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MIN Faculty
Department of Informatics

Multi-modal Localization using Wi-Fi Signal Strength and 2D Range Finder

Bachelor Thesis Defense

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Technical Aspects of Multimodal Systems

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Table of Contents

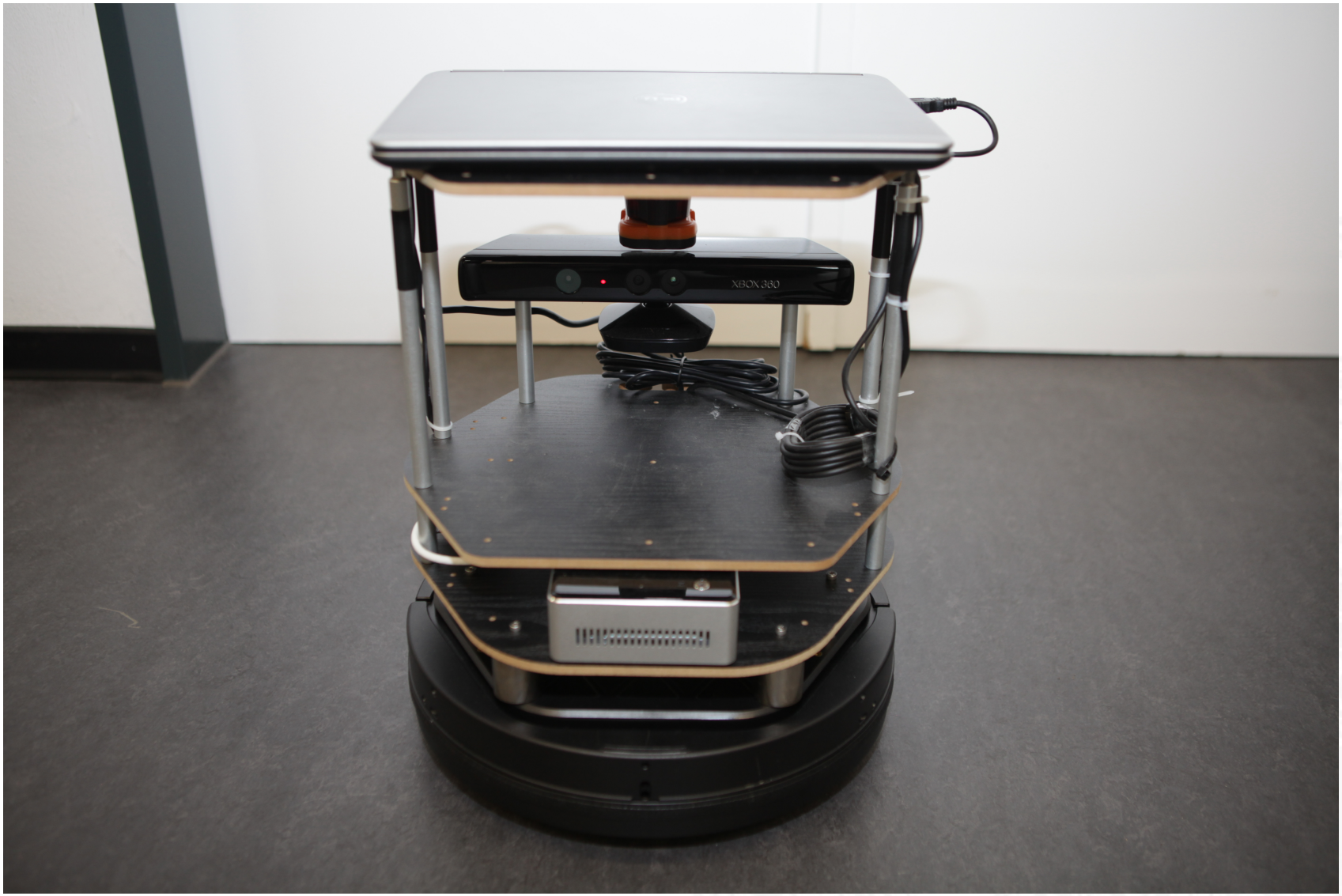
1. Motivation
2. Basics
3. Implementation
4. Demo
5. Experiments and Results
6. Conclusion
7. Outlook

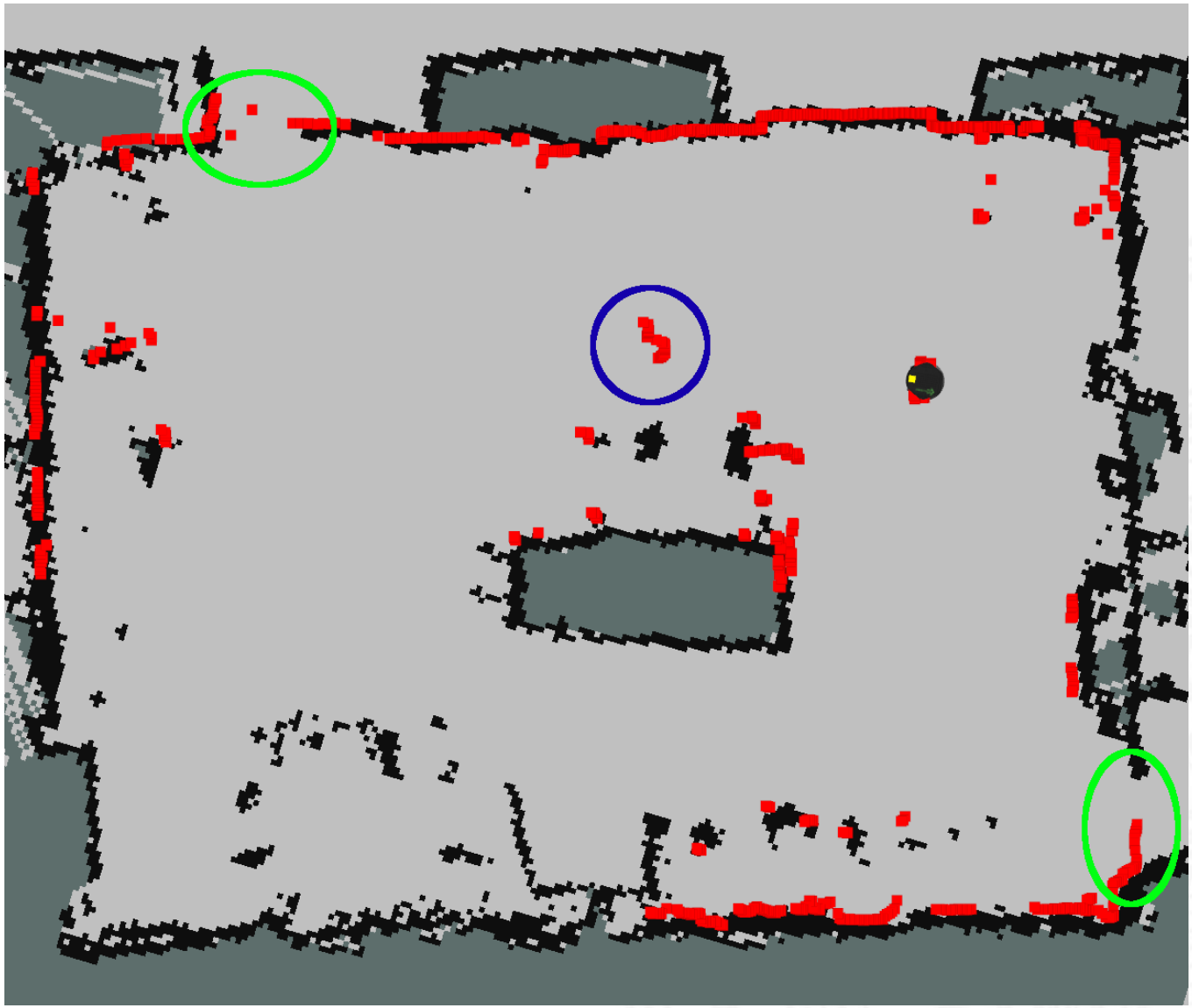
- Localization is important problem in robotics
- Example autonomous vehicle [Levinson et al., 2007]
  - GPS for rough global position
  - LIDAR for precise localization
- Specific LIDAR is popular in robotics
- GPS Signal unreliable

- Global localization
  - Problematic Situations
  - Often fails
- Wi-Fi signal strength to infer position
  - MAC-address
  - Signal strength for every access point
  - Multiple access points to infer exact position
  - Combining strength of laser range finder and Wi-Fi

Related Work

- Different approaches to Wi-Fi localization
- Propagation model [Serrano et al., 2004]
- Pre-recorded signals
  - Linear interpolation [Biswas and Veloso , 2010]
    - Recording data in grid-like fashion
    - Robot can only move on the grid lines
  - Gaussian processes [Ferris et al., 2006]
    - Regression
    - Recording data is not restricted
- Global Localization using Wi-Fi in different Contexts
  - Industrial Environment [Duvallet and Tews, 2008]
  - Iphone [Ito et al., 2014]


XBOX 360



- Environment measurement data (z)
  - Provided by sensors
- Control data (u)
  - commands given to the robot
  - odometers or gyros
- Sensor models
- belief ($bel(x)$)
- Computed Recursively

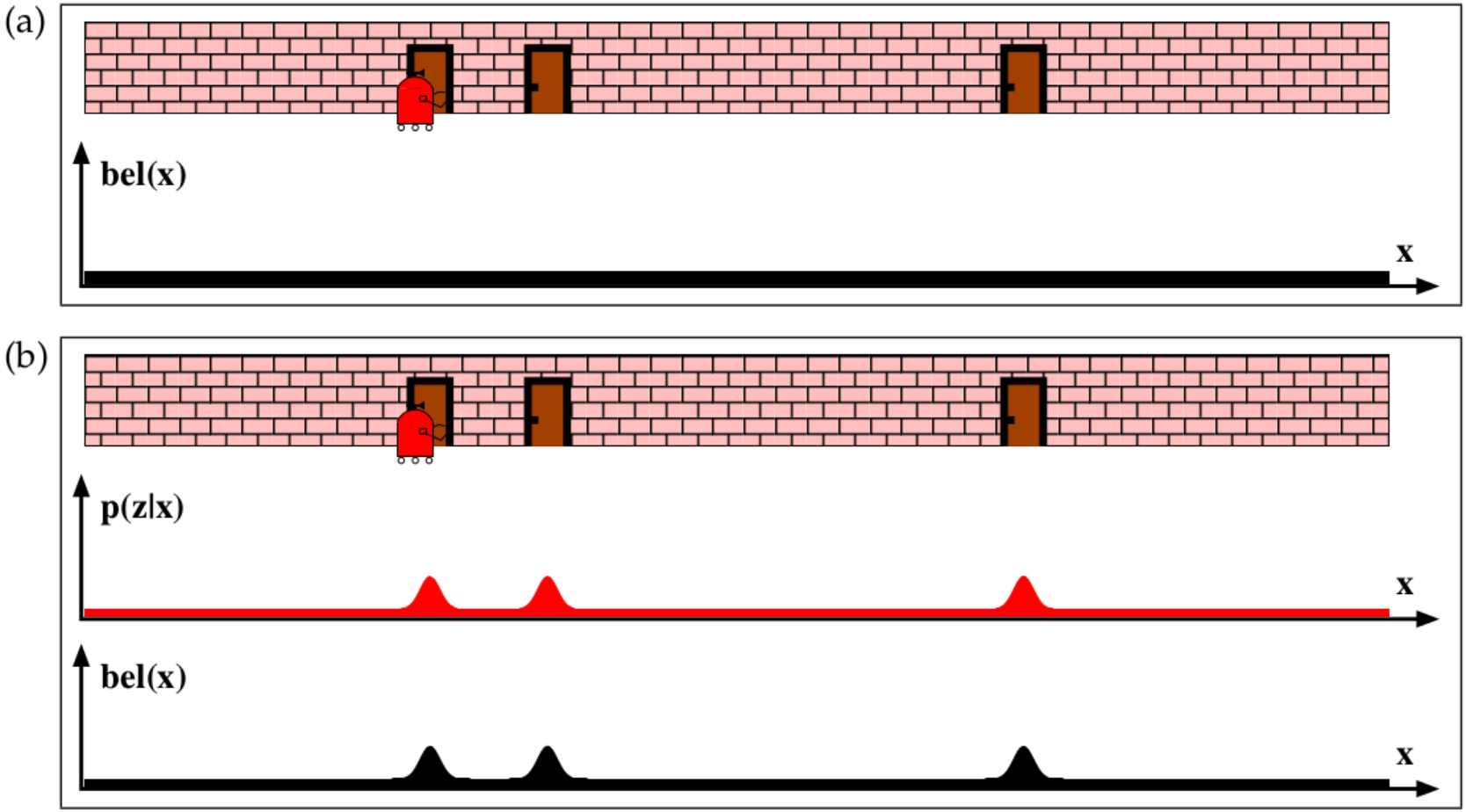
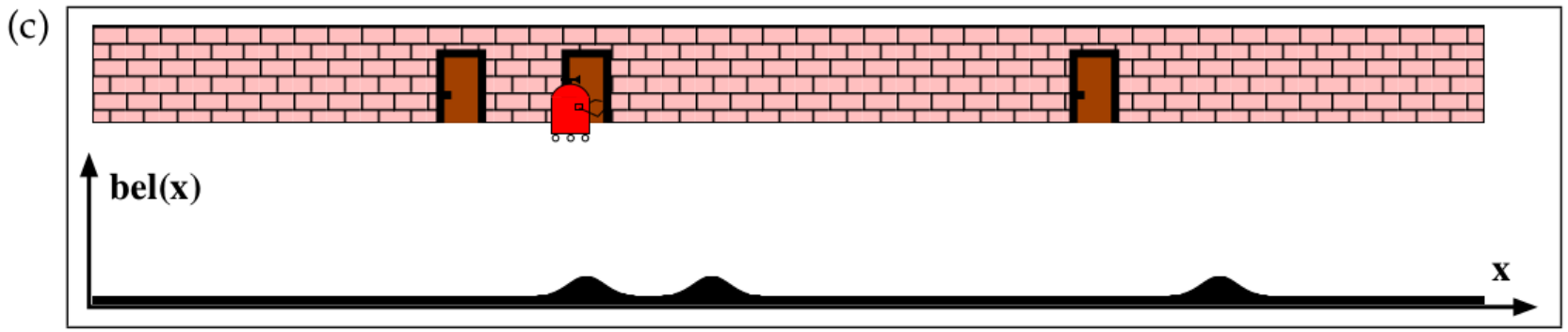


Figure : [Thrun et al., 2005]



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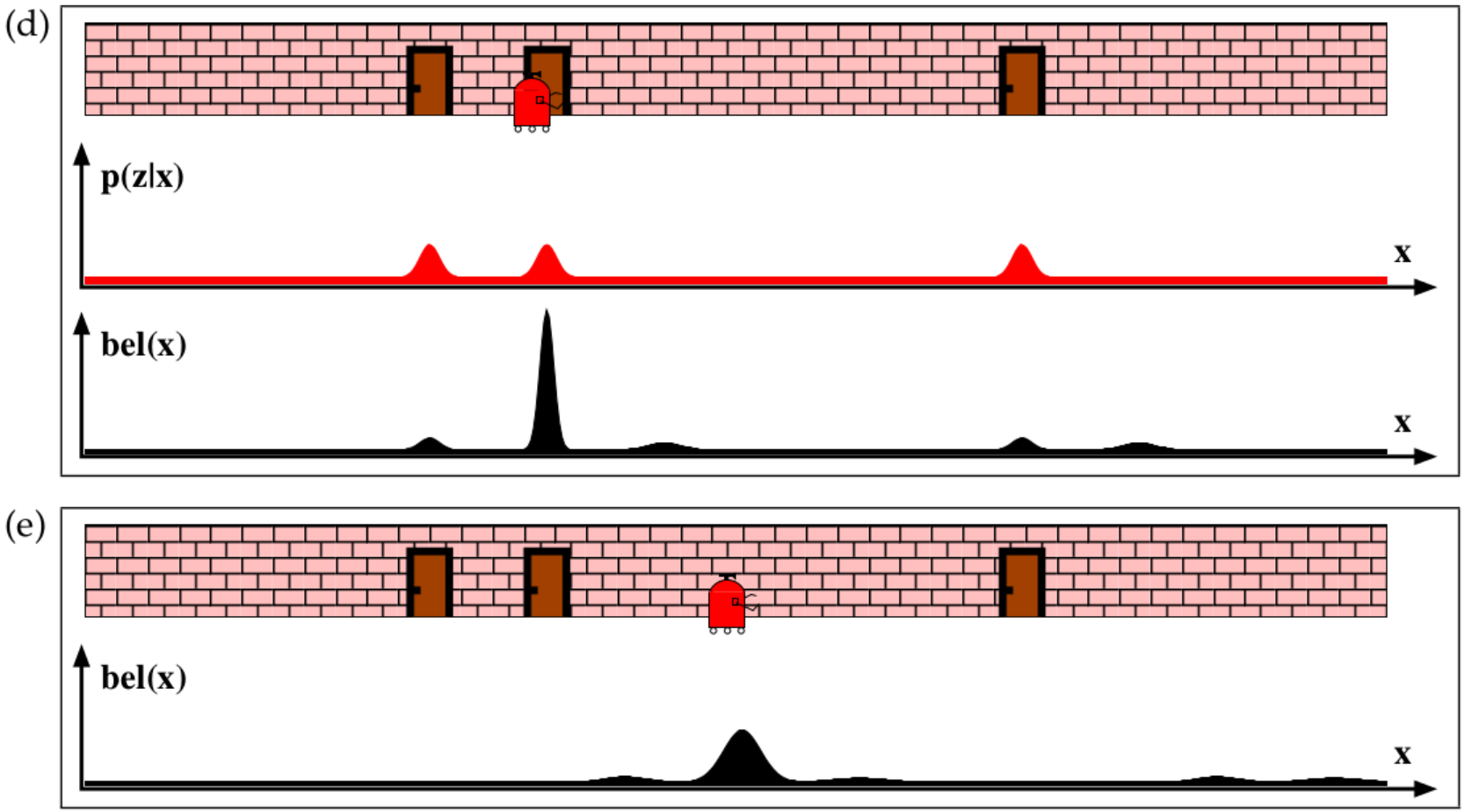

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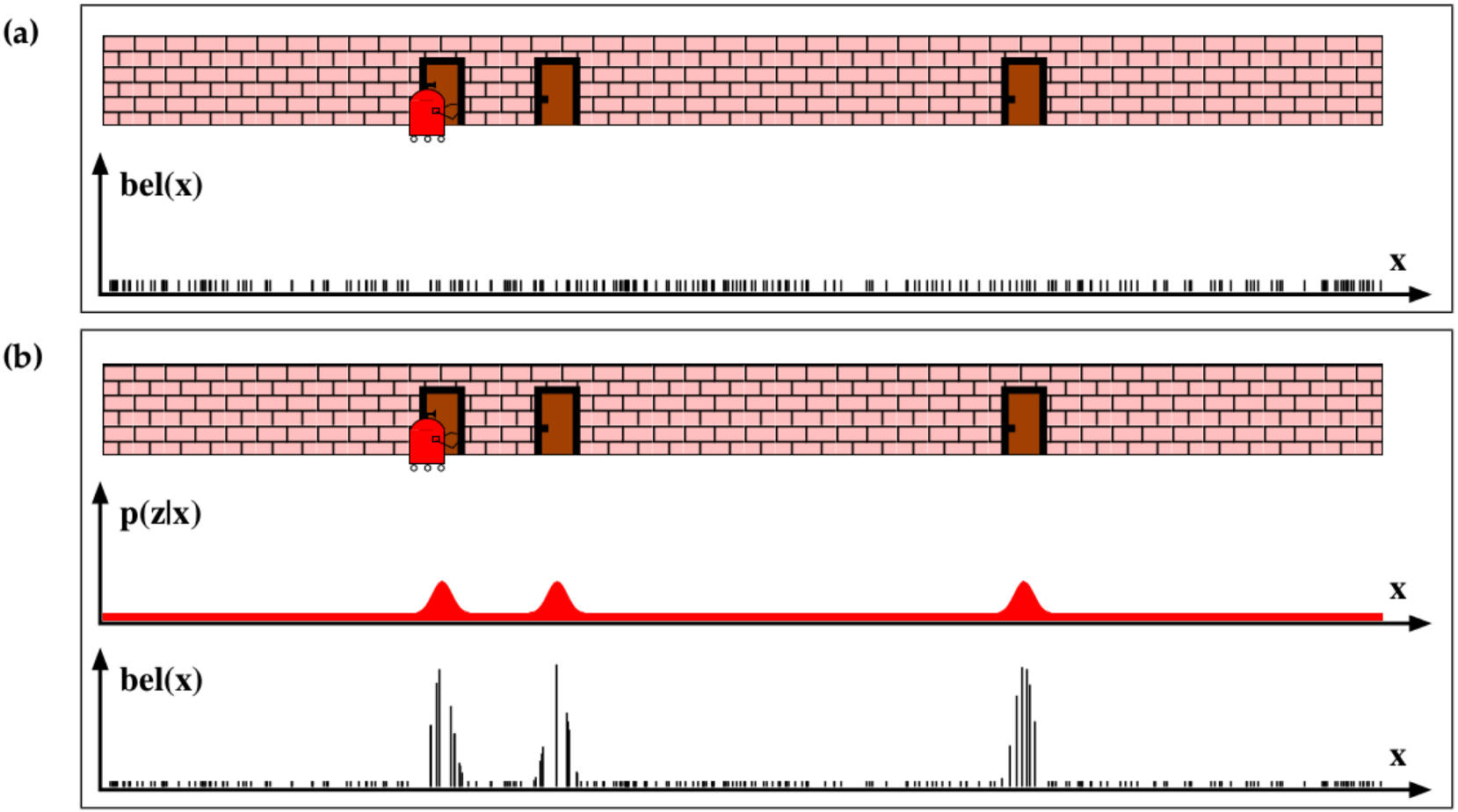

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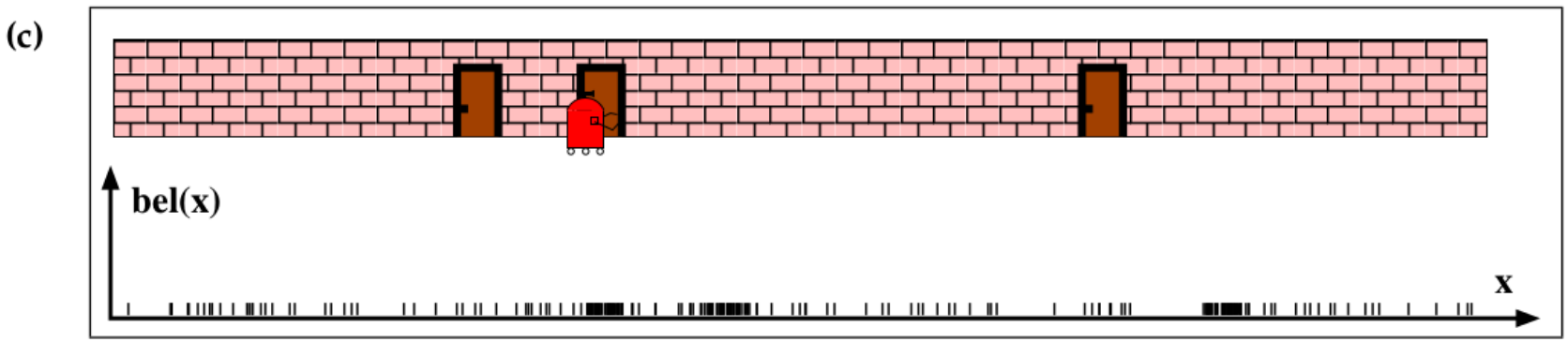

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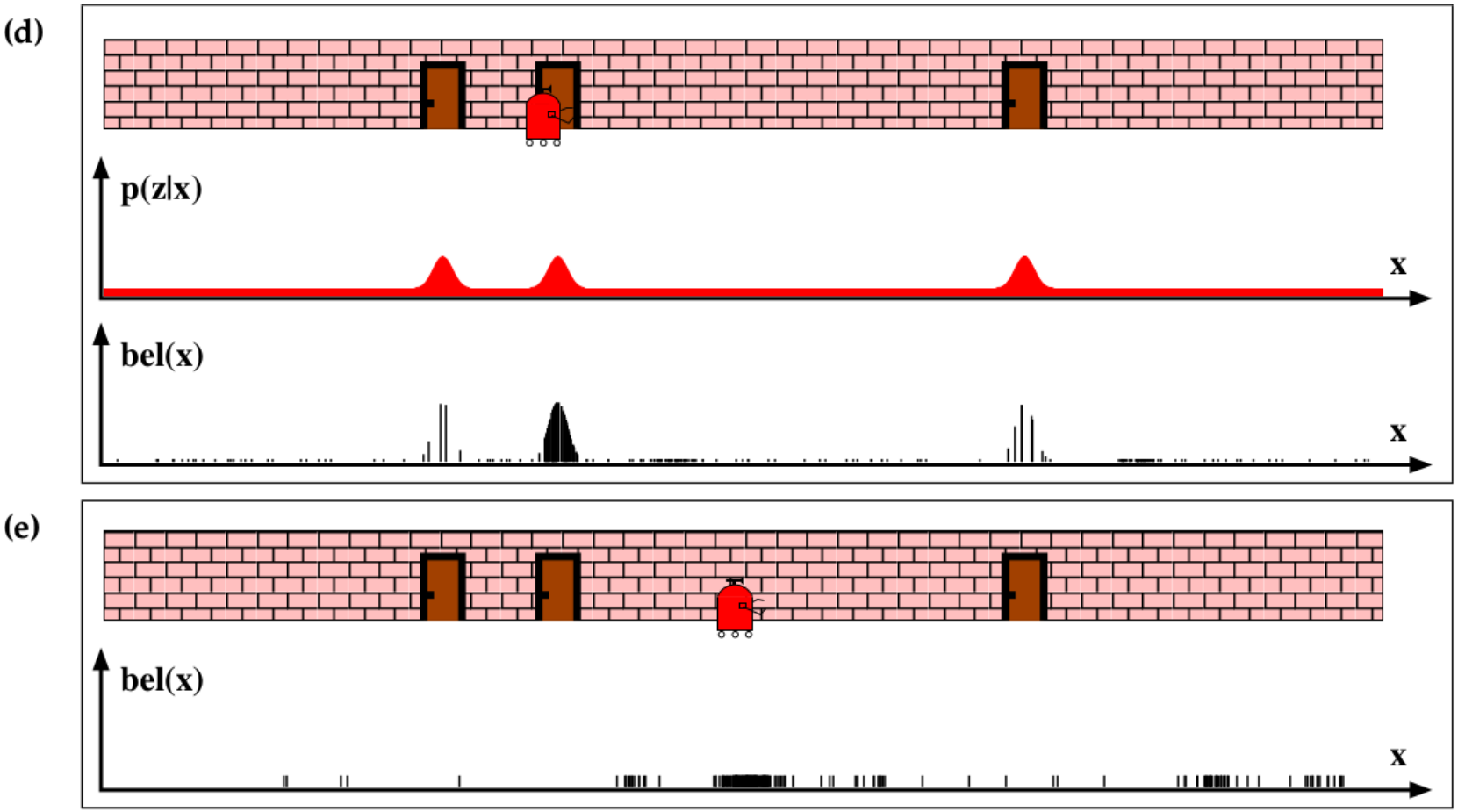

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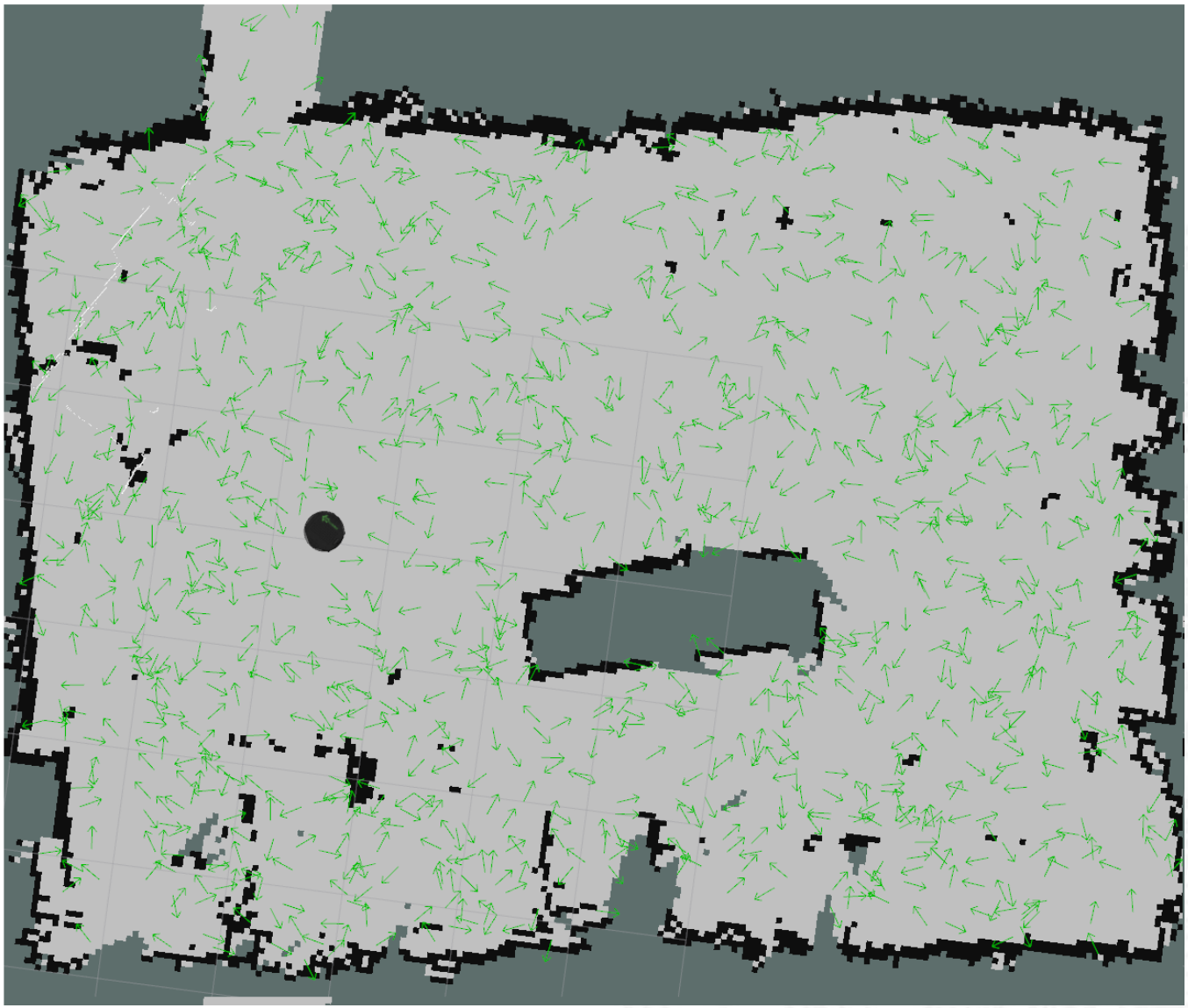
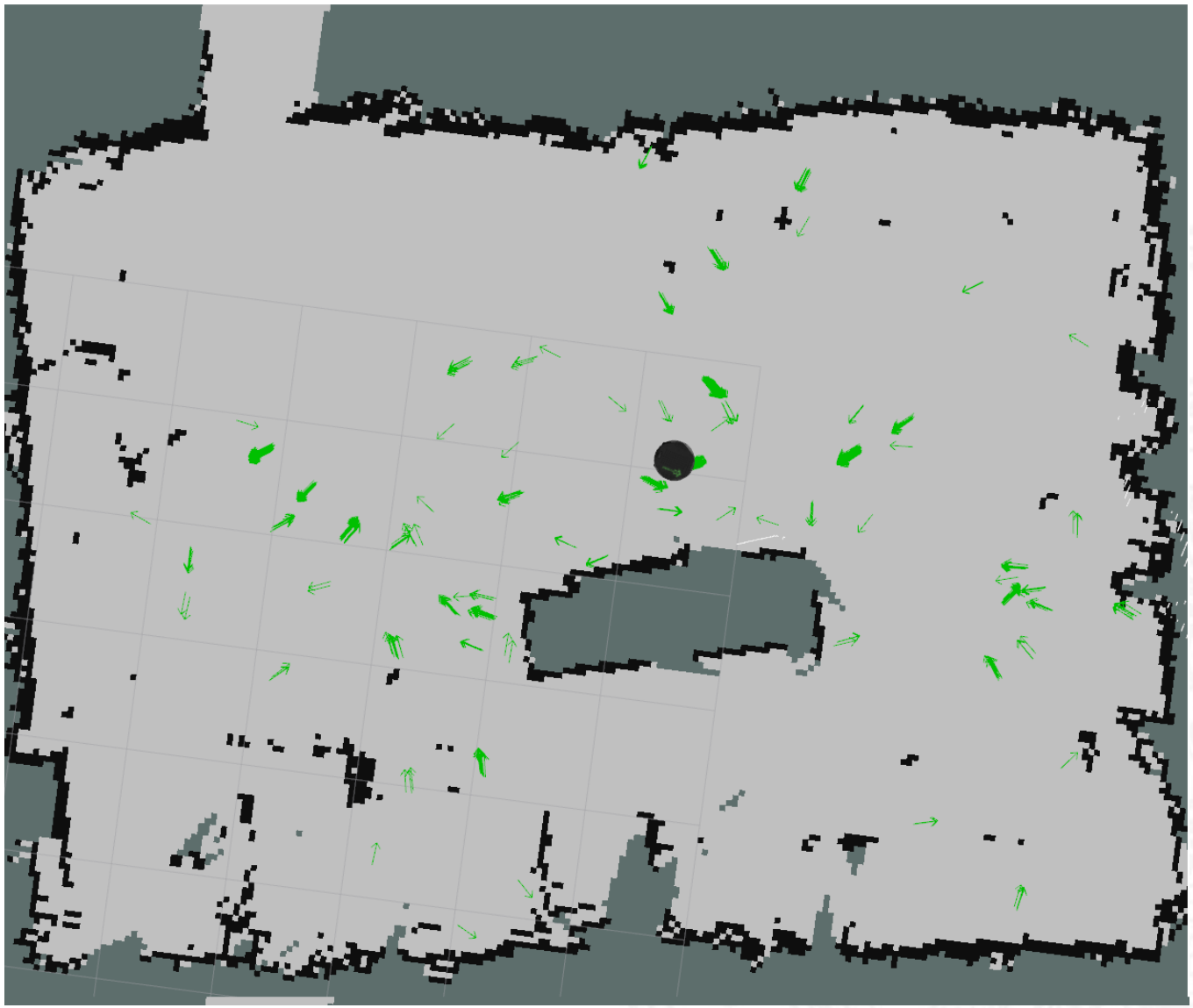
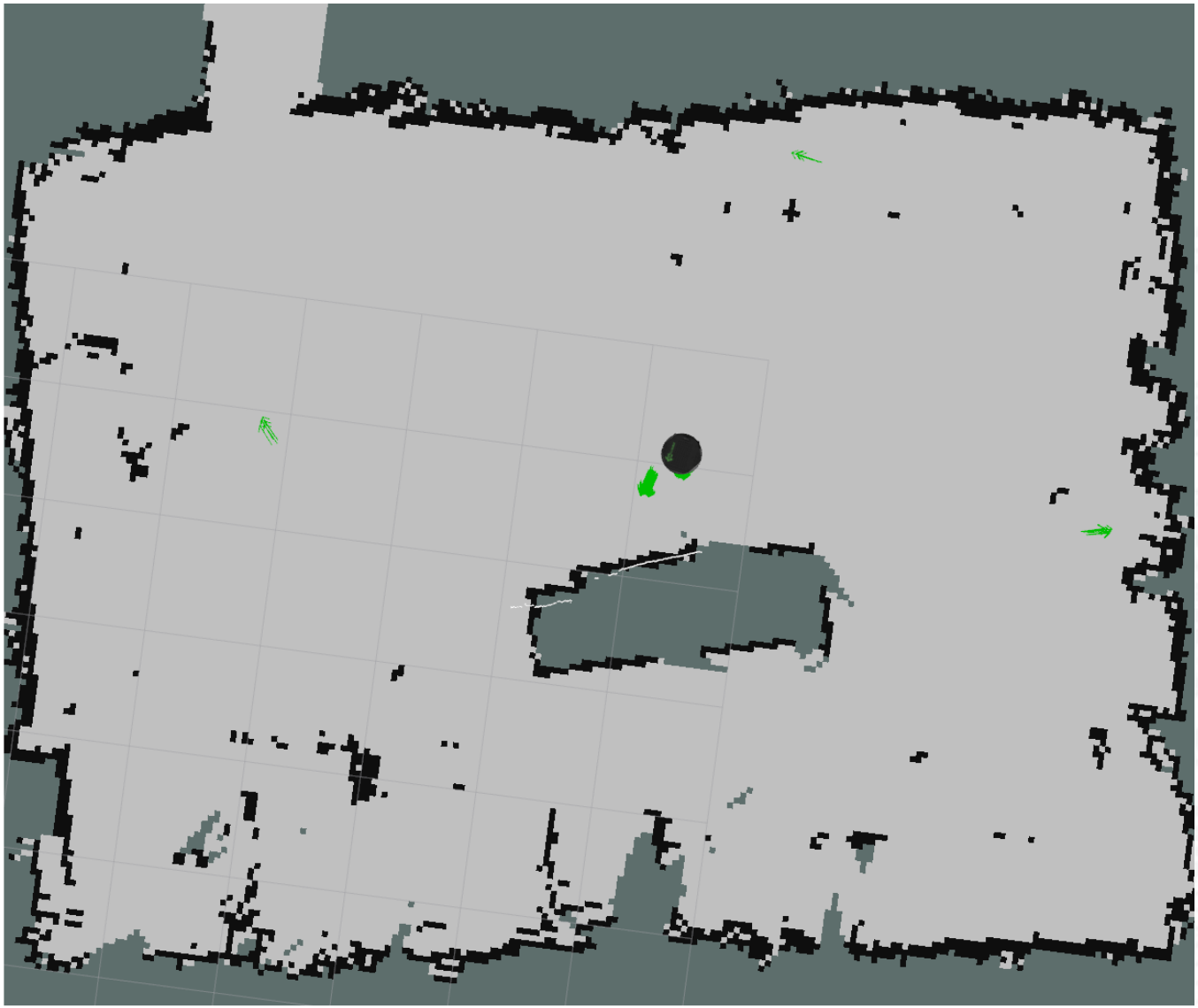
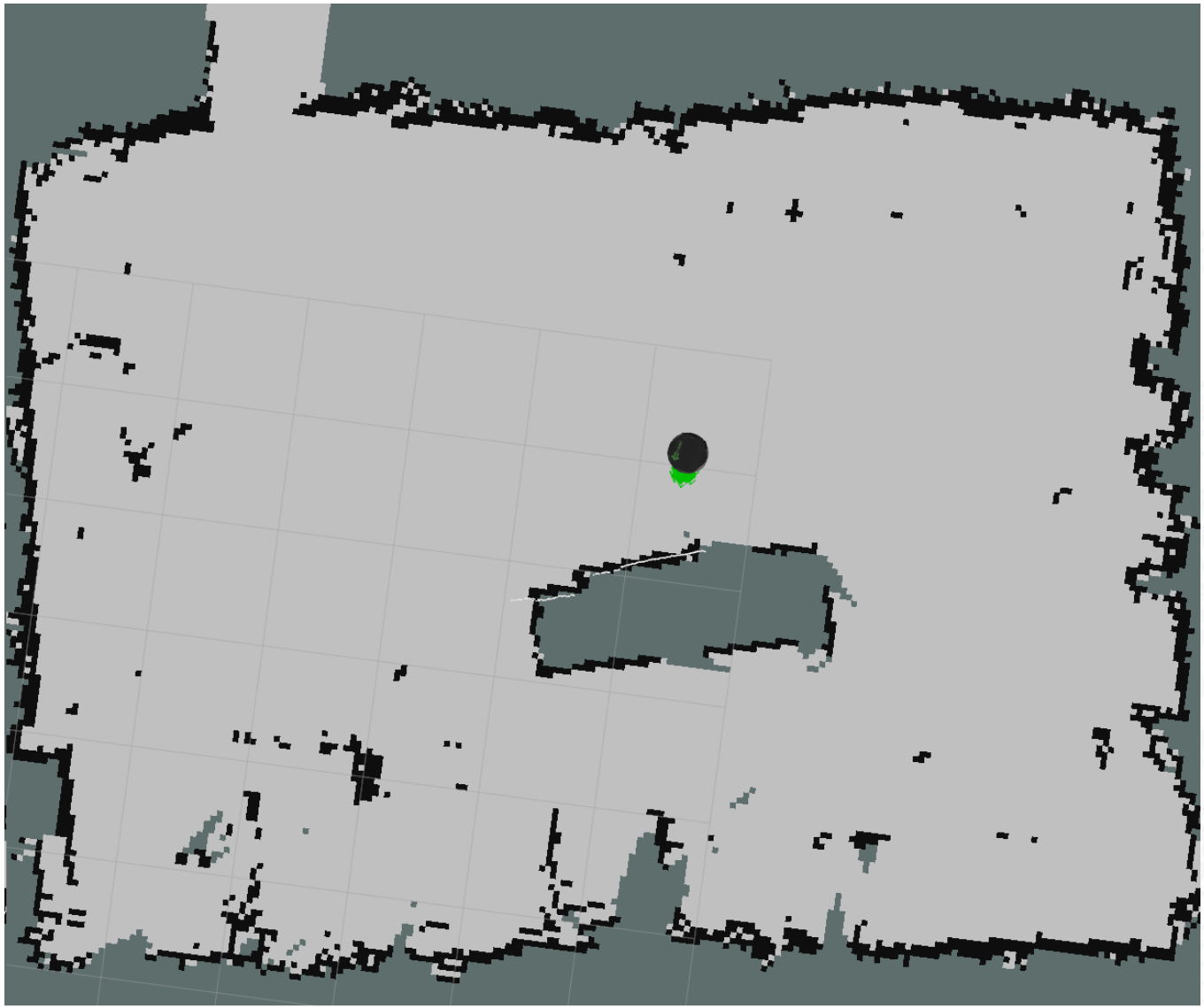








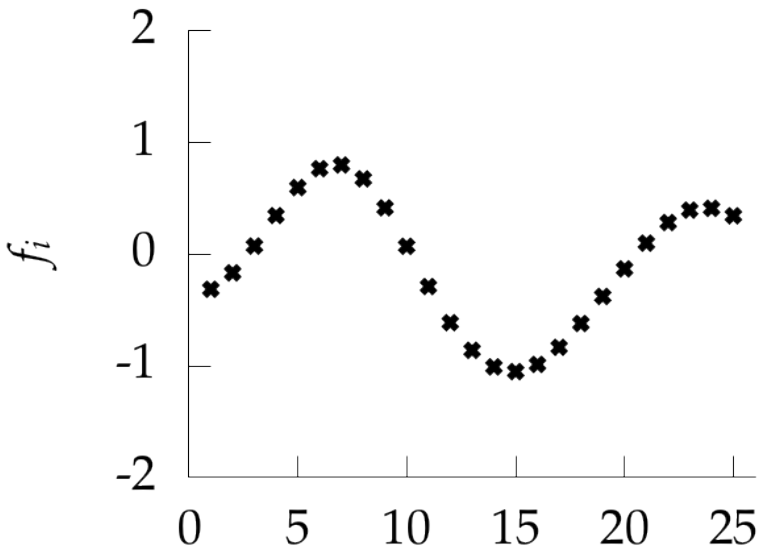
- Average of weights
- Comparing short-term with long-term
- Lower short-term than long-term indicates kidnapping
- Adding random particles to set

- SSID not unique
- MAC-address unique
- Signal Strength measured in dBm
  - The higher the value, the stronger the signal
  - Logarithmic measurement scale
  - Range from -40 dBm to -90 dBm
- Wi-Fi channels

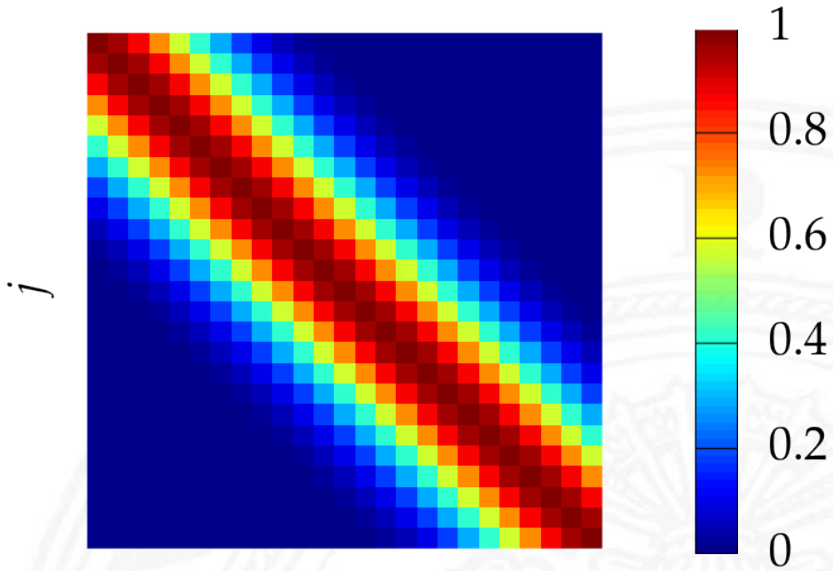
- Two common approaches to regression:
  - Restricting the classes of functions
  - Putting a prior over all functions
- Gaussian processes to put prior over all functions
- Gaussian processes are generalization of Gaussian distributions
  - Gaussian distribution: distribution over scalars or vectors
  - Gaussian process: distribution over functions

Wi-Fi Sensor Model

Covariance



(a) A 25 dimensional correlated random variable (values plotted against index)



(b) colormap showing correlations between dimensions

Figure : [Lawrence, 2013]

- Prior is defined by a covariance function
- Different covariance functions will lead to different results
- Radial basis function (RBF) kernel
- $k(x_p, x_q) = \sigma_f^2 \exp(-\frac{1}{2\ell^2}(x_p - x_q)^2) + \sigma_n^2 \delta_{pq}$
- Hyperparameters: σ_f, ℓ, σ_n

Wi-Fi Sensor Model

Hyperparameters

- $\sigma_f = 10, \ell = 50$

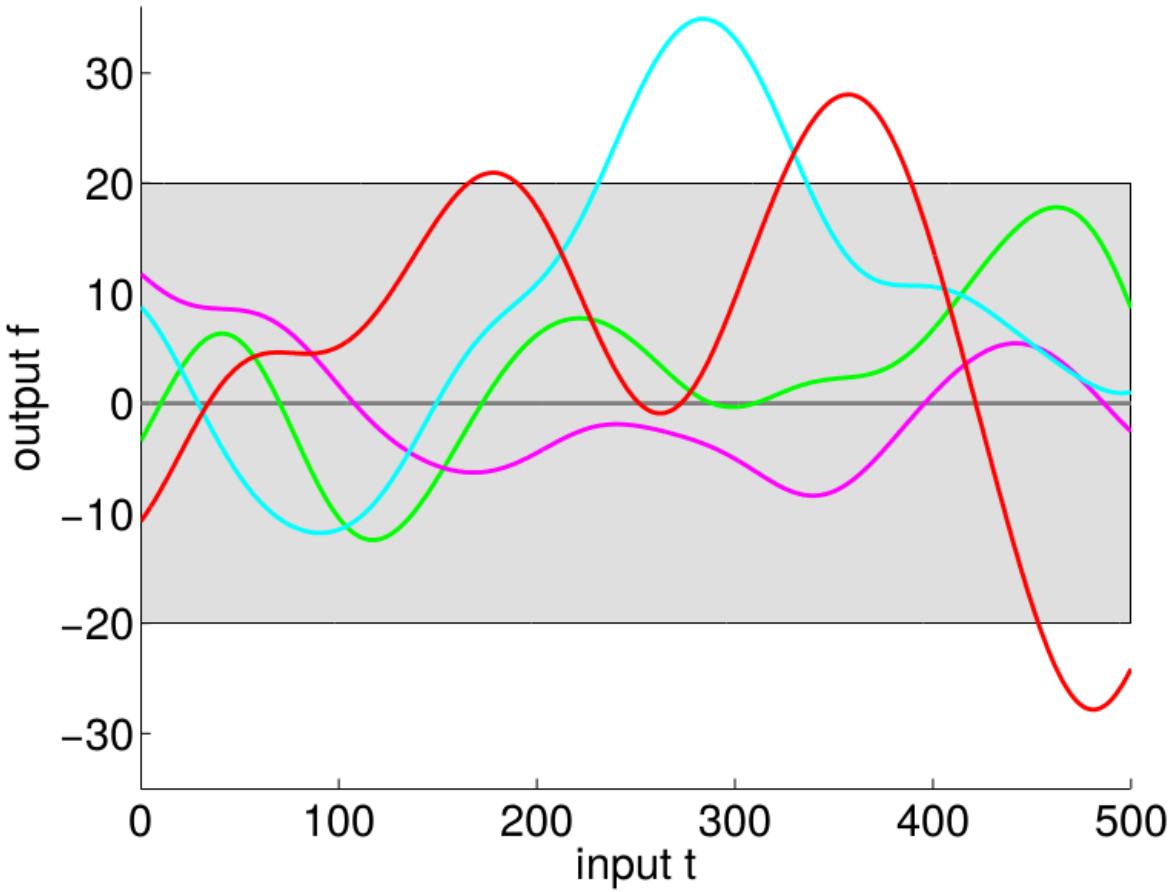


Figure : [Cunningham, 2012]

Wi-Fi Sensor Model

Hyperparameters

- $\sigma_f = 4, \ell = 50$

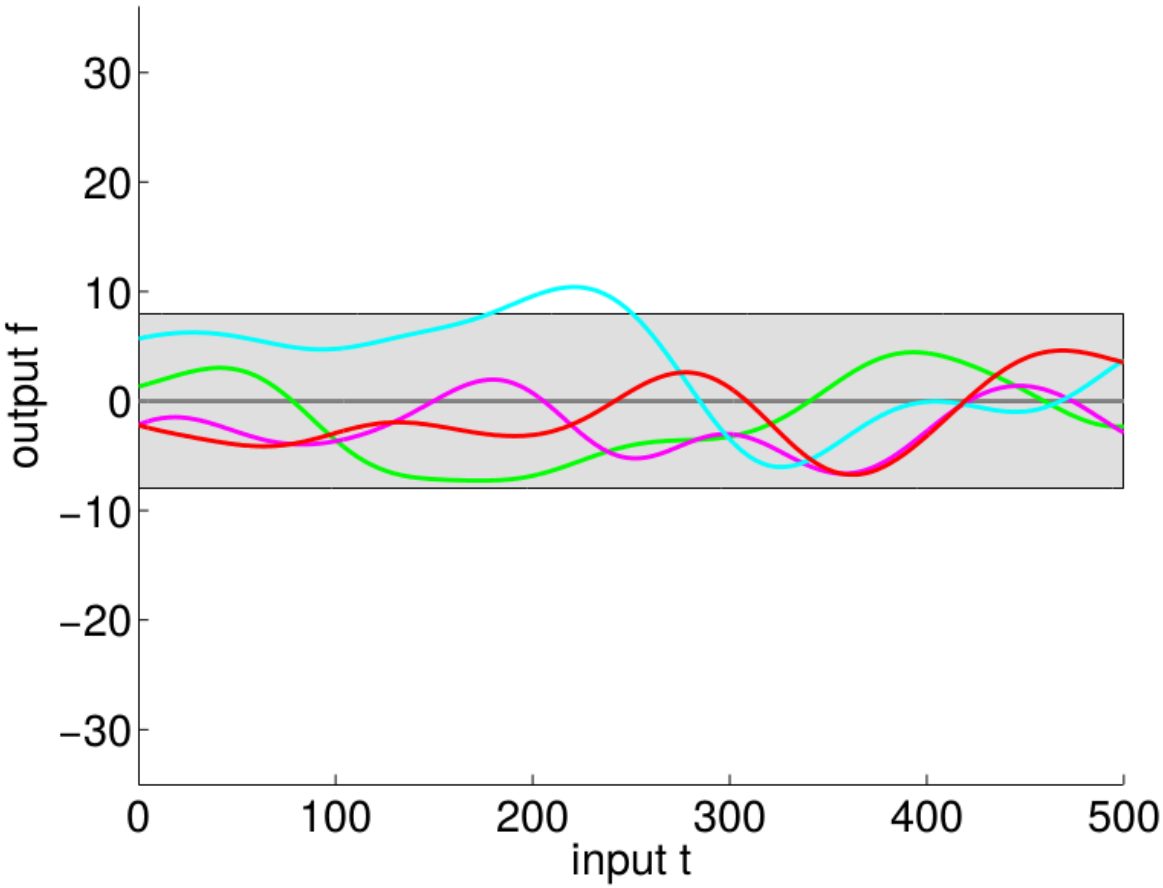


Figure : [Cunningham, 2012]

Wi-Fi Sensor Model

Hyperparameters

- $\sigma_f = 4, \ell = 10$

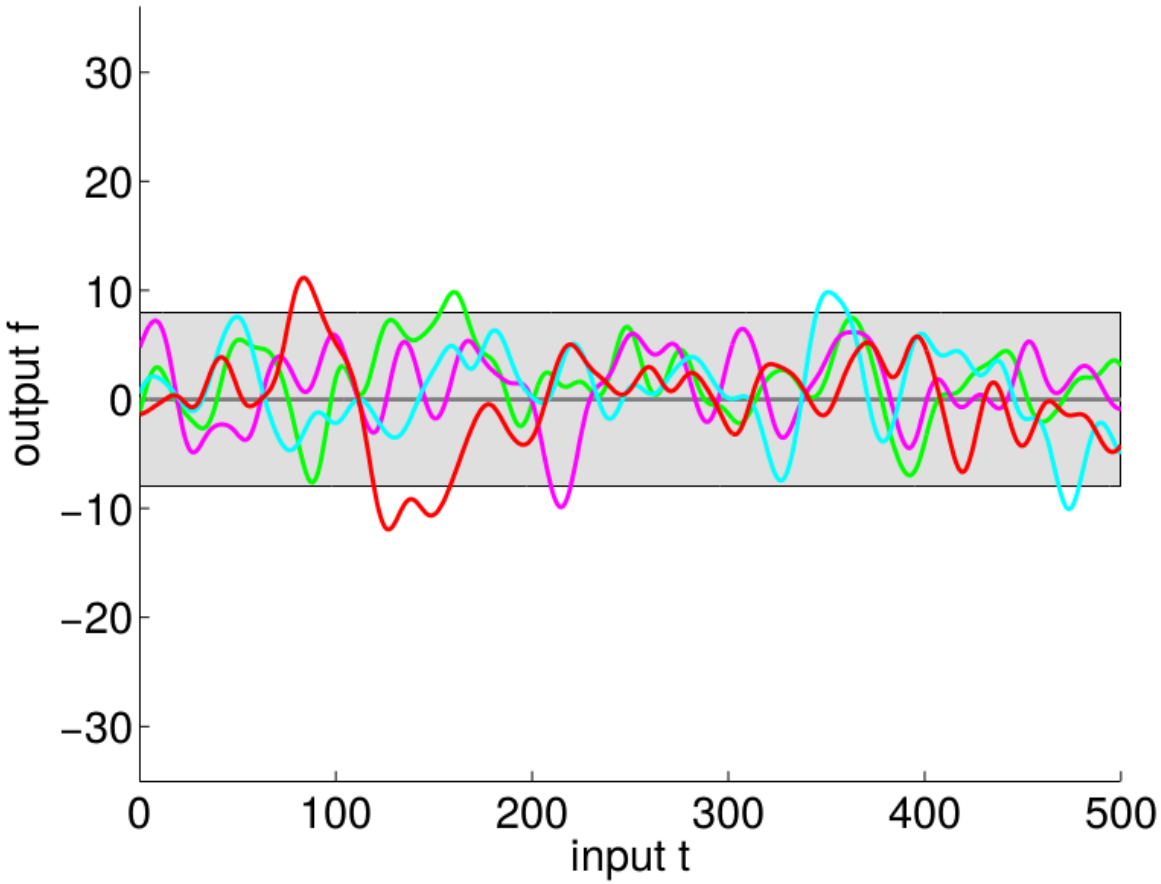
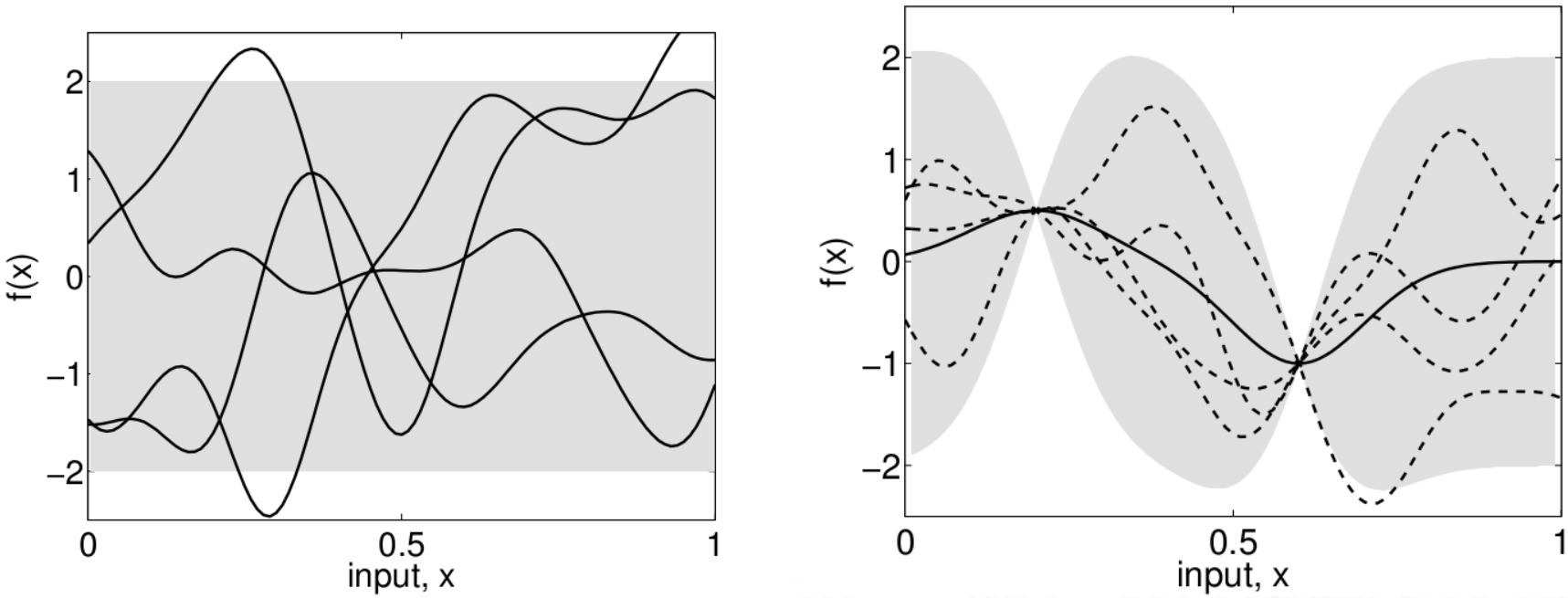


Figure : [Cunningham, 2012]



(a) prior (b) posterior

Figure : [Rasmussen and Williams, 2005]

- Gaussian distribution for every coordinate
- probability of signal strength
- Compute weights

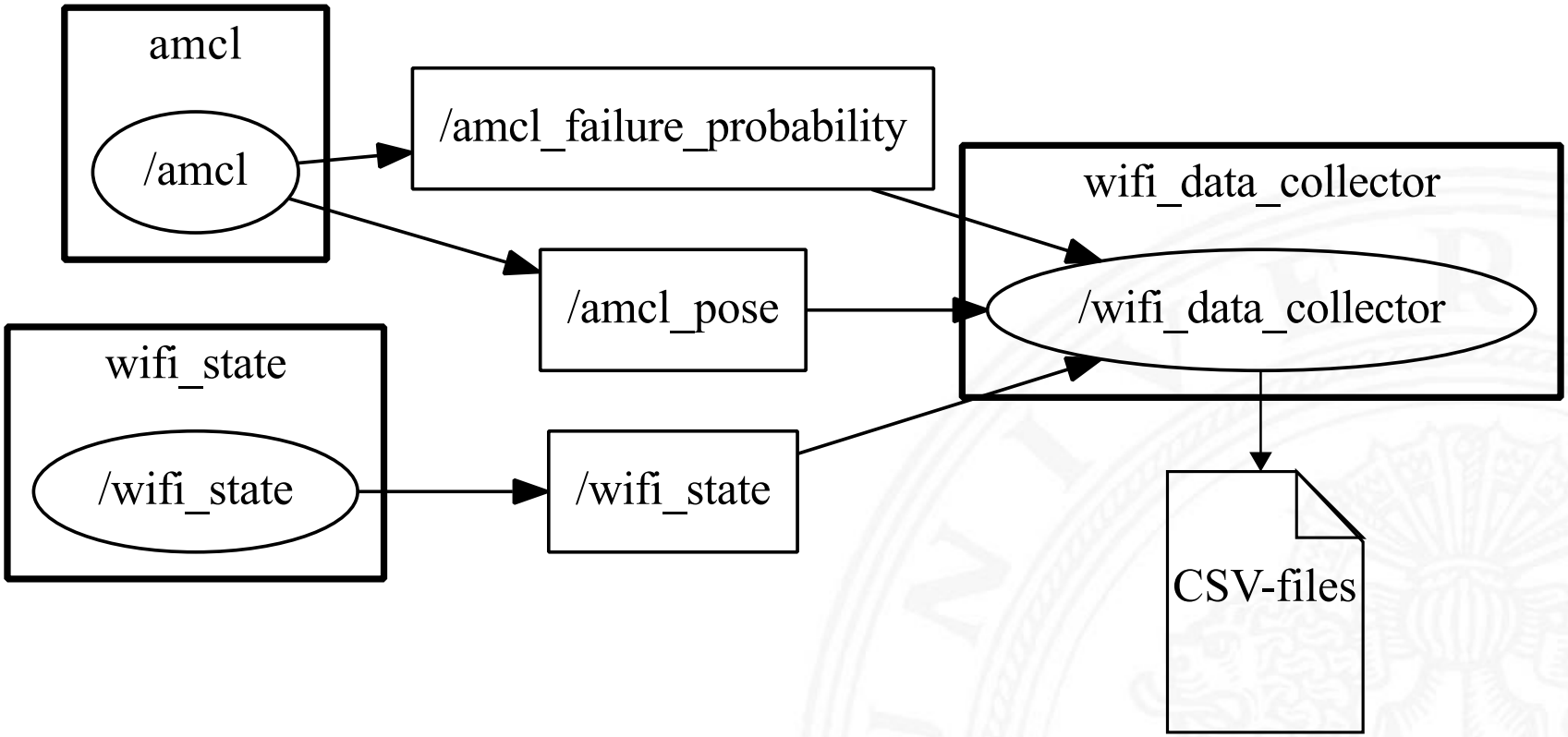
- Hyperparameters can be learned
- Log-likelihood function
  - The higher the log-likelihood, the better the fit
  - Using derivatives to search maximum
- Resilient backpropagation [Blum and Riedmiller, 2013]
  - Sign of partial first order derivatives

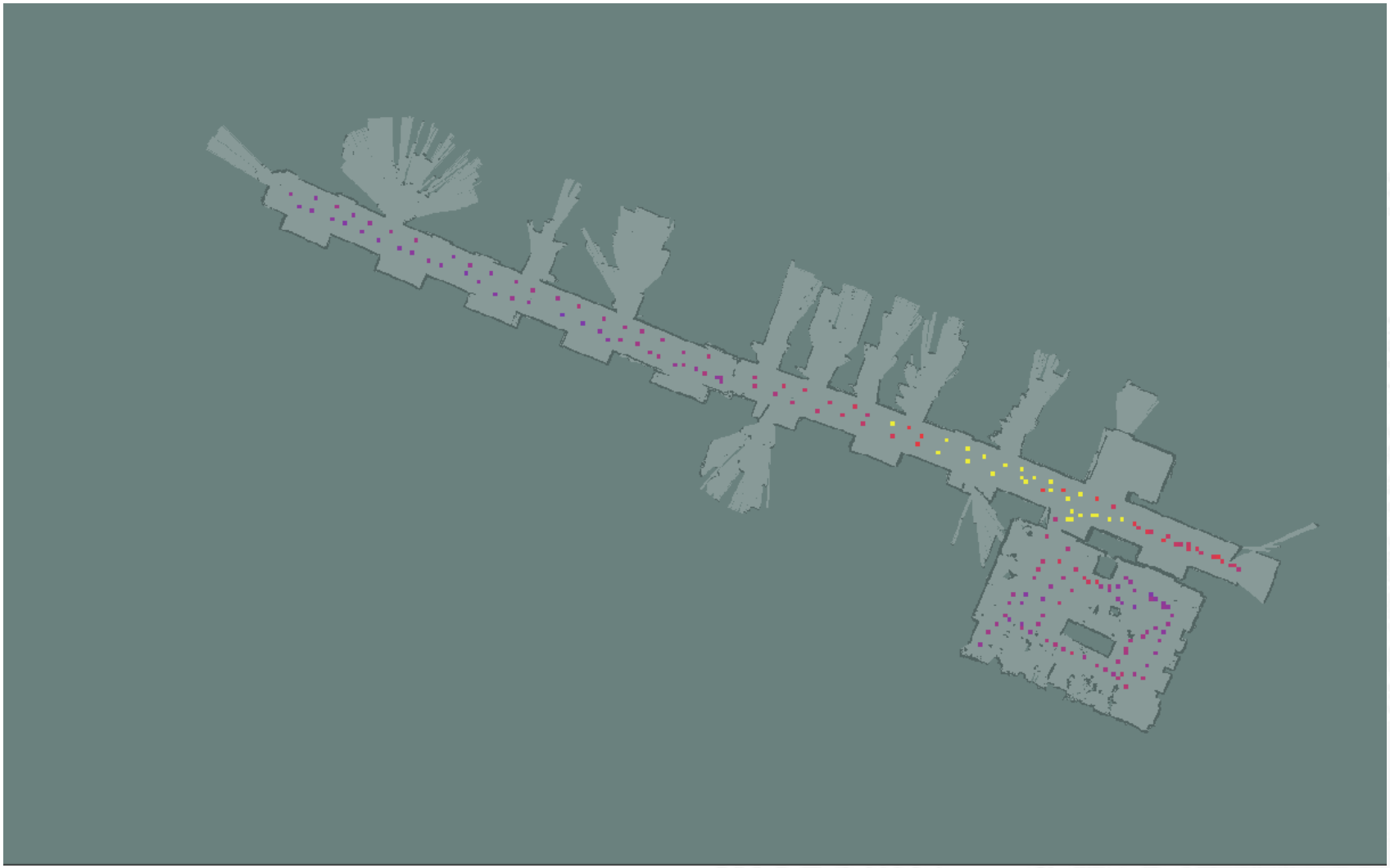
- Implemented with ROS
- Using AMCL for localization
  - failure probability
- `turtlebot_teleop` and `move_base` to move the robot

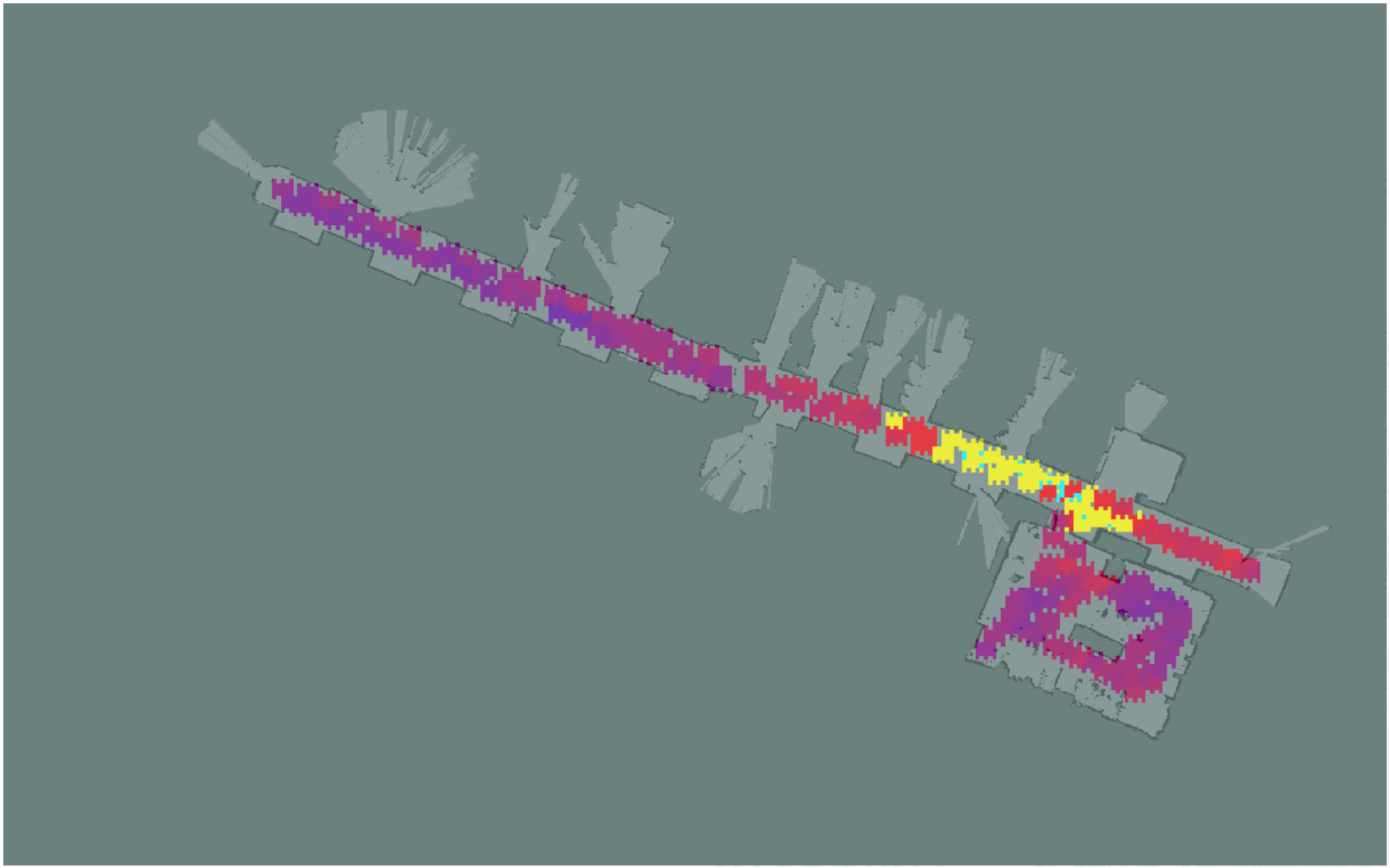
Wi-Fi publisher

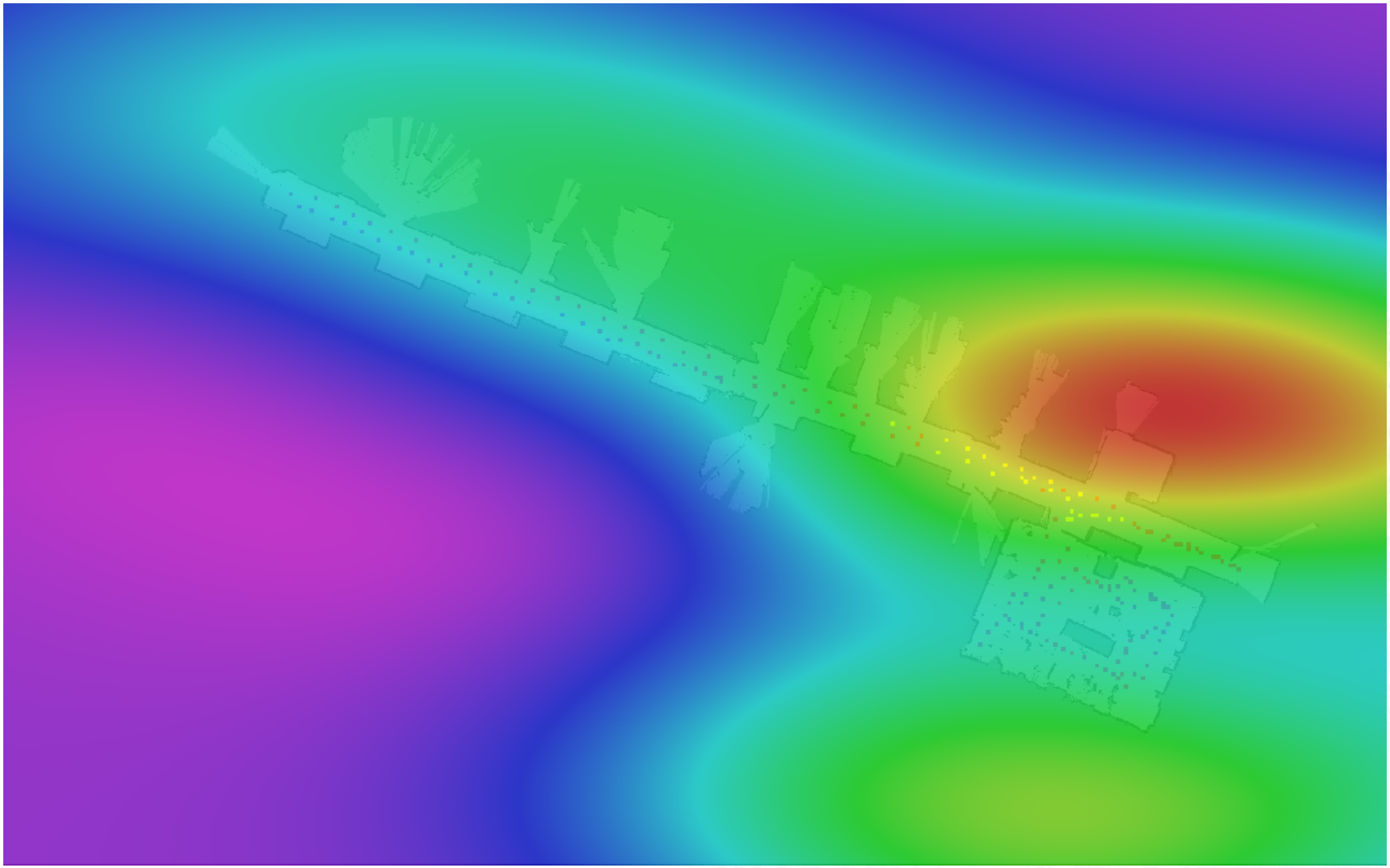
- Needed data:
  - MAC-address
  - Wi-Fi signal strength
- Using terminal command
  - `sudo iw dev wlan0 scan`
  - `sudo iw dev wlan0 scan freq 2432`

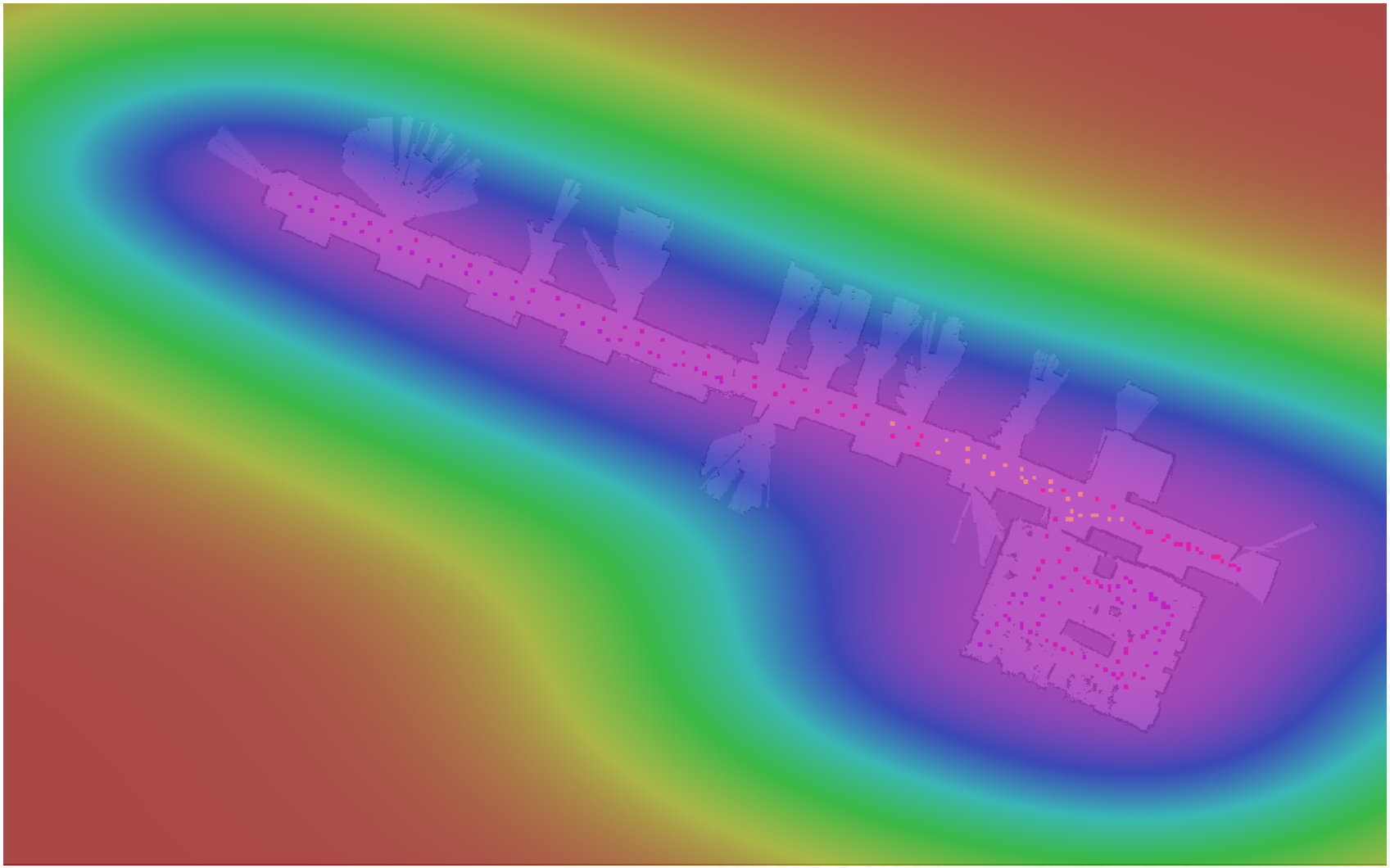
Wi-Fi Data Collector







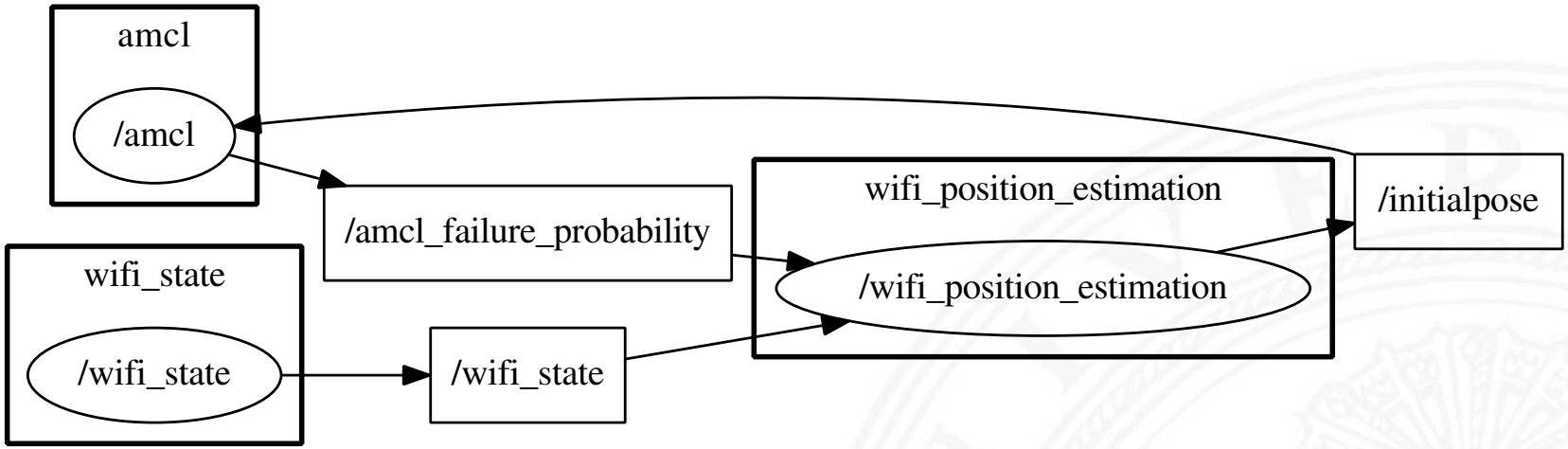




Wi-Fi Position Estimation

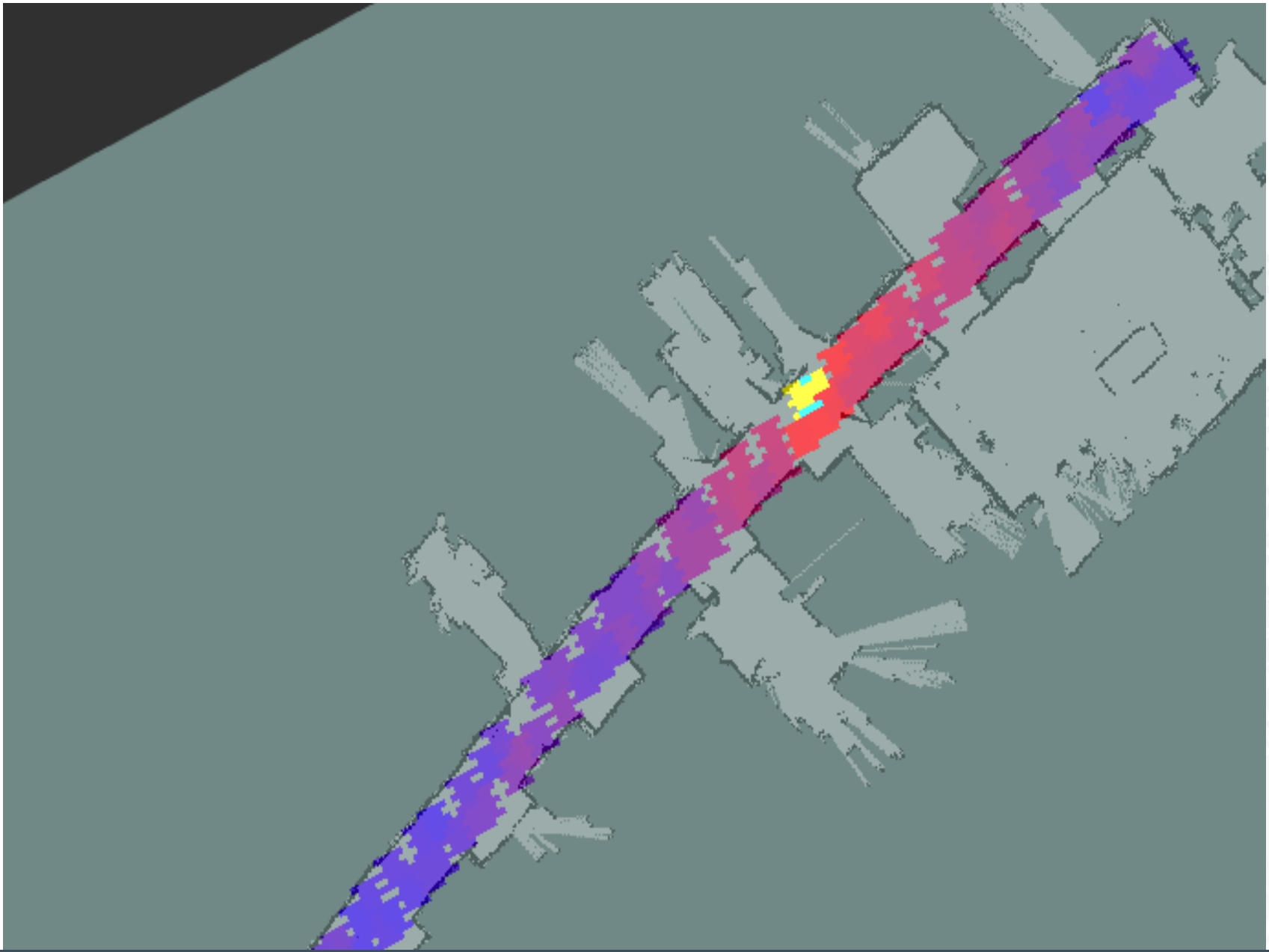
- Gaussian process for every MAC-address
- Train processes at first start
- Particles spread over map
- Compute weight for every MAC-address observed
- Multiply weights
- Highest weight is most likely position

Wi-Fi Position Estimation

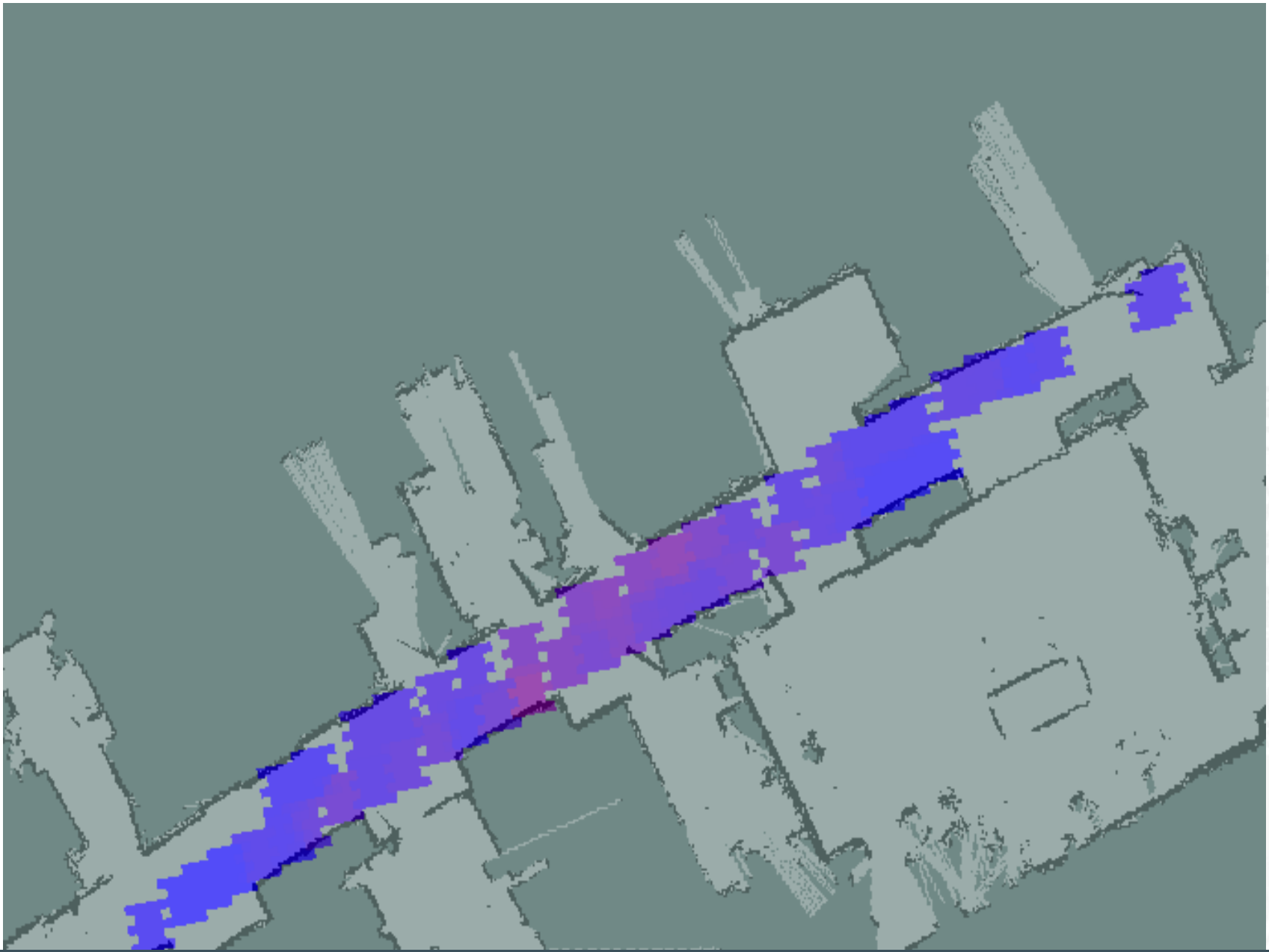


Demo Time

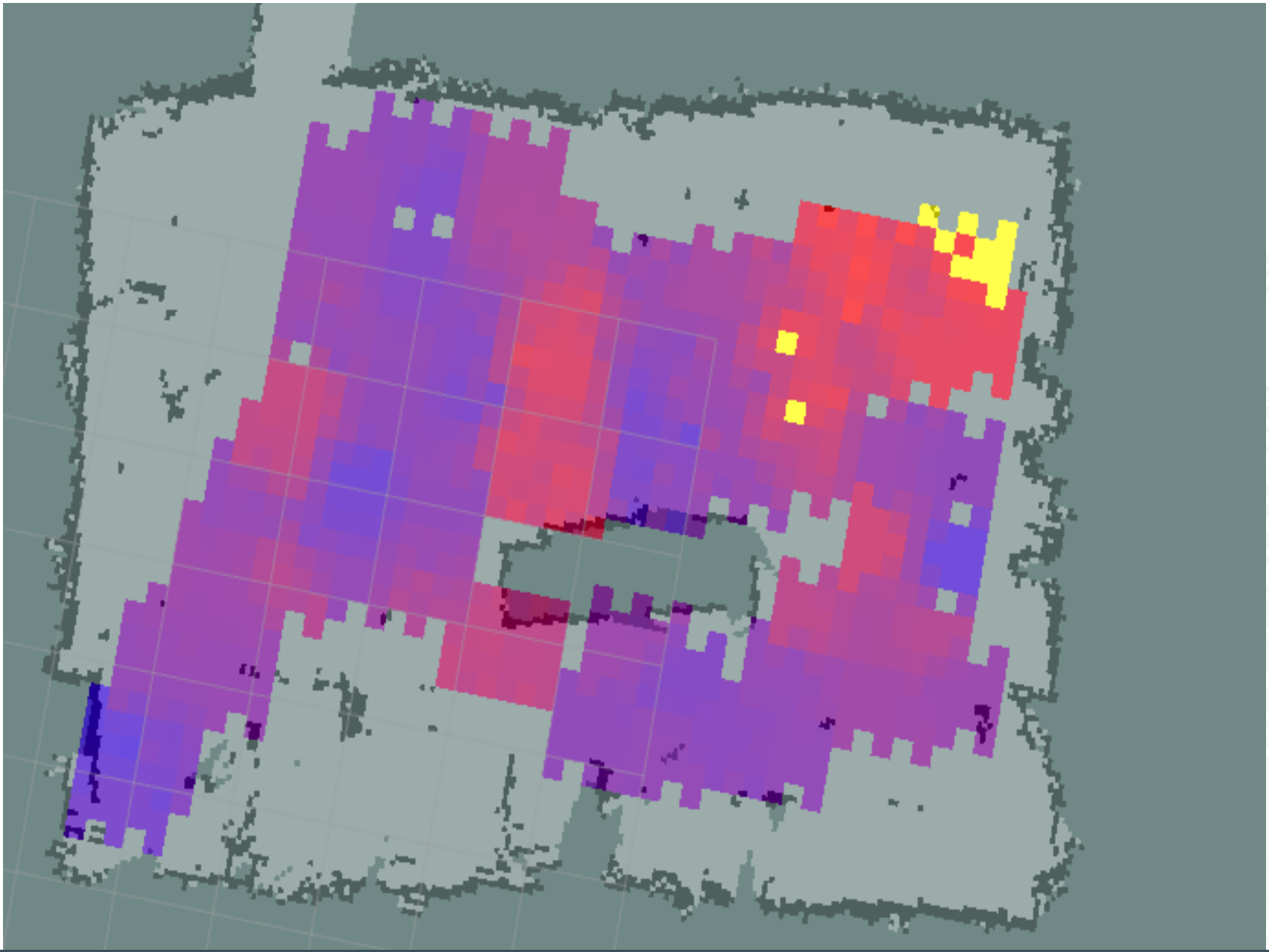
Wi-Fi data



Wi-Fi data



Wi-Fi data



Experiment 1

- 20 different goals on the hallway the robot drives to
- At each point the groundtruth is recorded using AMCL
- Wi-Fi position estimation is used at each goal
- Compare Wi-Fi position estimation with AMCL ground truth
- Mean error of **1.81 meters**

Experiment 2

- Robot drives to 20 different goals on the hallway
- At each goal the Wi-Fi position estimation is called
- AMCL gets the result as new initial position
- When the robot arrives at the next goal, the difference to the true pose is recorded
- Wi-Fi position estimation used for global localization
  - Mean error of **2.23 meters**
  - Successful in **9 out of 19 tries**
- Common method for global localization
  - Mean error of **17.34 meters**
  - Successful in **1 out of 19 tries**

Experiment 3

- Using average weights to detect kidnapped robot
- Robot drives hallway up and down
- After some time the localization is initialized to random place on map
- Kidnapped robot was detected in **10 out of 10 tries**

Conclusion

- Wi-Fi position estimation is accurate enough to give AMCL initial pose
- Improved global localization
- Localization failure detection works
- Problems:
  - laser range finder's problems remain, but to lesser extent
  - No information about orientation
  - Computation time
  - Wi-Fi scan time

Outlook

- Different kernel to heighten accuracy
- Compass for orientation
- Speeding up Wi-Fi scan
- Speeding up computation time
- Applying the Wi-Fi model directly in AMCL
- Using Wi-Fi sensor model directly for failure detection

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