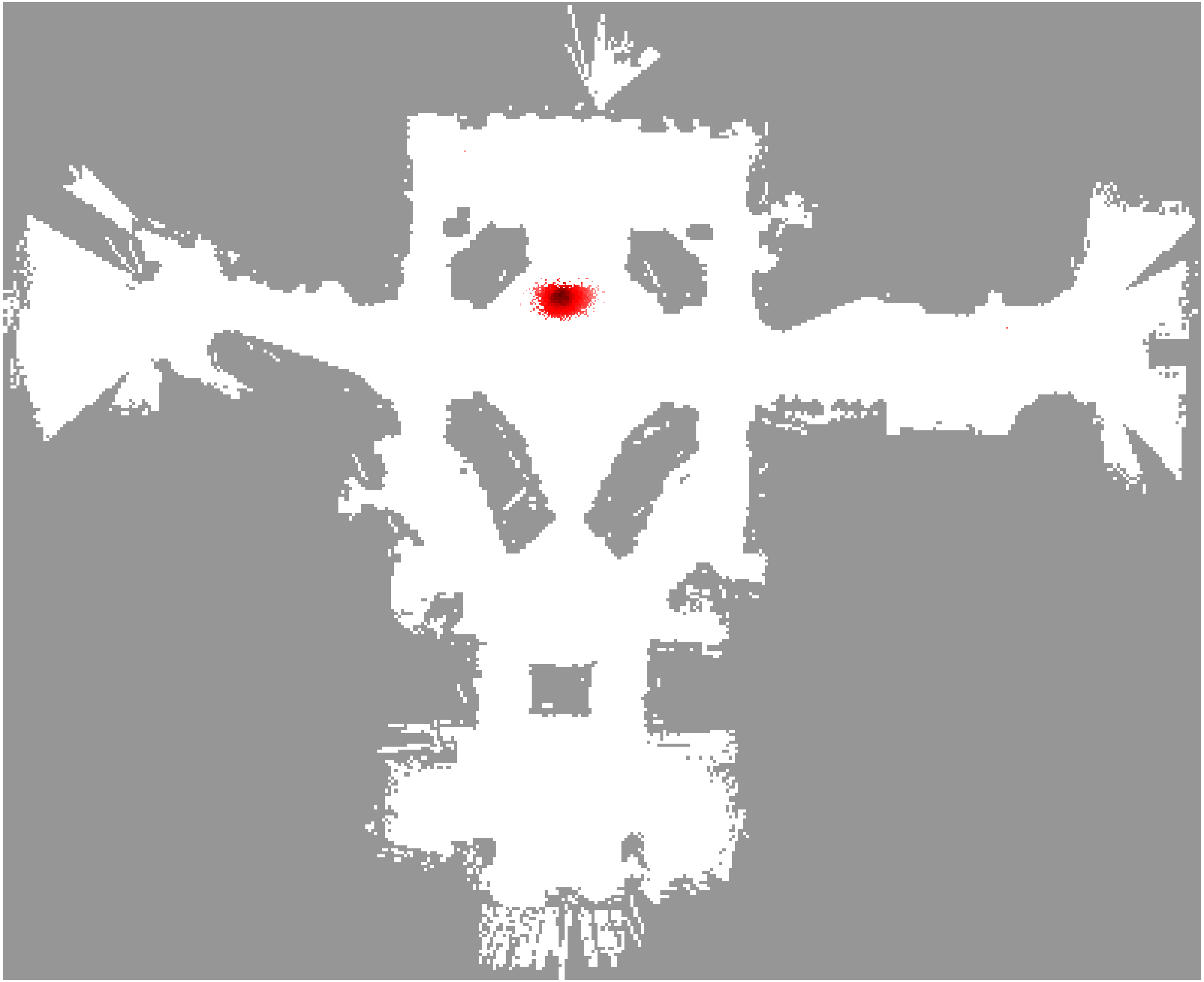


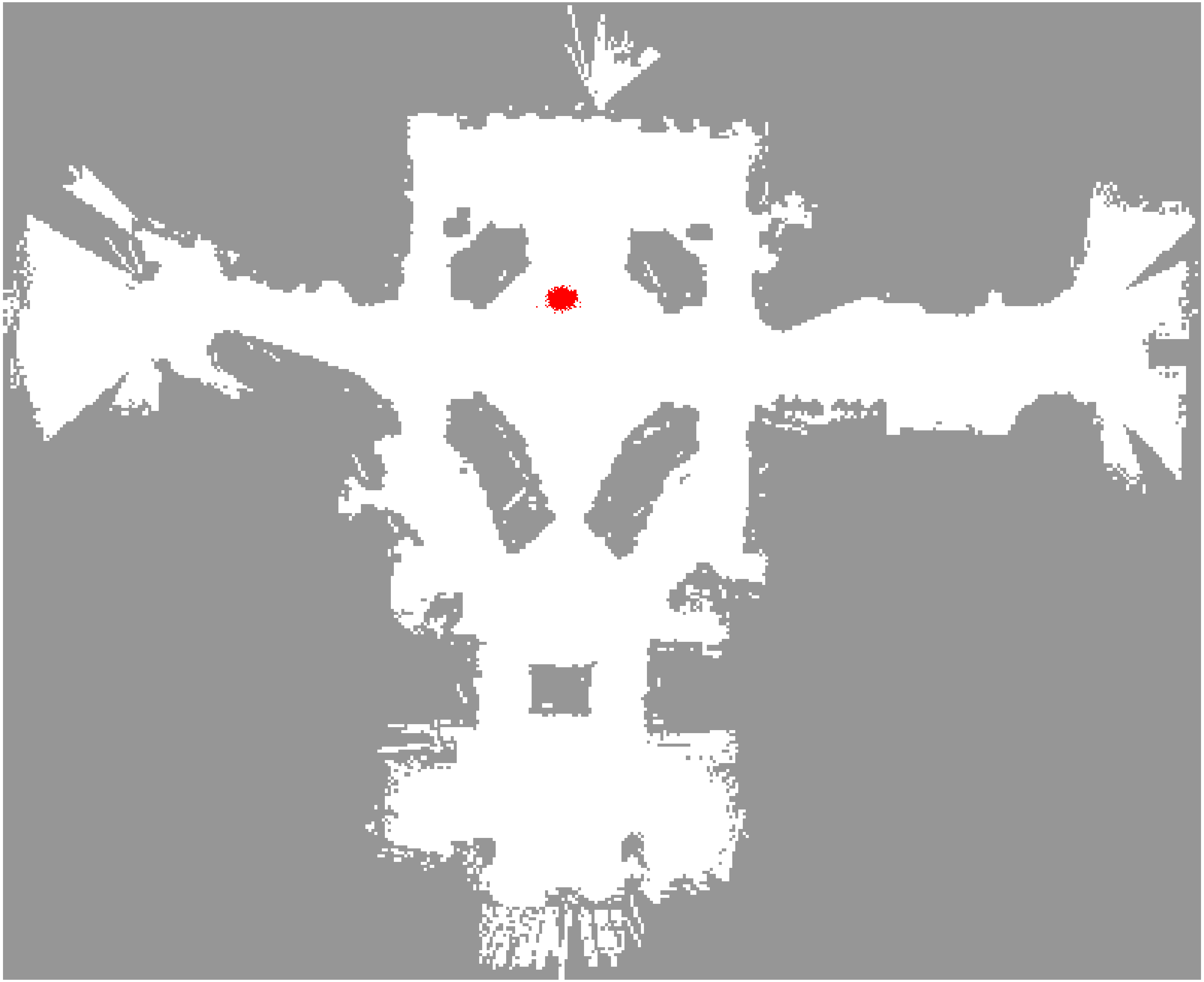


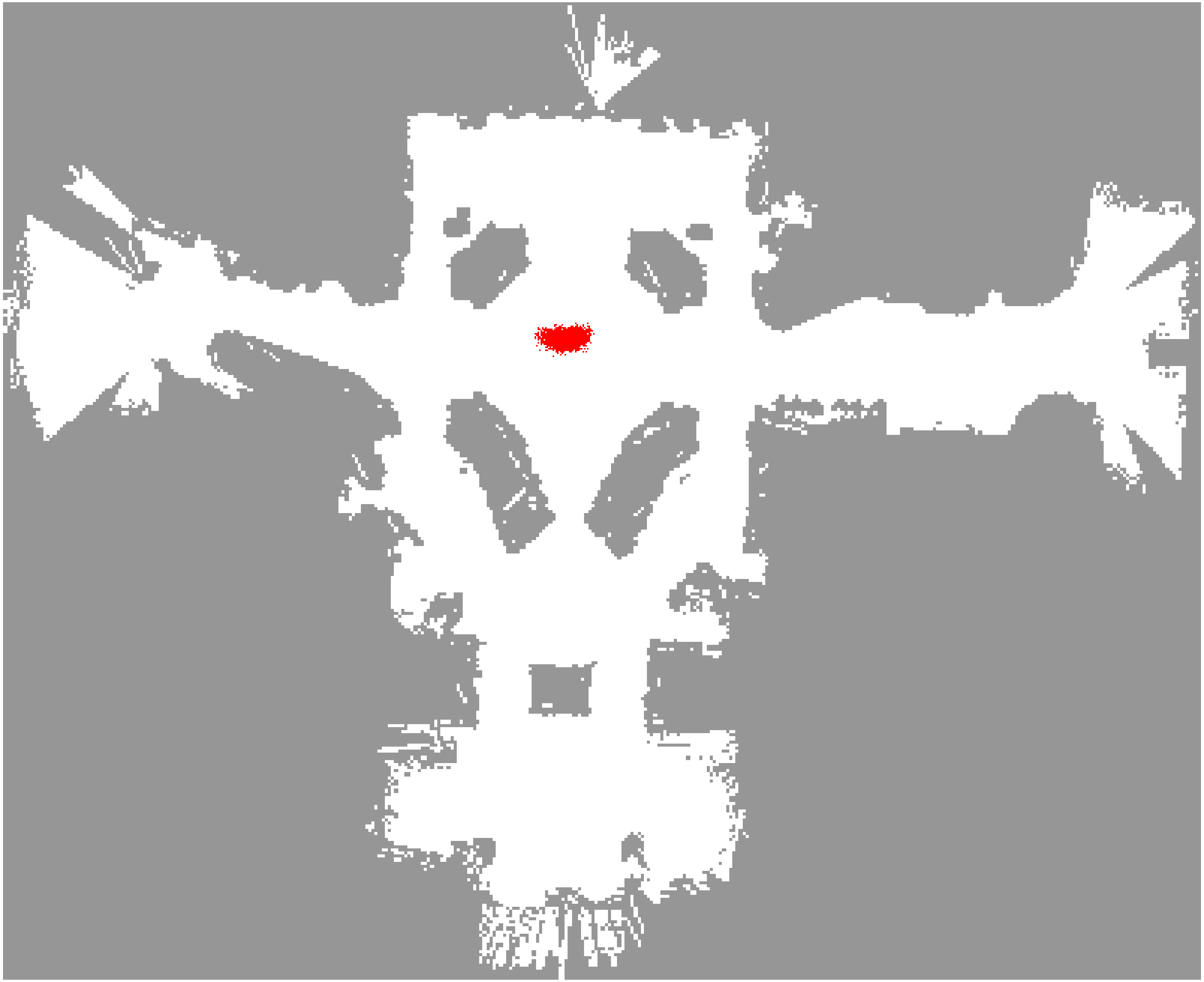


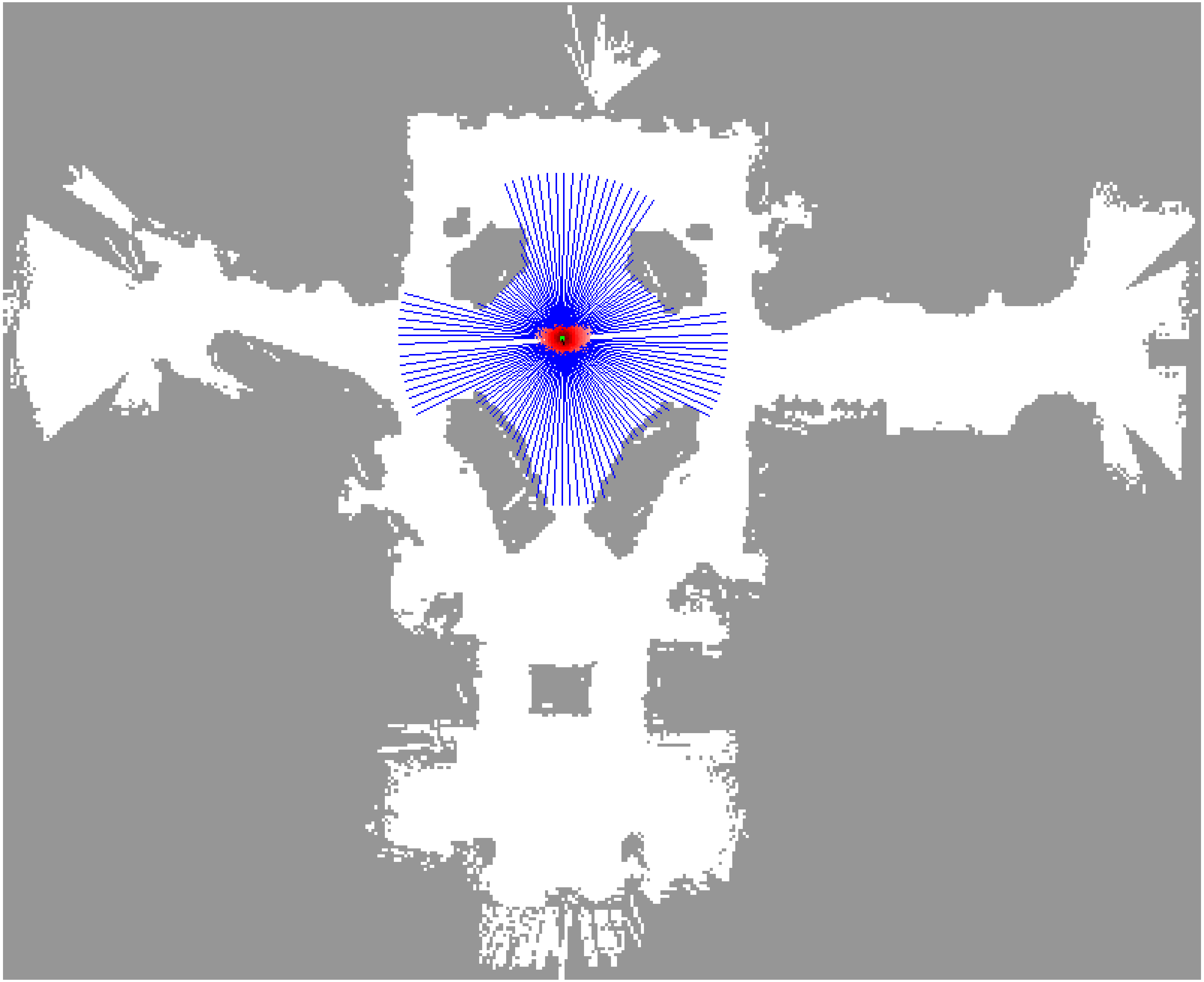




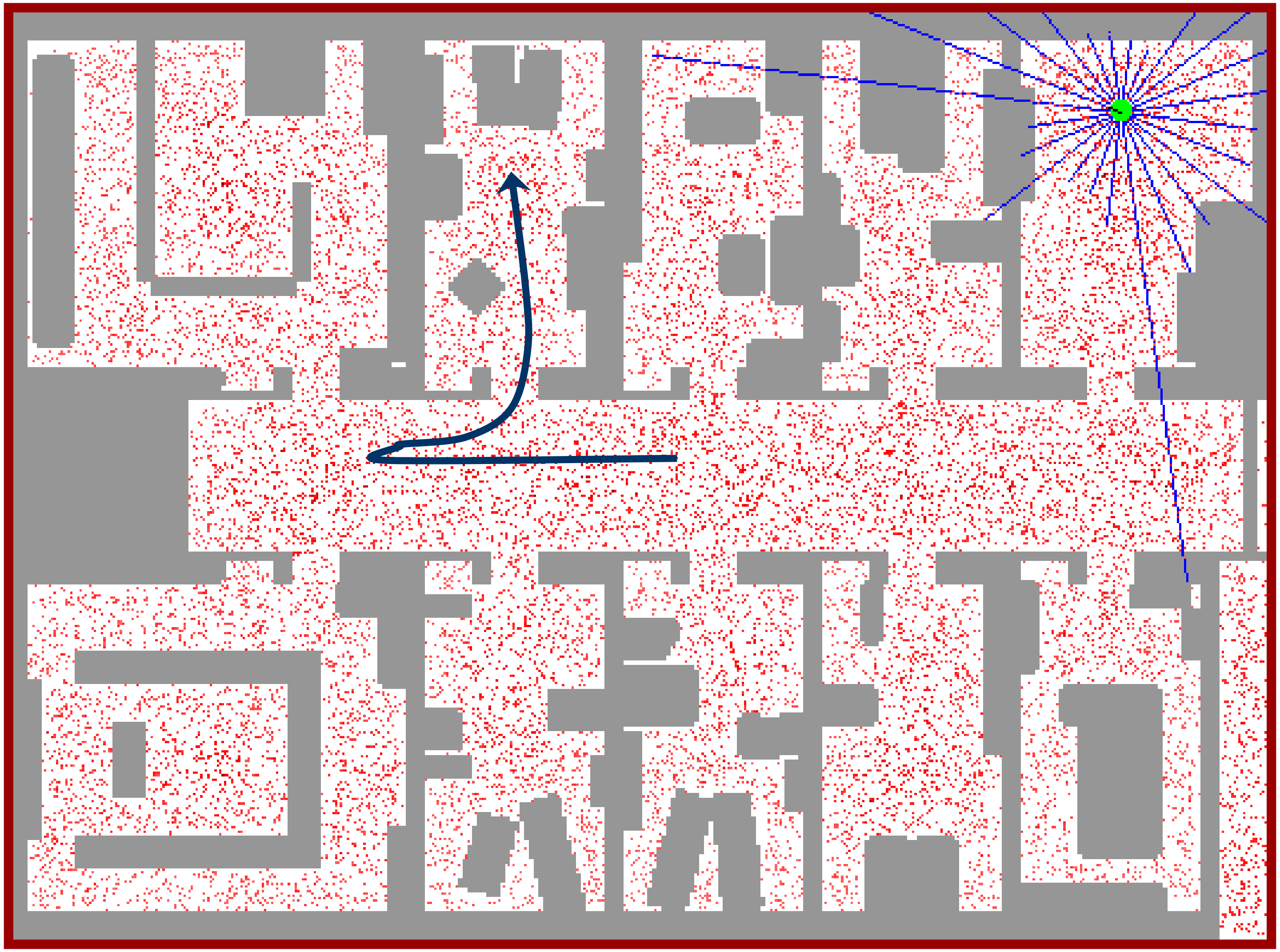




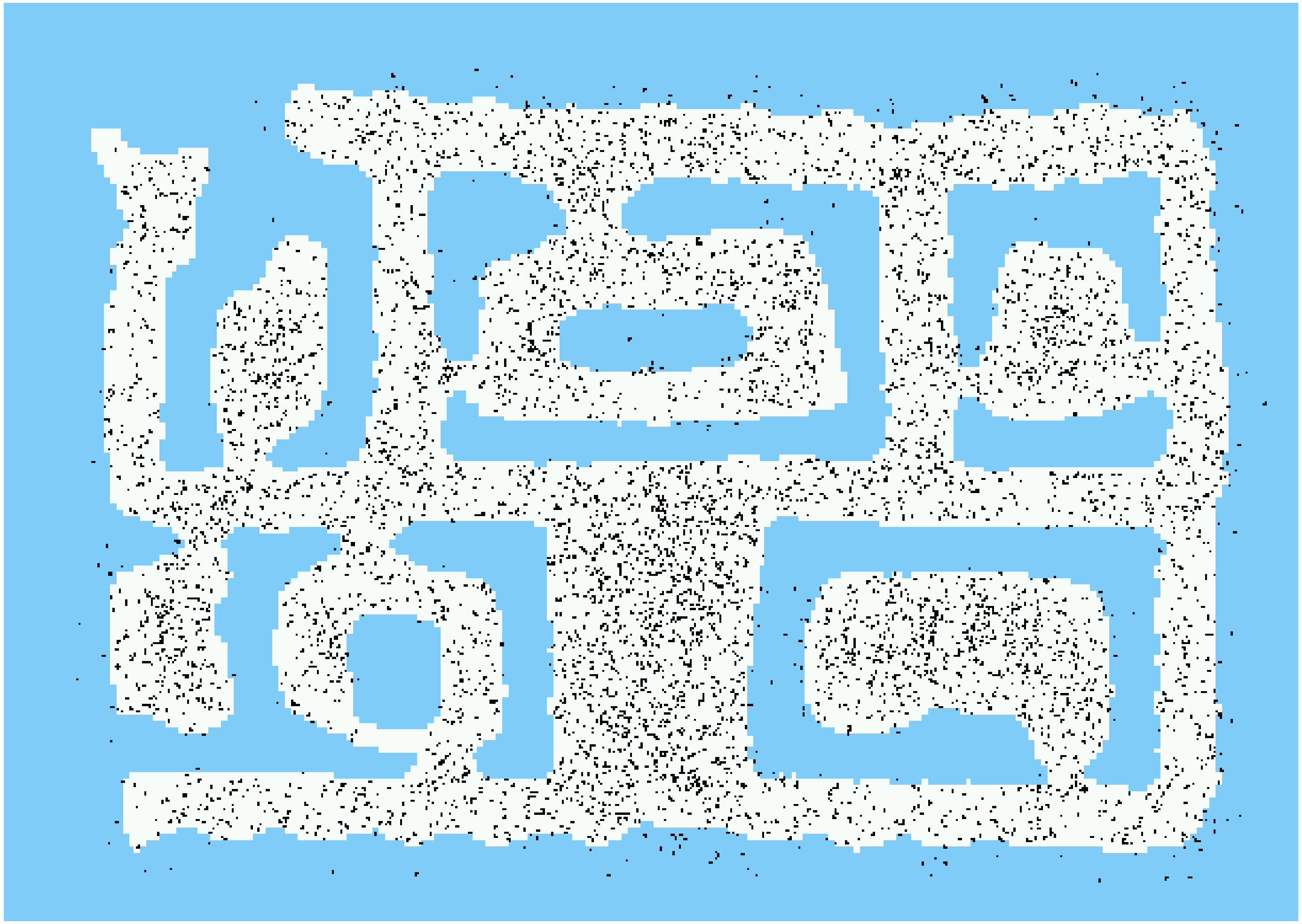




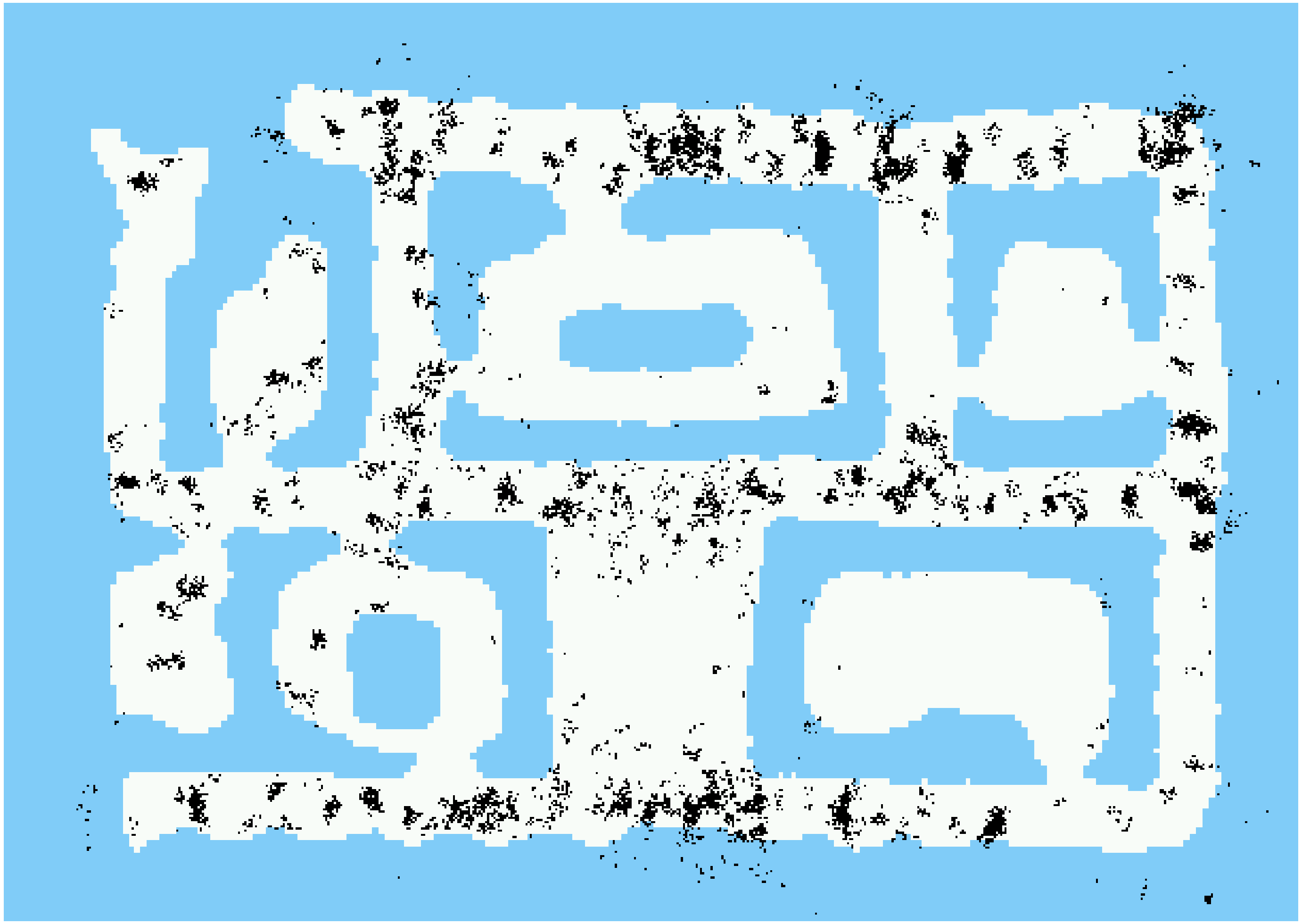
Sample-based Localization (sonar)



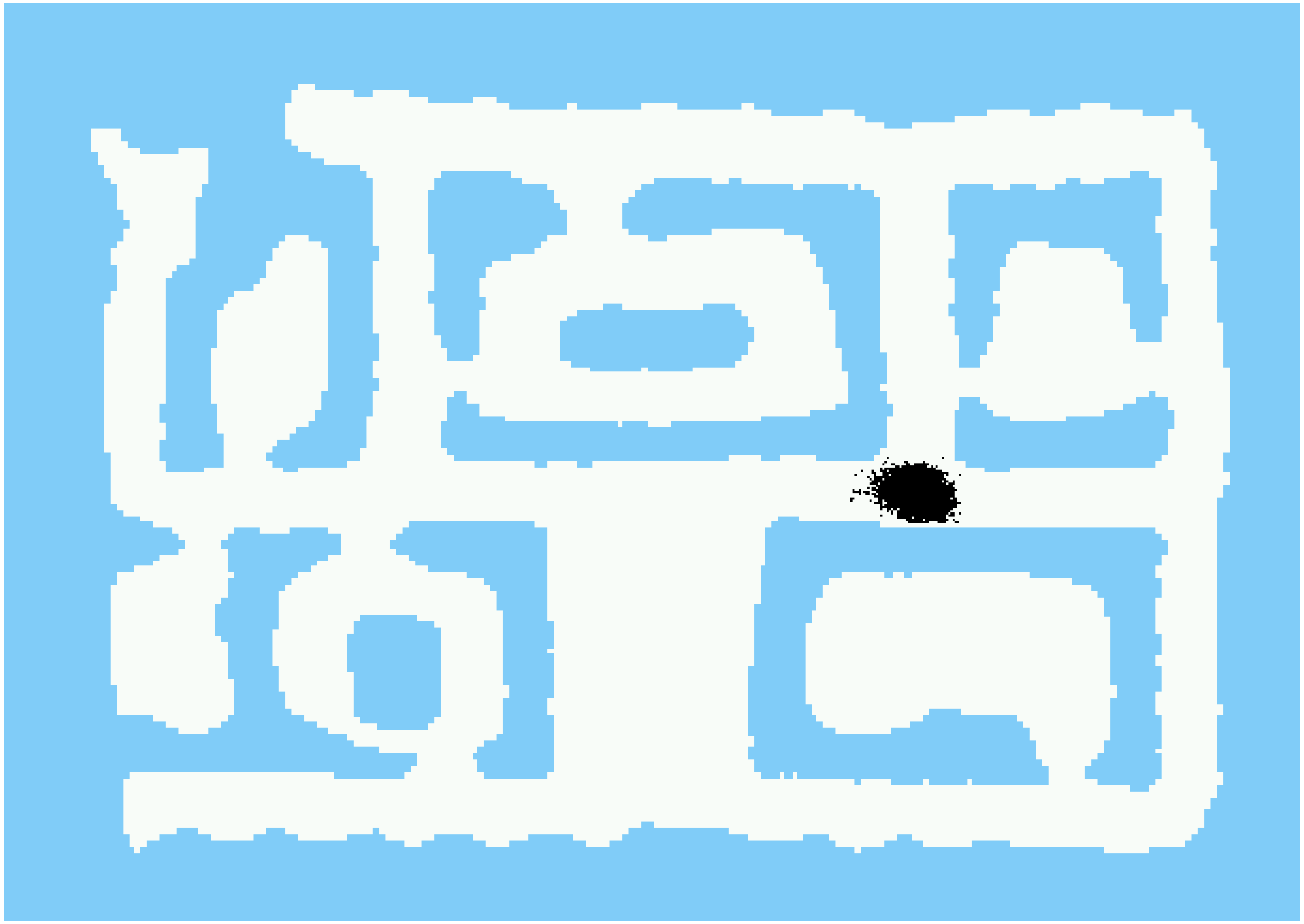
Initial Distribution



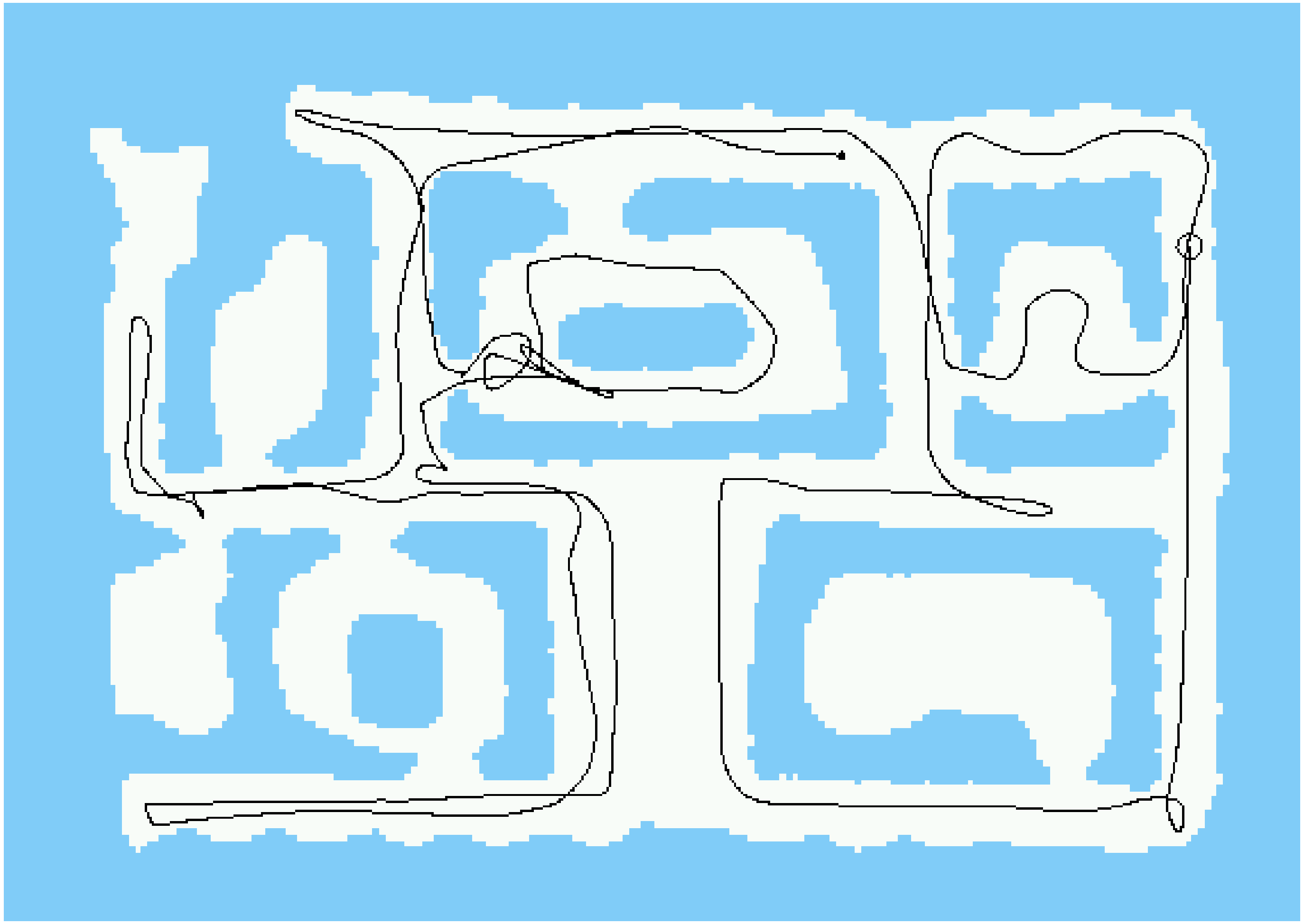
After Incorporating Ten Ultrasound Scans



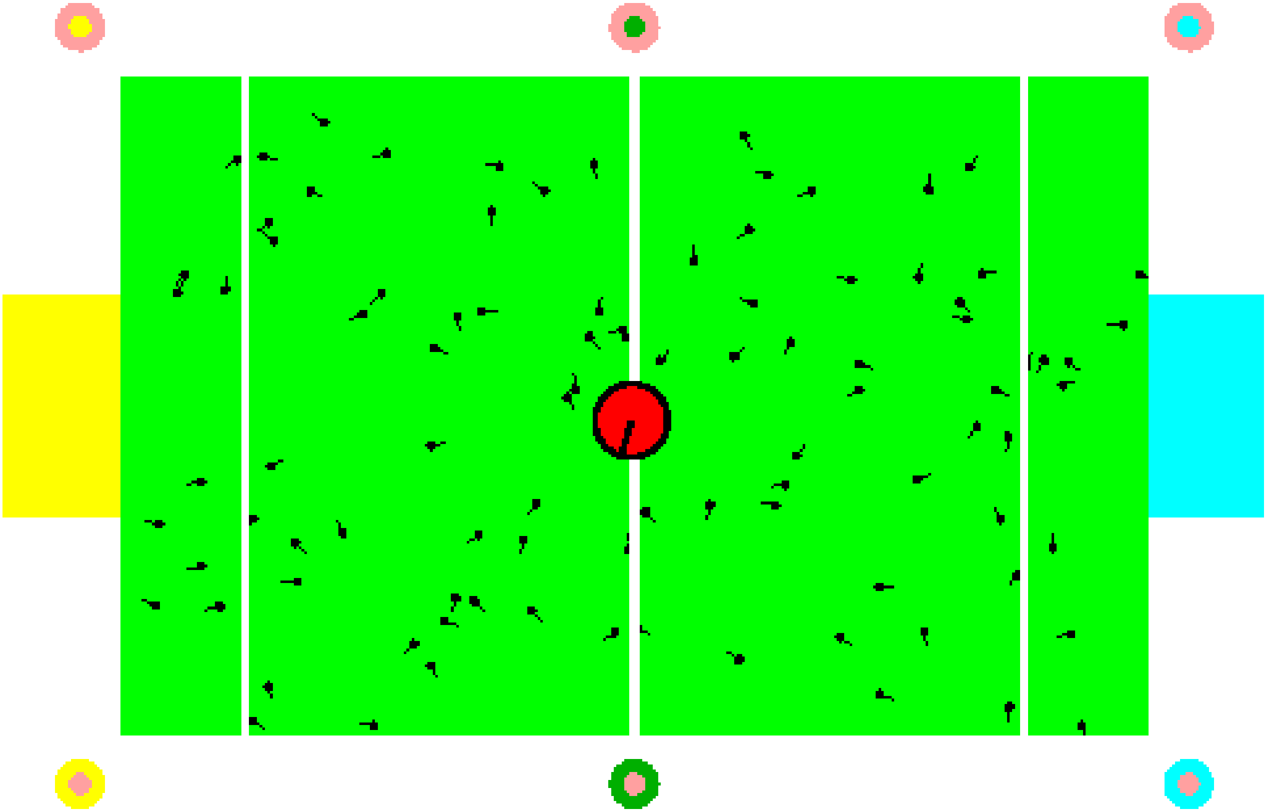
After Incorporating 65 Ultrasound Scans



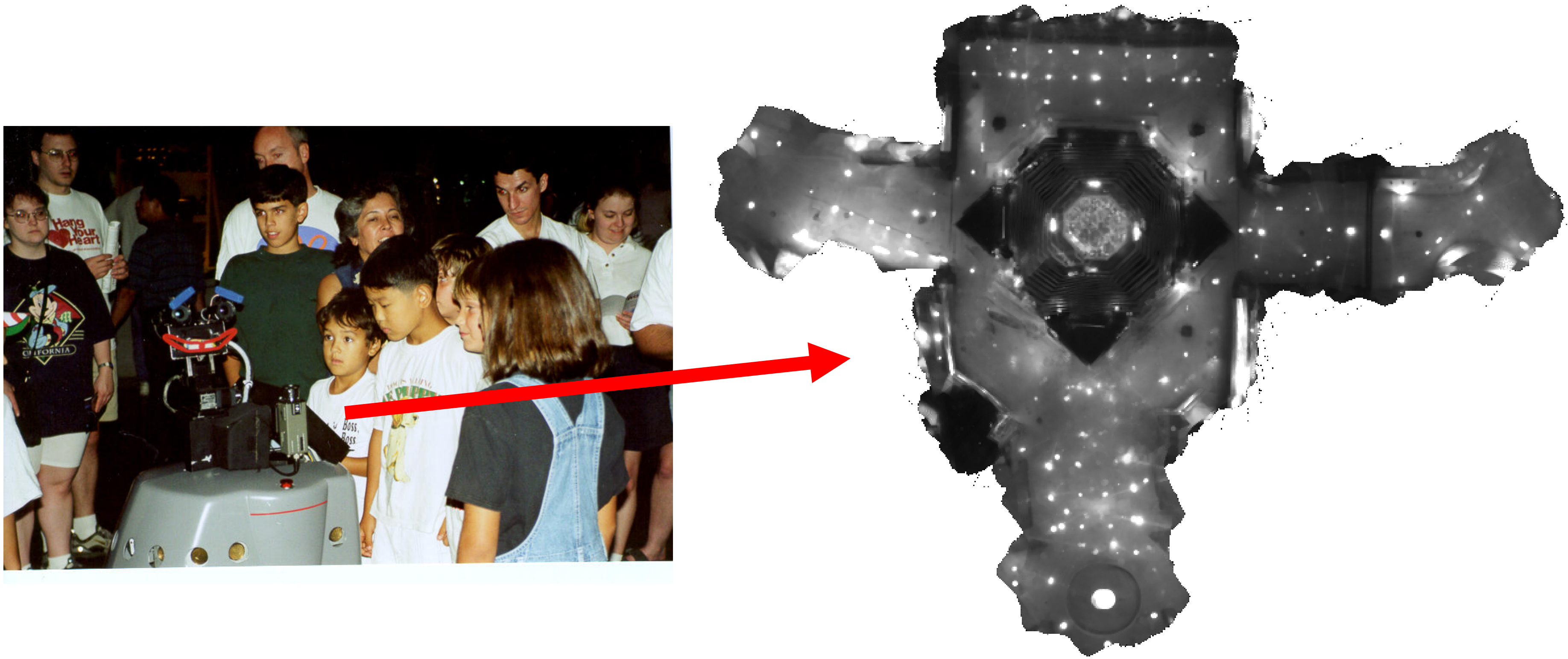
Estimated Path



Localization for AIBO robots

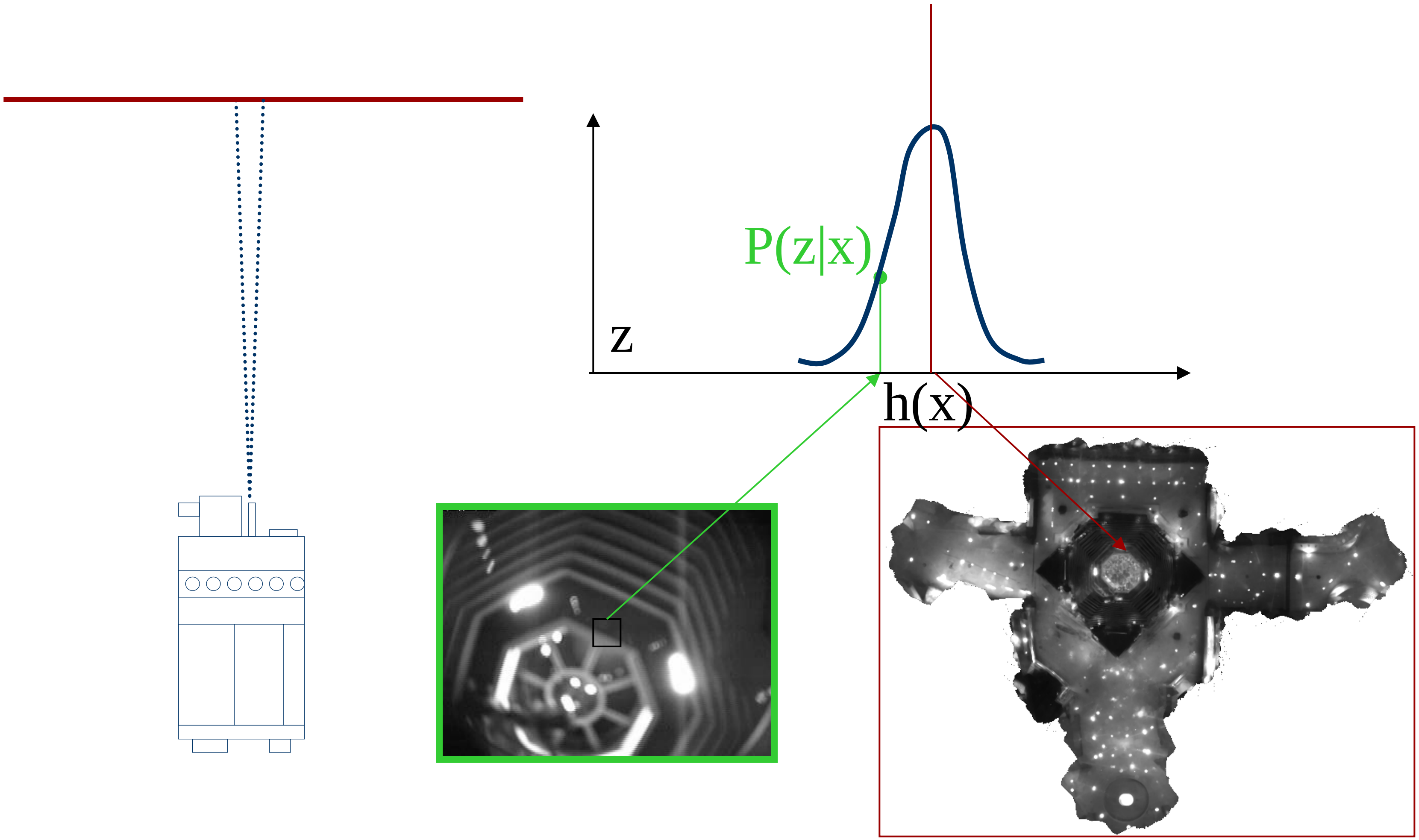


Using Ceiling Maps for Localization



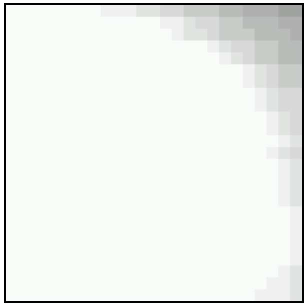
[Dellaert et al. 99]

Vision-based Localization

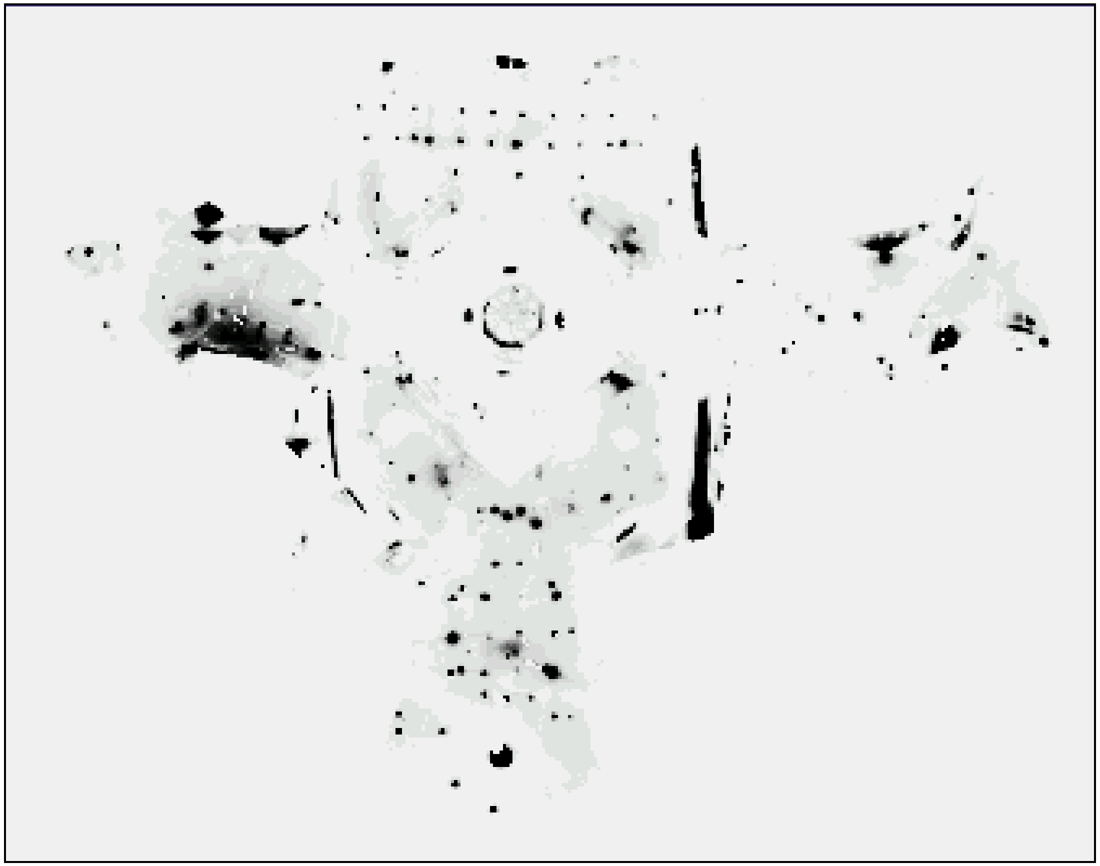


Under a Light

Measurement z:

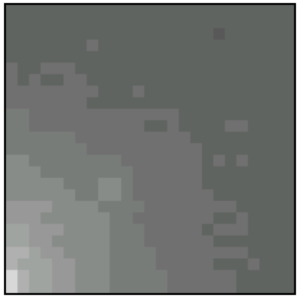


***P(z|x)*:**

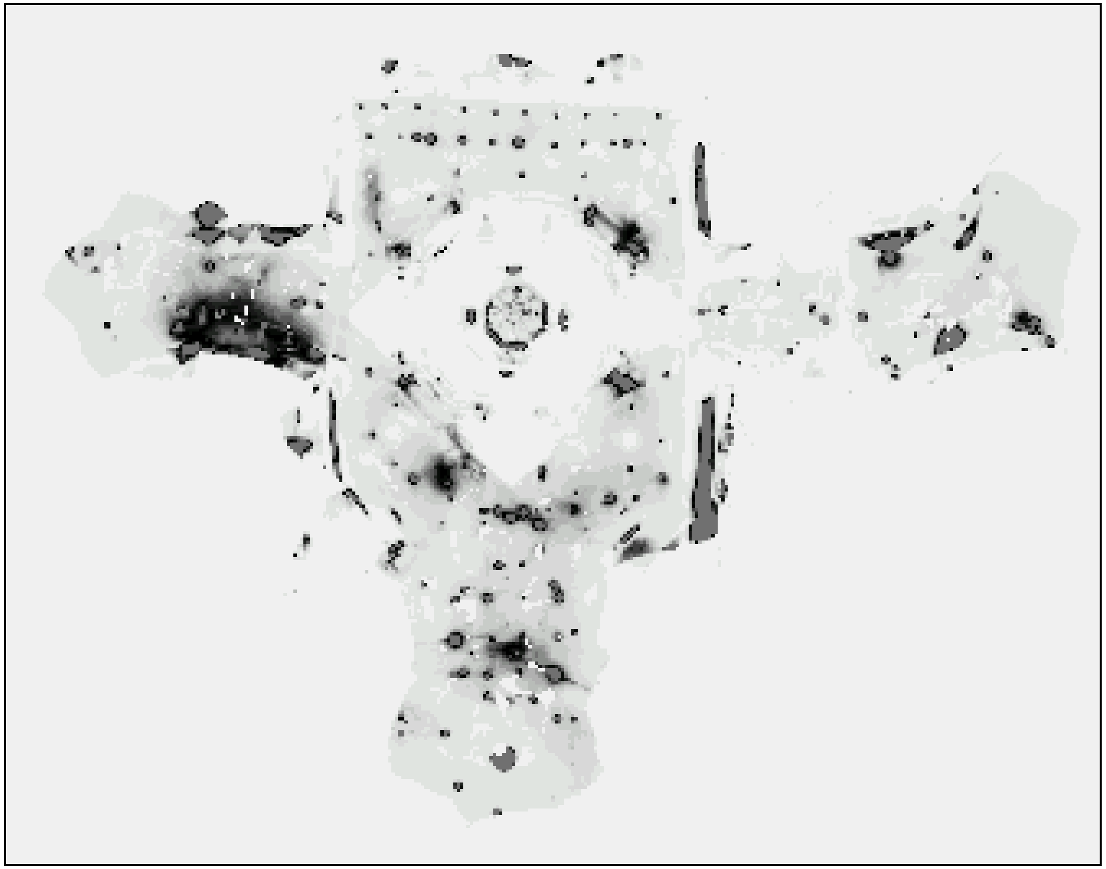


Next to a Light

Measurement z:



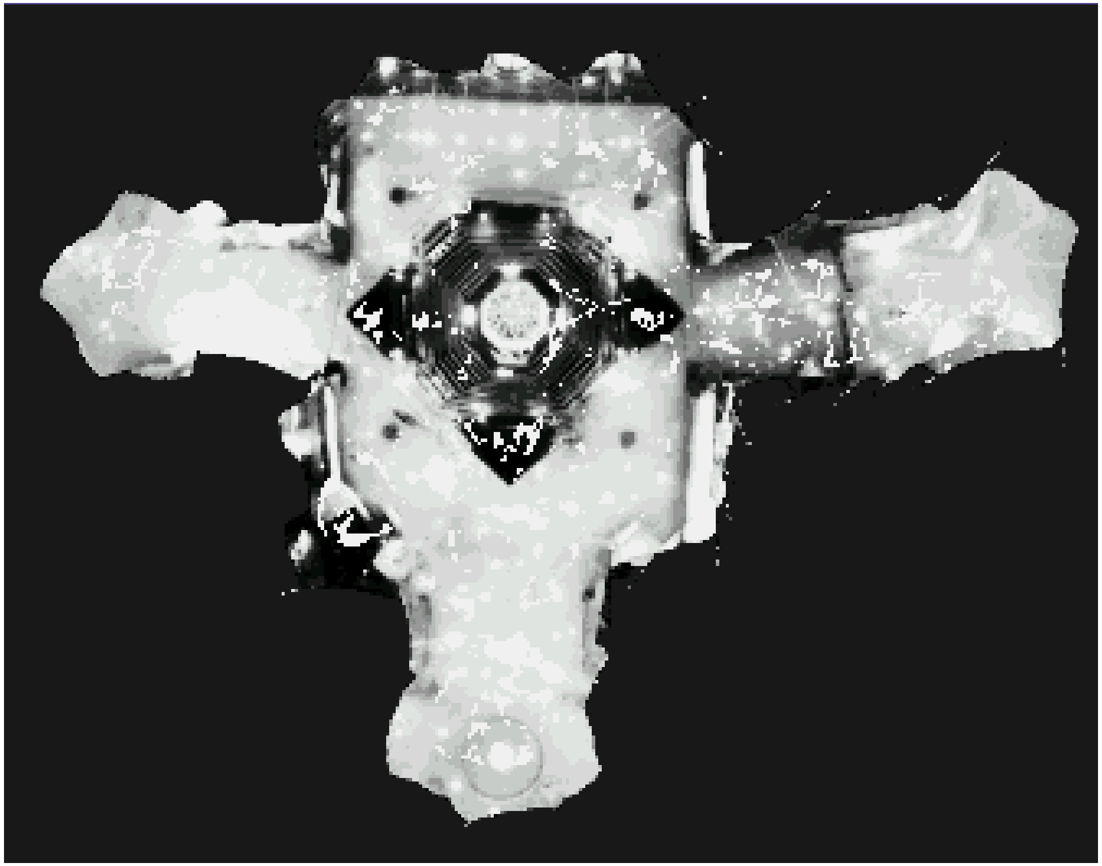
***P(z|x)*:**



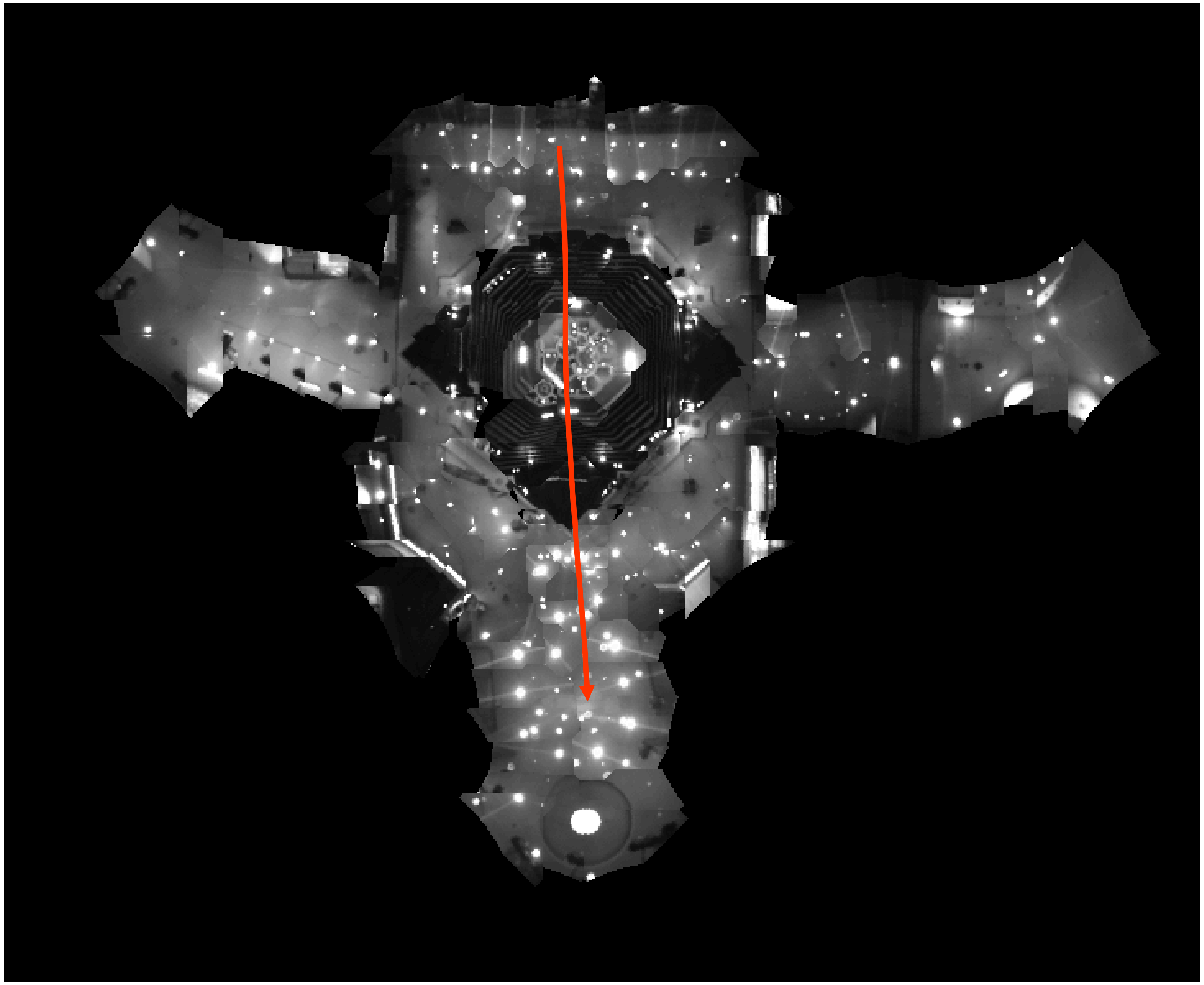
Elsewhere

Measurement z:

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



Global Localization Using Vision



Limitations

- The approach described so far is able
  - to track the pose of a mobile robot and
  - to globally localize the robot
- How can we deal with localization errors (i.e., the kidnapped robot problem)?

Approaches

- Randomly insert a fixed number of samples
- This assumes that the robot can be teleported at any point in time
- Alternatively, insert random samples proportional to the average likelihood of the particles

Summary – Particle Filters

- Particle filters are an implementation of recursive Bayesian filtering
- They represent the posterior by a set of weighted samples
- They can model non-Gaussian distributions
- Proposal to draw new samples
- Weight to account for the differences between the proposal and the target
- Monte Carlo filter, Survival of the fittest, Condensation, Bootstrap filter

Summary – PF Localization

- In the context of localization, the particles are propagated according to the motion model.
- They are then weighted according to the likelihood of the observations.
- In a re-sampling step, new particles are drawn with a probability proportional to the likelihood of the observation.