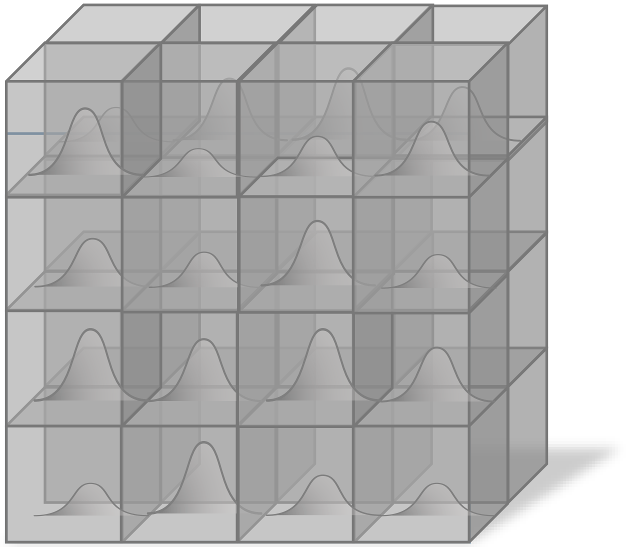

Confidence-rich Grid Mapping

A planning-oriented representation of the environment

Ali-akbar Agha-mohammadi[1], Eric Heiden[2], Karol Hausman[2], Gaurav S. Sukhatme[2]

[1] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, USA
[2] University of Southern California, Los Angeles, USA

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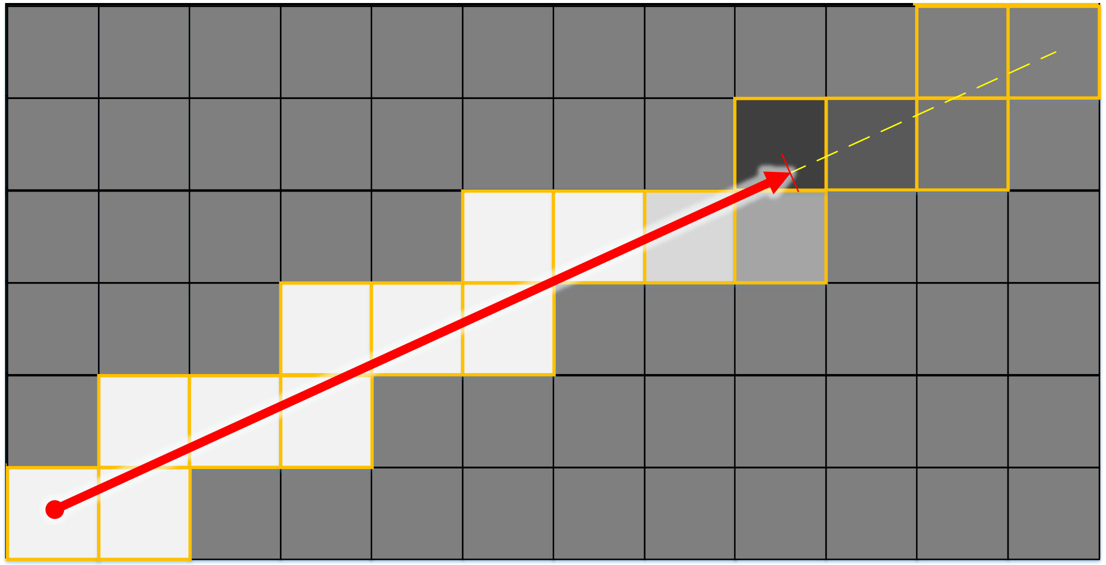
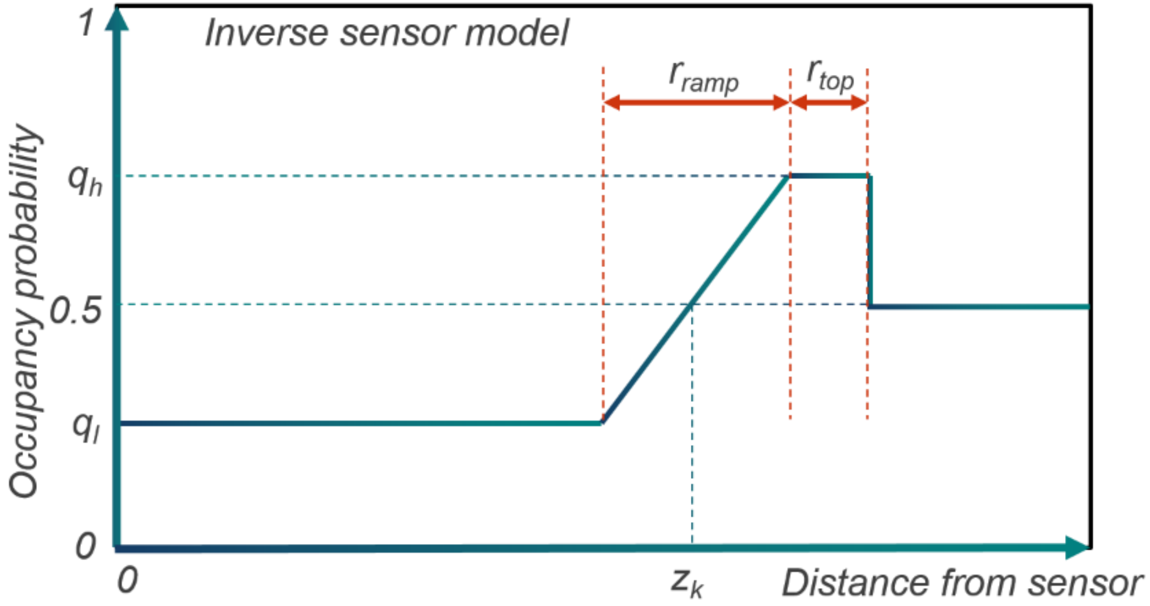
Traditional Occupancy Grid Mapping



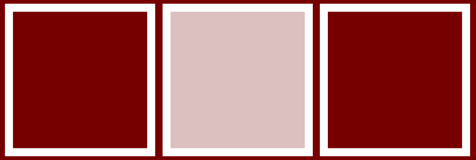


Odds of occupancy: $r_k^i = \dfrac{p\left(m^i = 1 \middle| z_{0:k}, x_{0:k}\right)}{p\left(m^i = 0 \middle| z_{0:k}, x_{0:k}\right)}$

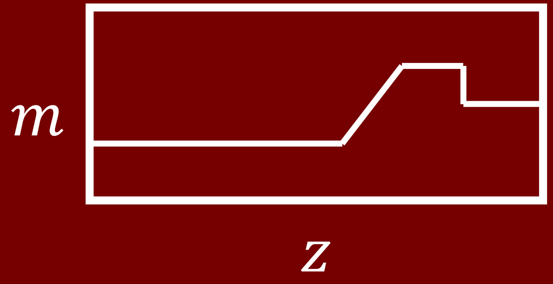
Hornung, A., Wurm, K. M., Bennewitz, M., Stachniss, C., & Burgard, W. (2013).
OctoMap: An efficient probabilistic 3D mapping framework based on octrees. *Autonomous Robots*, *34*(3), 189–206.

Traditional Mapping Approaches

1. Voxel independence assumption



2. Hand-engineered Inverse Sensor Models

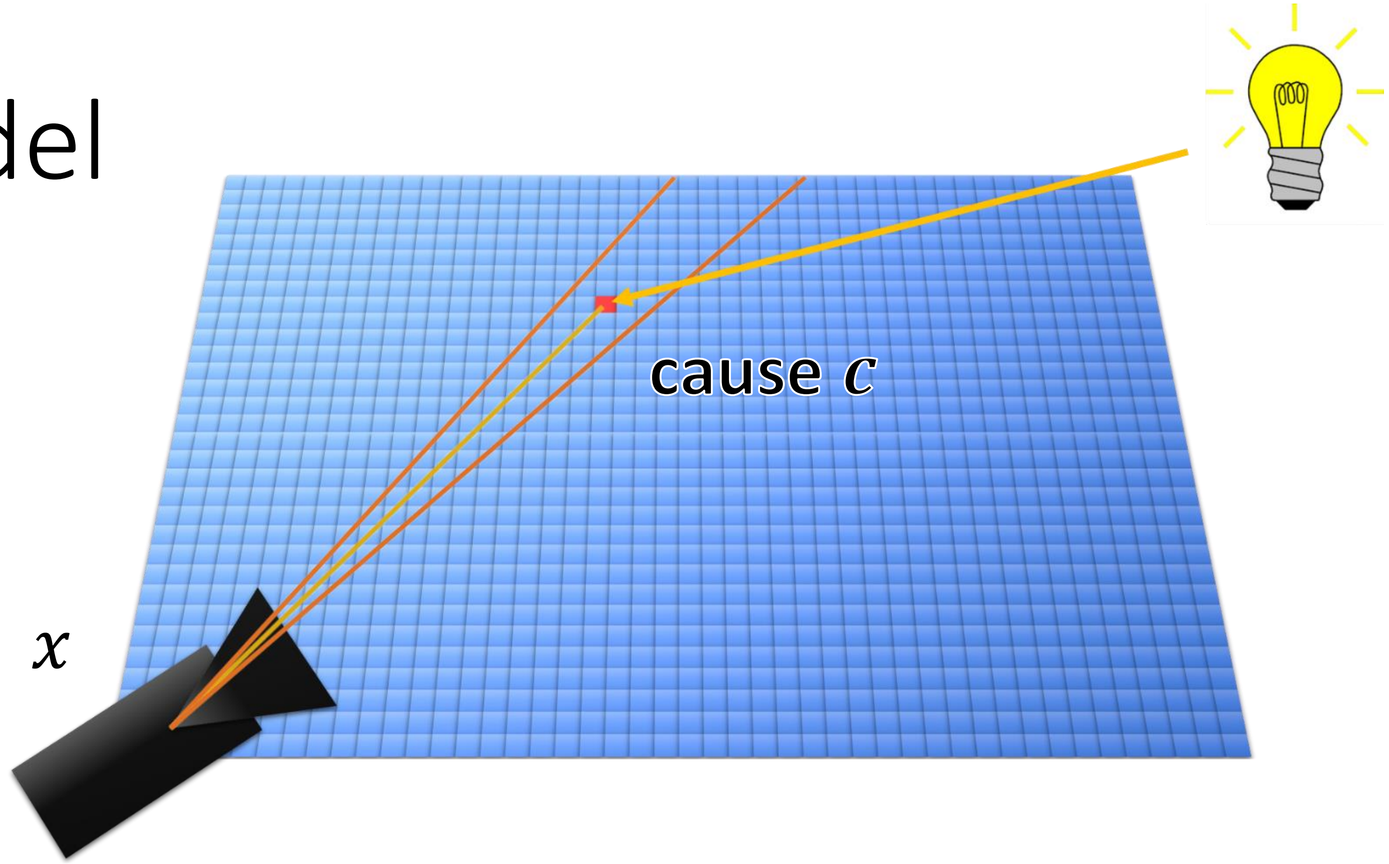


3. Unreliable representation of confidence (scalar occupancies)

4. Poor runtime complexity for learning Gaussian Processes

$$O(n^3)$$

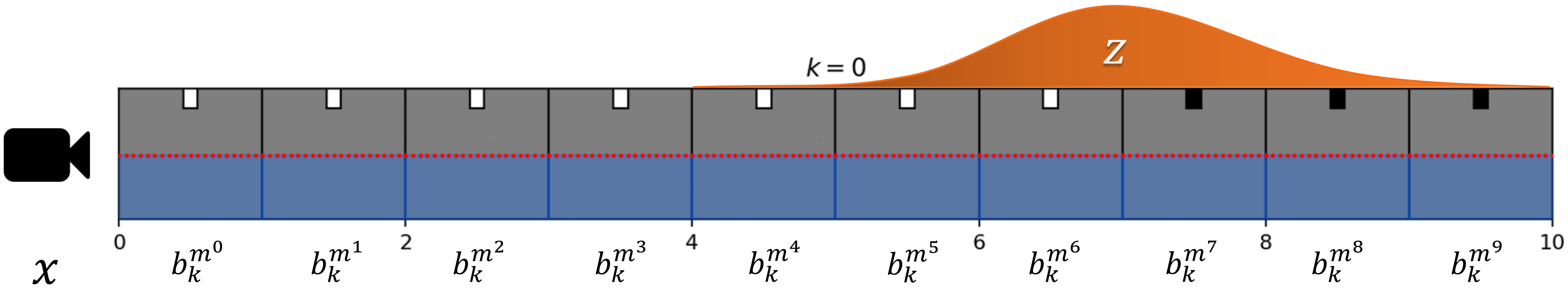
Sensor Cause Model



Cause probability:

$$p(c|b^m) = \Pr(\underbrace{B^c}_{\text{Bouncing}}, \underbrace{R^c}_{\text{Reaching}}|b^m) = \hat{m}^c \prod_{l=1}^{c^l-1}\left(1-\hat{m}^{g(l,x)}\right)$$

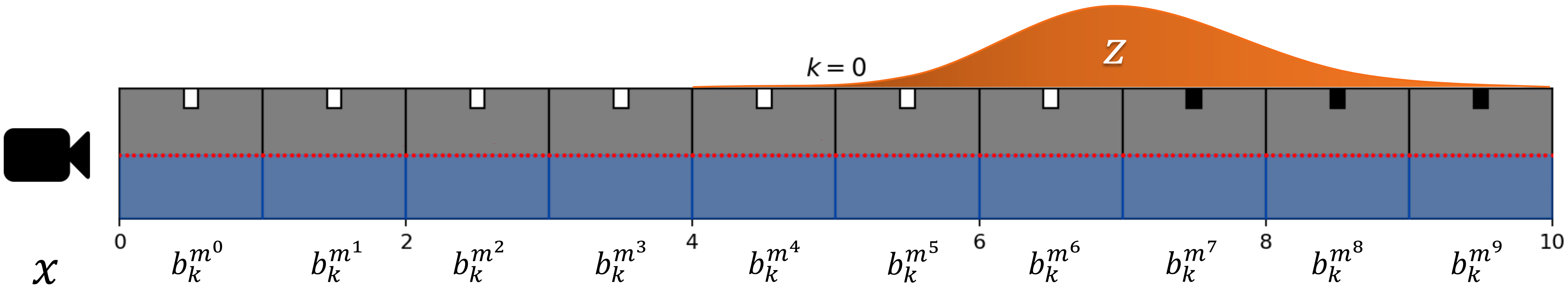
Confidence-rich Mapping



Belief of voxel i at step $k \in [0, 20]$

$$b_k^{m^i} = p(m^i | z_{0:k}, x_{0:k}) = \sum_{c_k \in \mathbb{C}(x)} p(m^i | c_k, z_{0:k}, x_{0:k}) \cdot p(c_k | z_{0:k}, x_{0:k})$$

Confidence-rich Mapping



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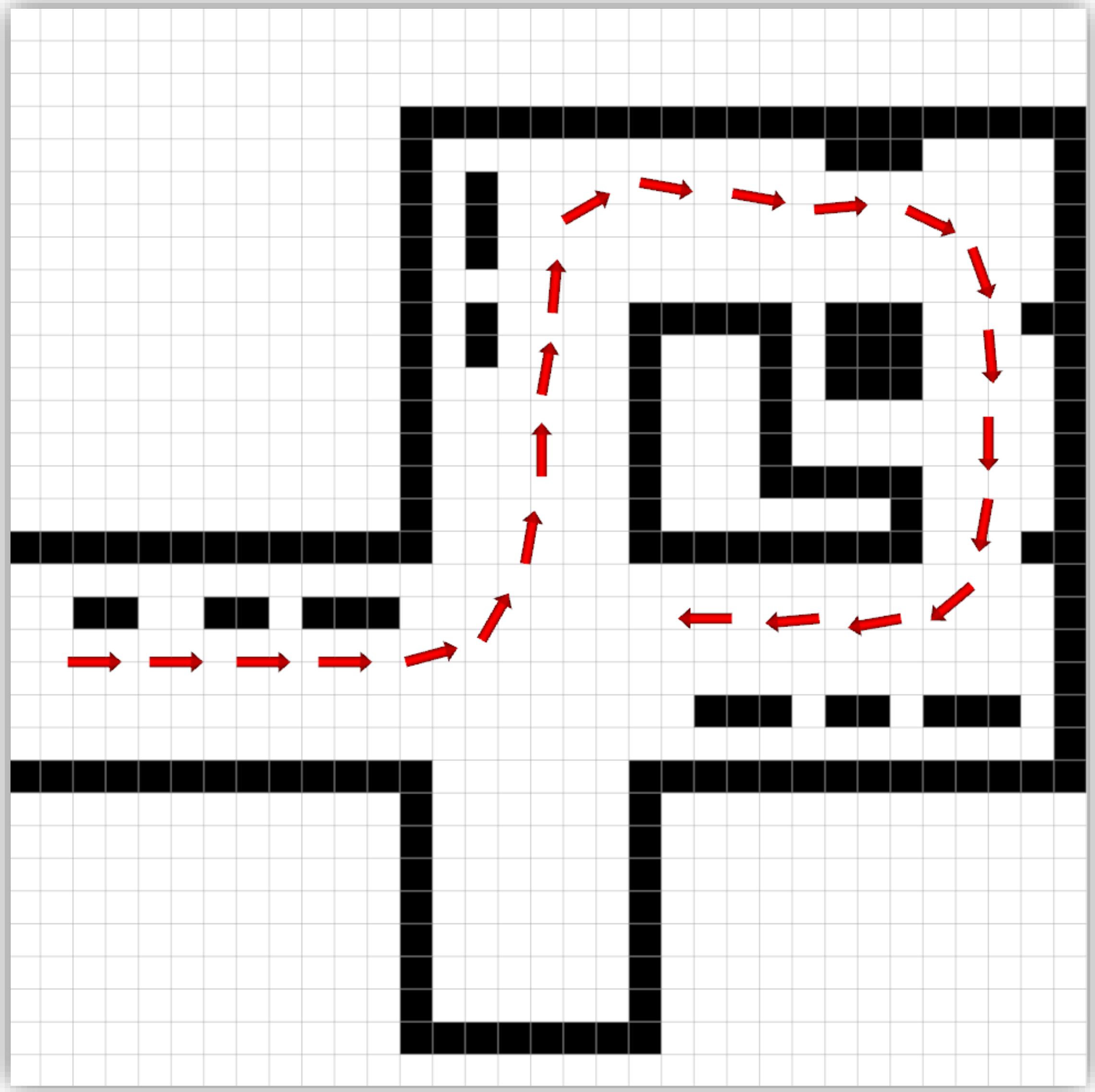
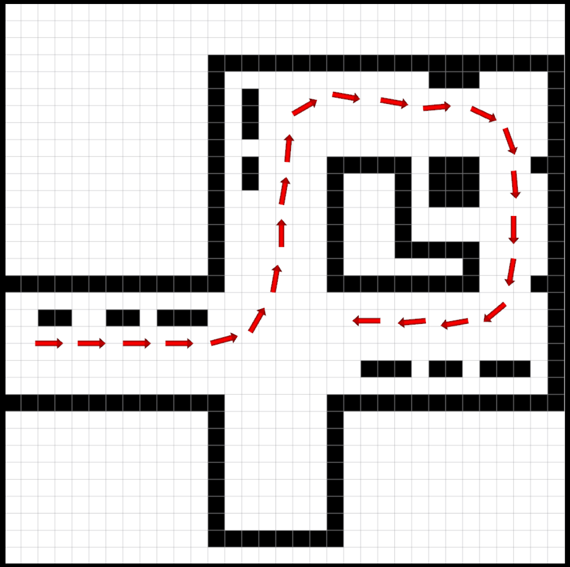
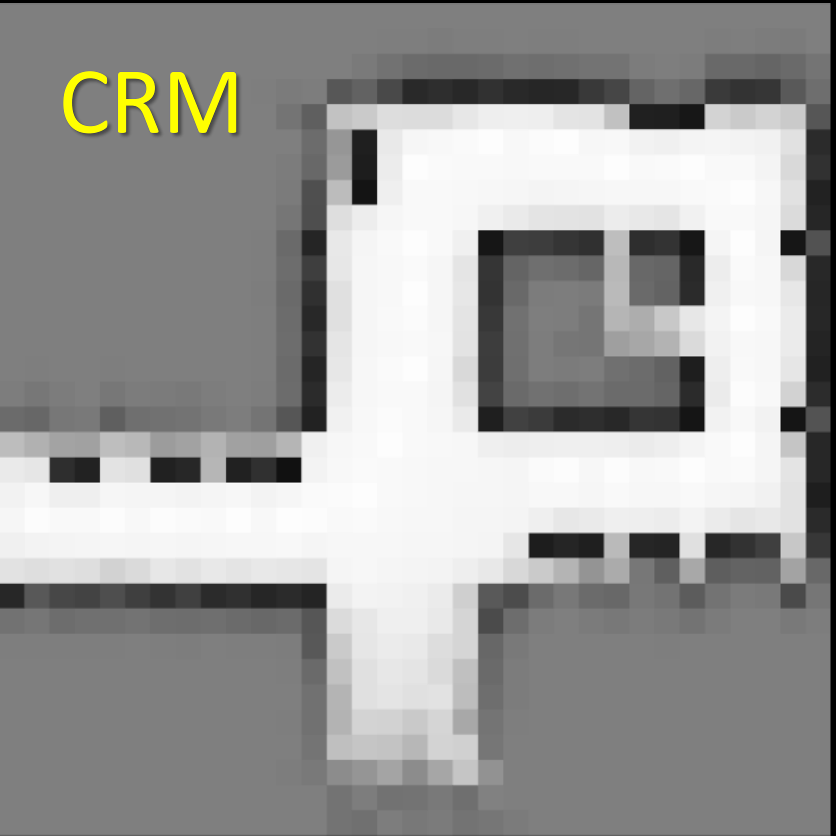
2D Simulation

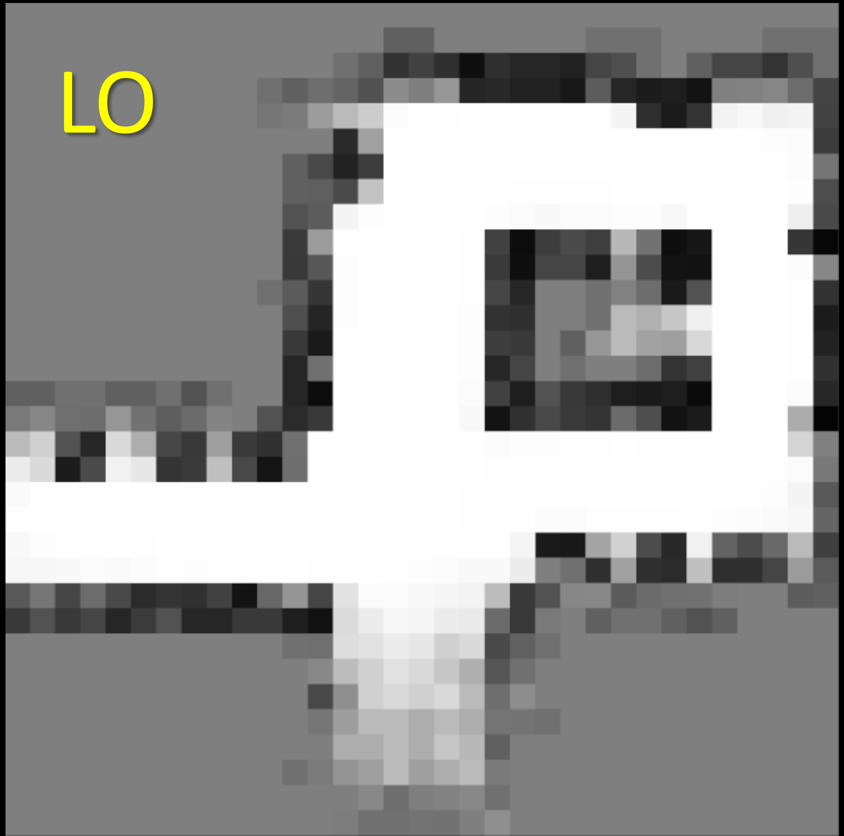
1. Mean (Error)
2. Confidence
3. Consistency

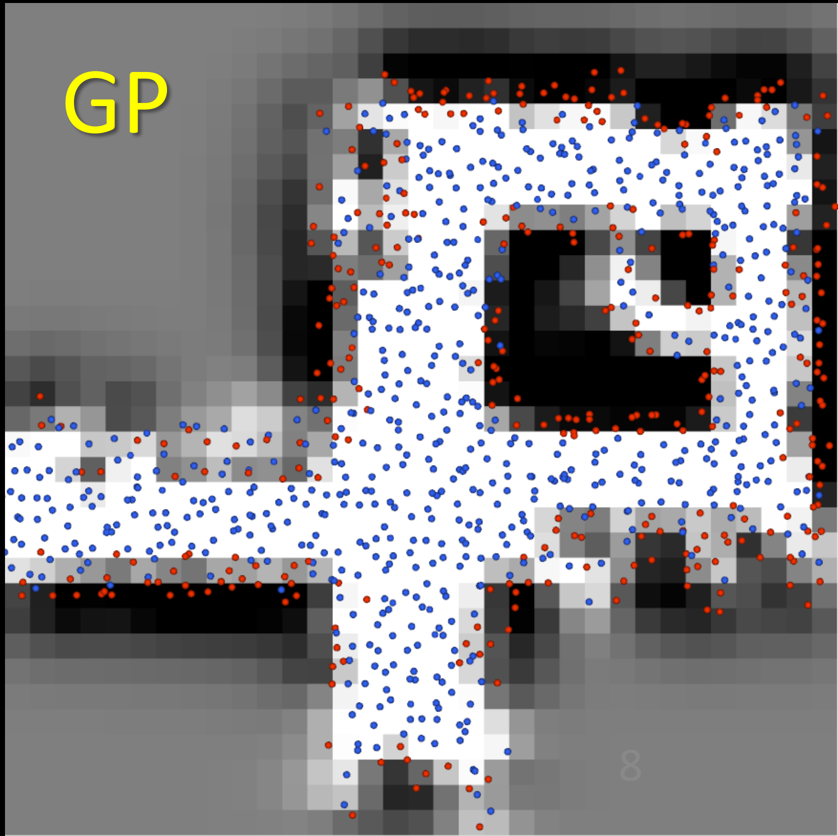


Estimated
Occupancy
Mean

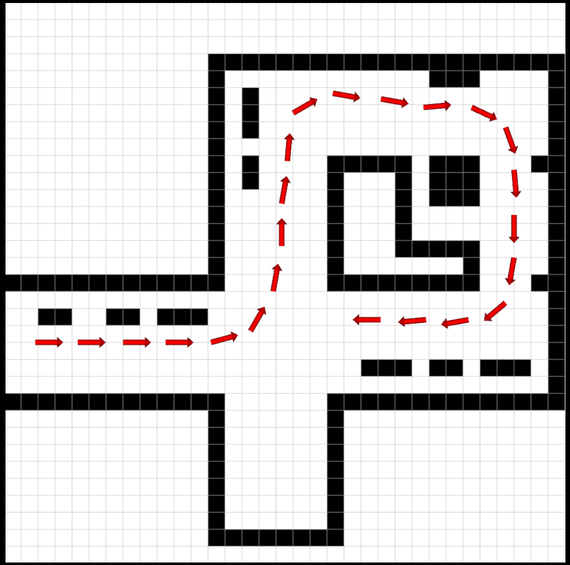


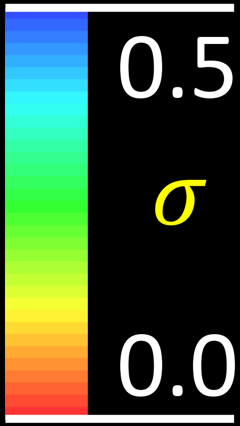


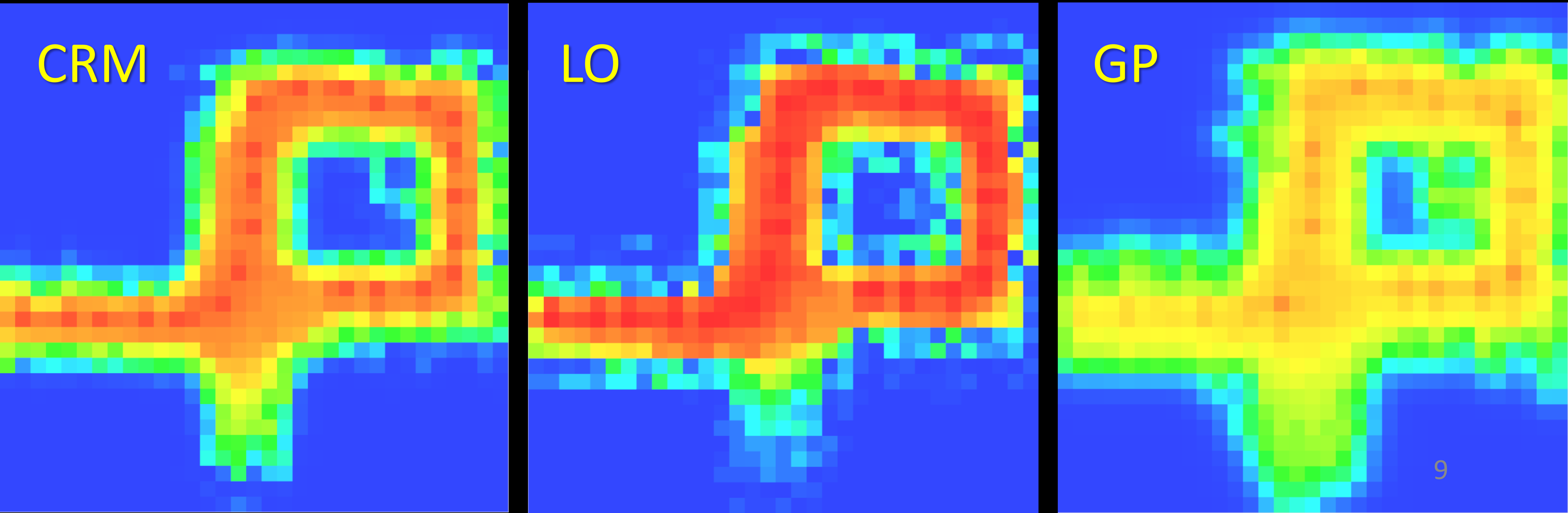




Estimated
Occupancy
Standard Deviation

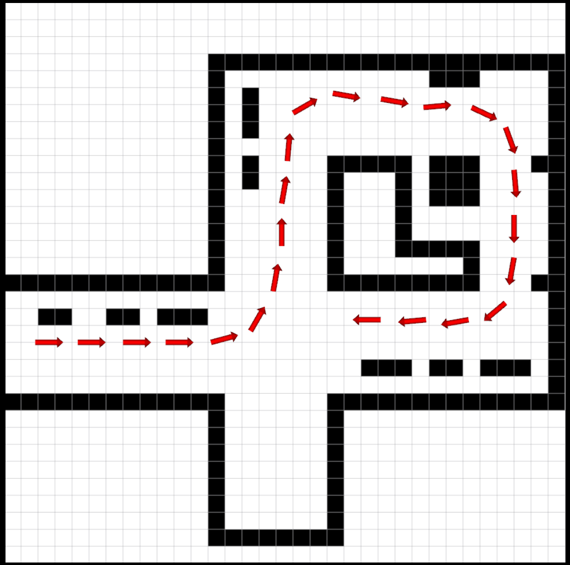


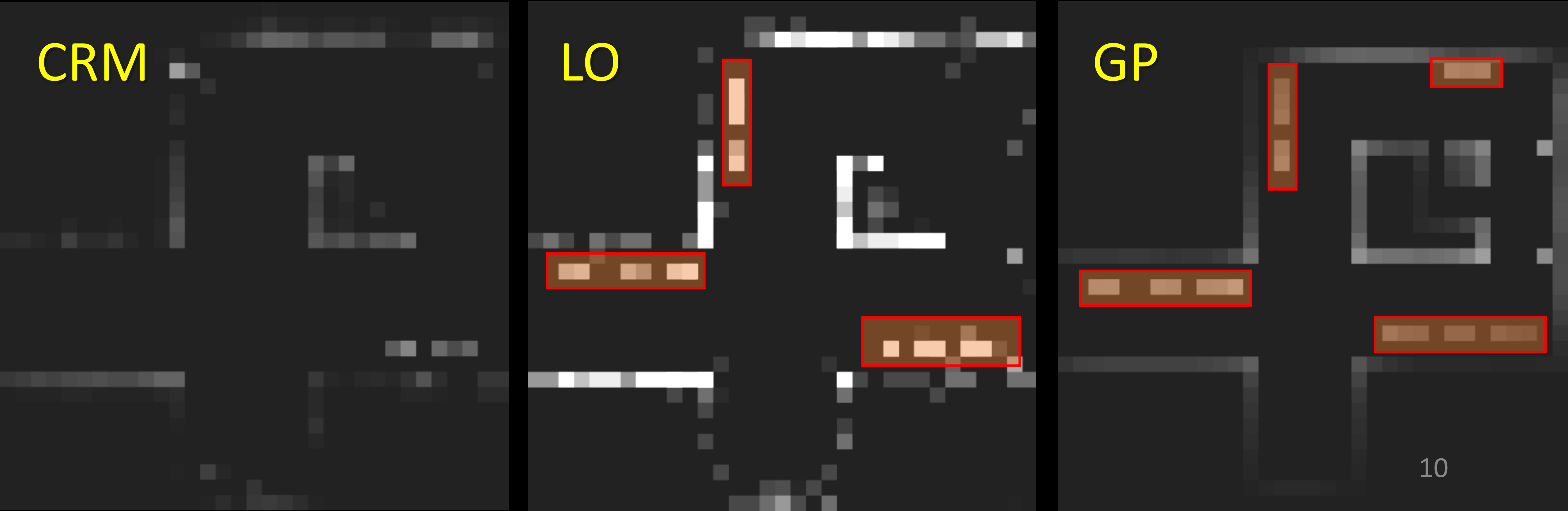




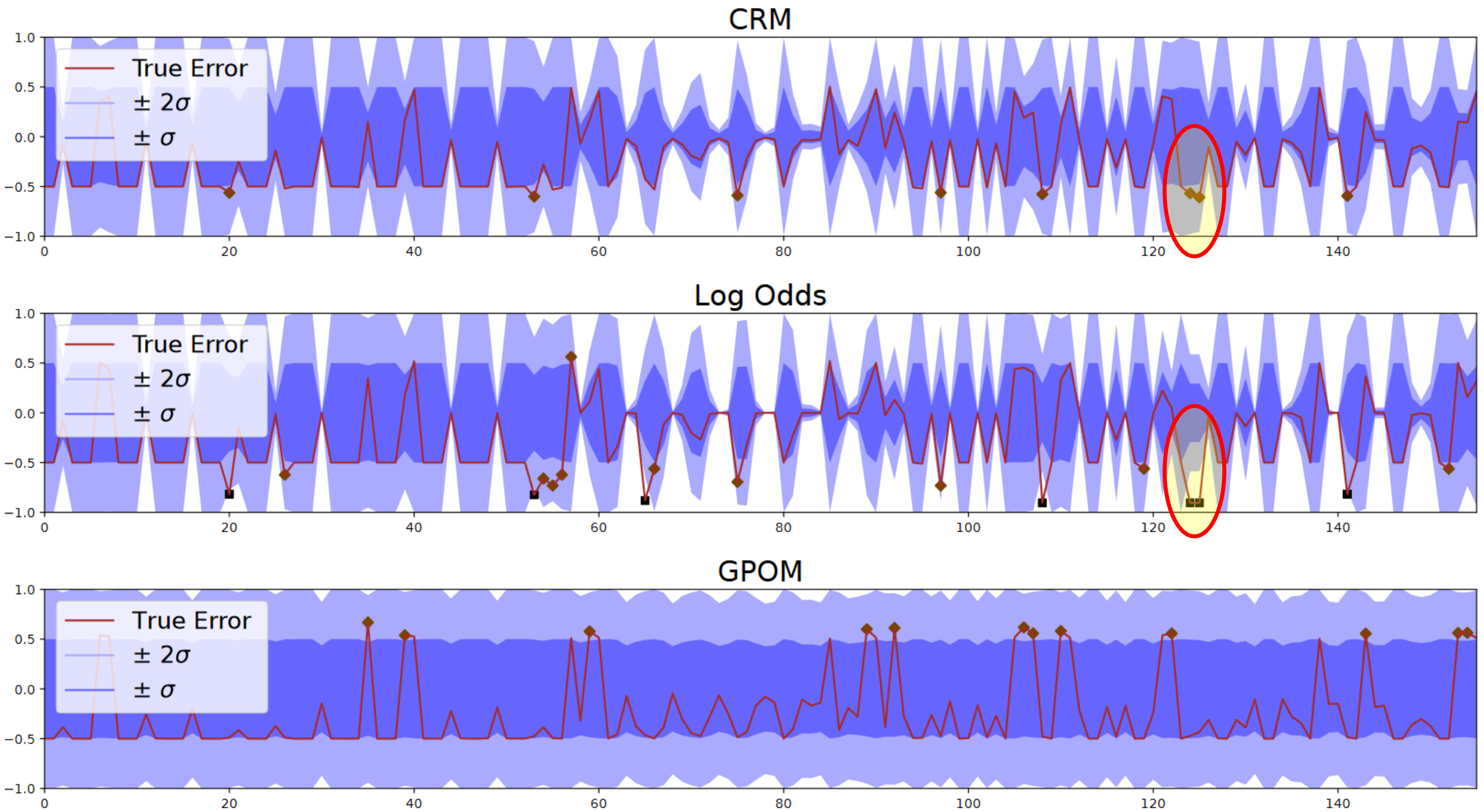
Estimated Occupancy *Inconsistency*

$$|e^i| > \sigma\left(b^{m^i}\right)$$

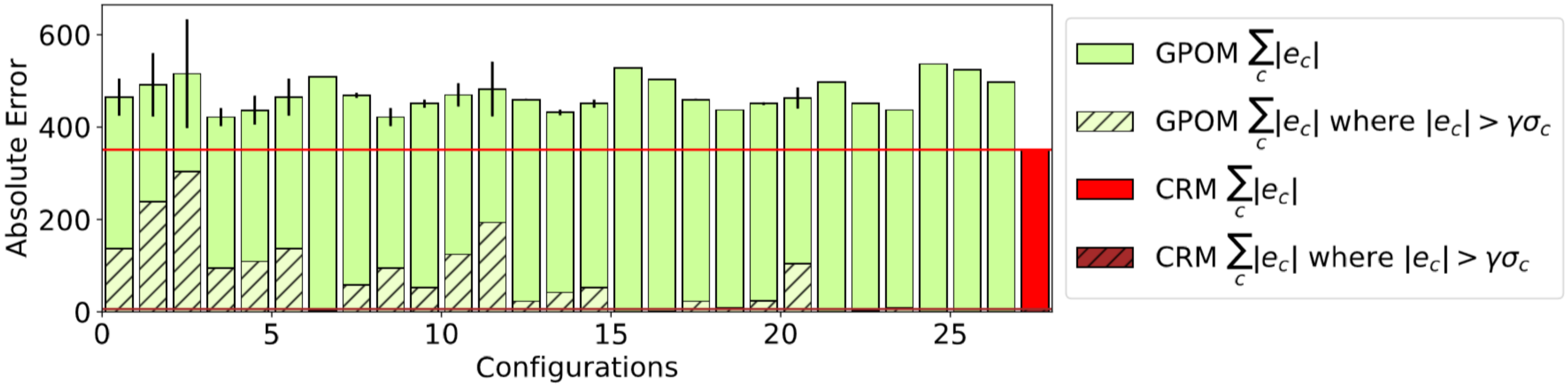


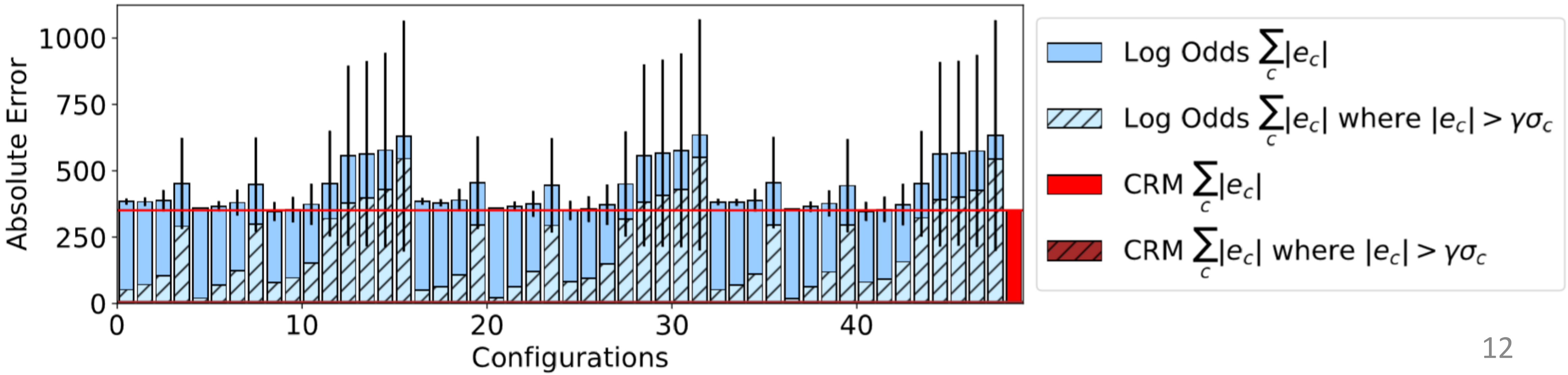


Inconsistencies

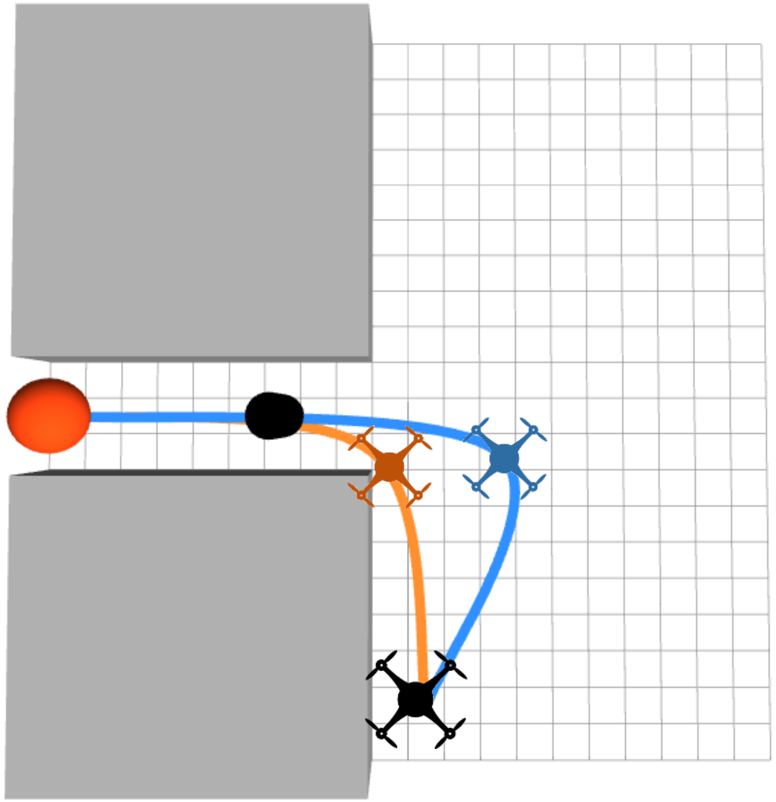


Mapping Error & Inconsistency





Planning in Confidence-rich Maps



Optimizing for ***Lower Confidence Bound (LCB)***

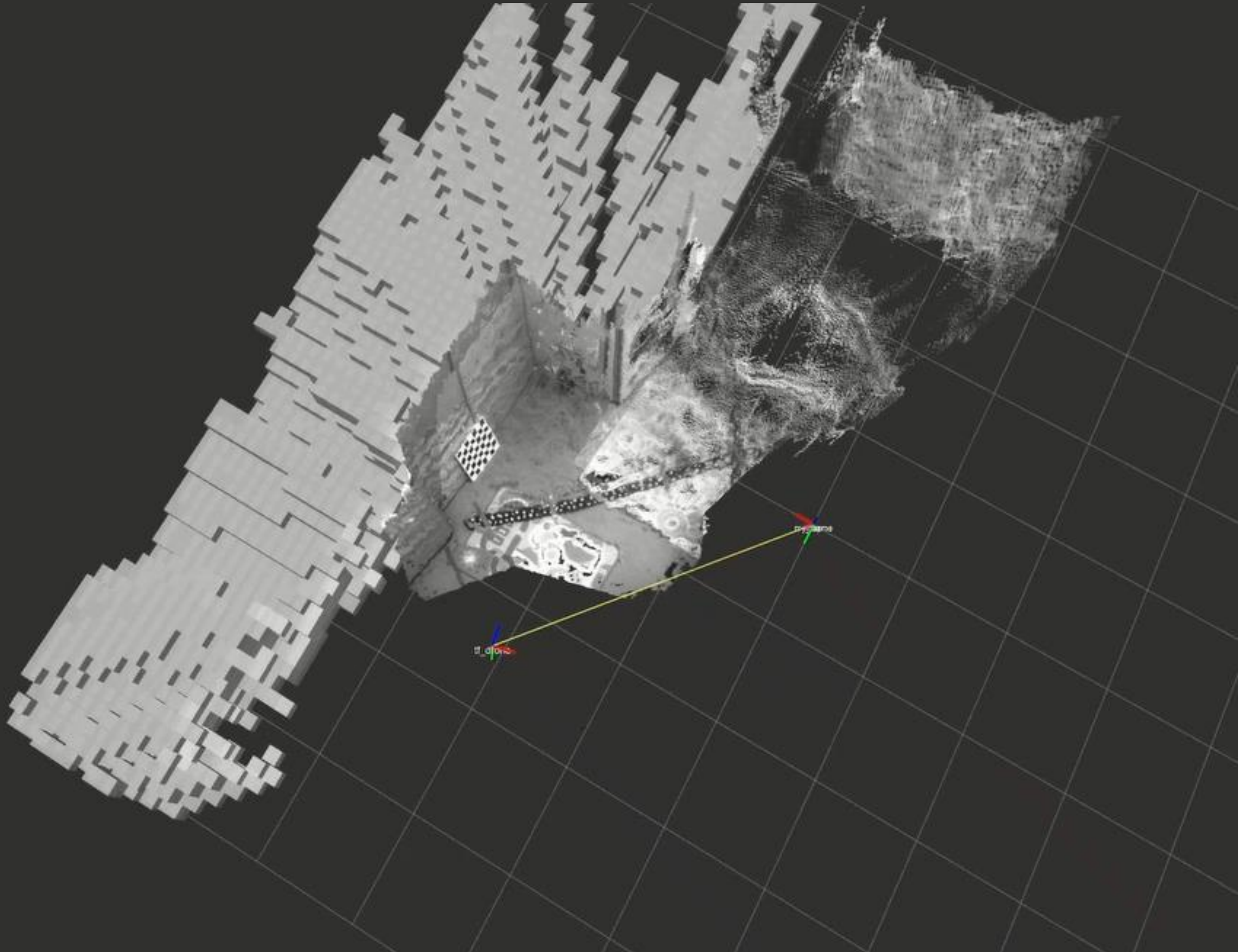
$$\mathrm{LCB} = \mathbb{E}[R(\mathbf{x})] - \kappa\sigma[R(\mathbf{x})]$$

Reduction in re-planning stops up to 70%

Speed-up in traversal time up to 34%

Heiden, E., Hausman, K., Sukhatme, G. S., Agha-mohammadi, A.
Planning High-speed Safe Trajectories in Confidence-rich Maps. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2017*.

EuRoC MAV Dataset



Confidence-rich Grid Mapping

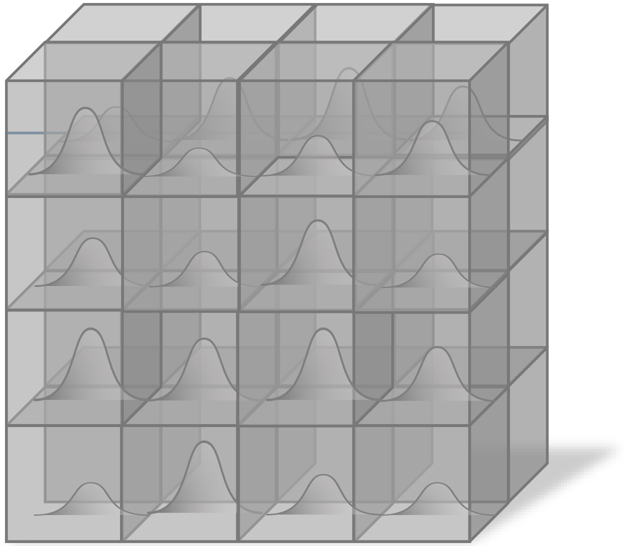
Ali-akbar Agha-mohammadi[1], Eric Heiden[2], Karol Hausman[2], Gaurav S. Sukhatme[2]

Novel grid mapping

- *Confidence* is encoded
- *Voxel dependence* is captured
- *No hand-engineering* of IMS

Consistent maps

- Variance *consistently* describes error
- Captures perceptual *surprises*
- Enables *fast and provably-safe planning*



ROBOTIC EMBEDDED SYSTEMS LABORATORY USC

JPL

[1] Jet Propulsion Laboratory, California Institute of Technology, Pasadena, USA

[2] University of Southern California, Los Angeles, USA

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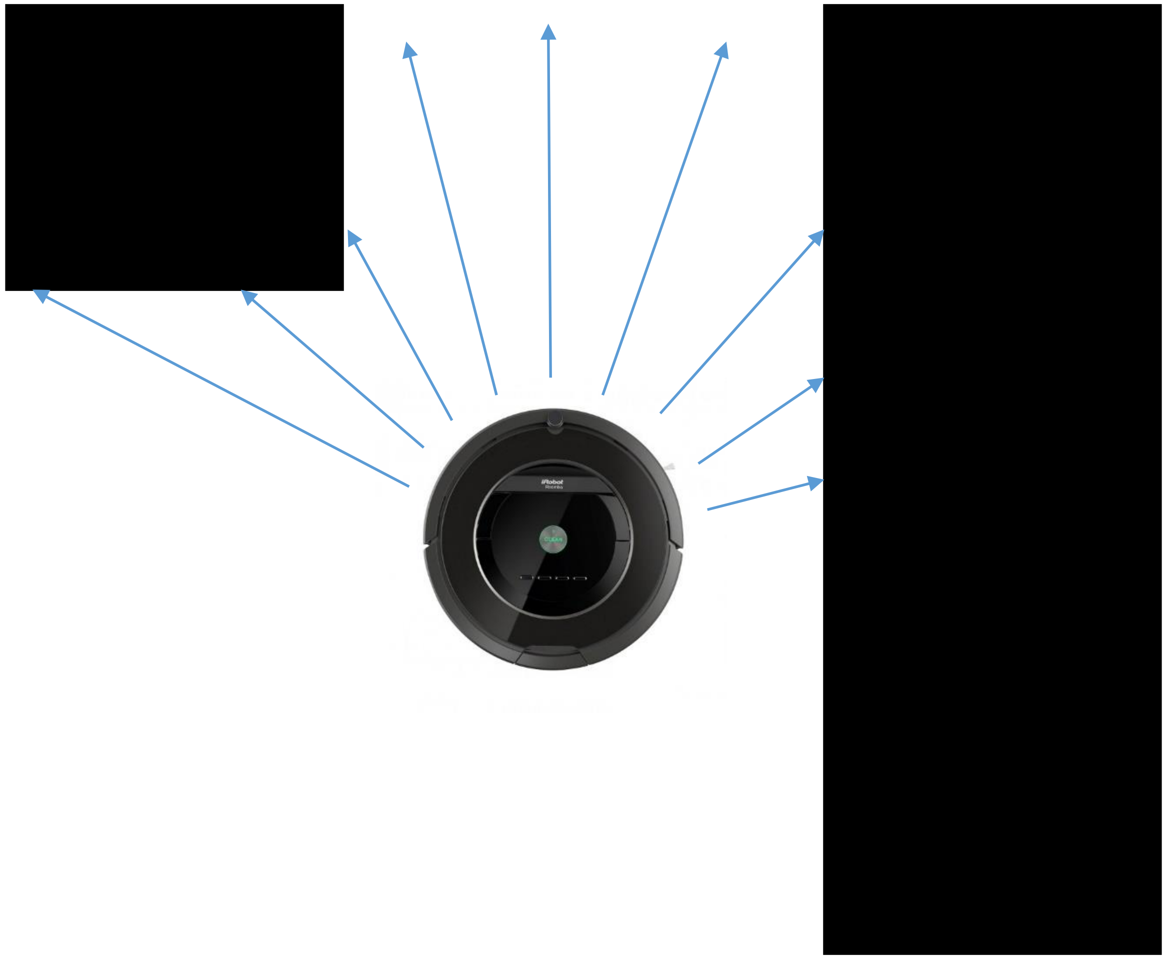
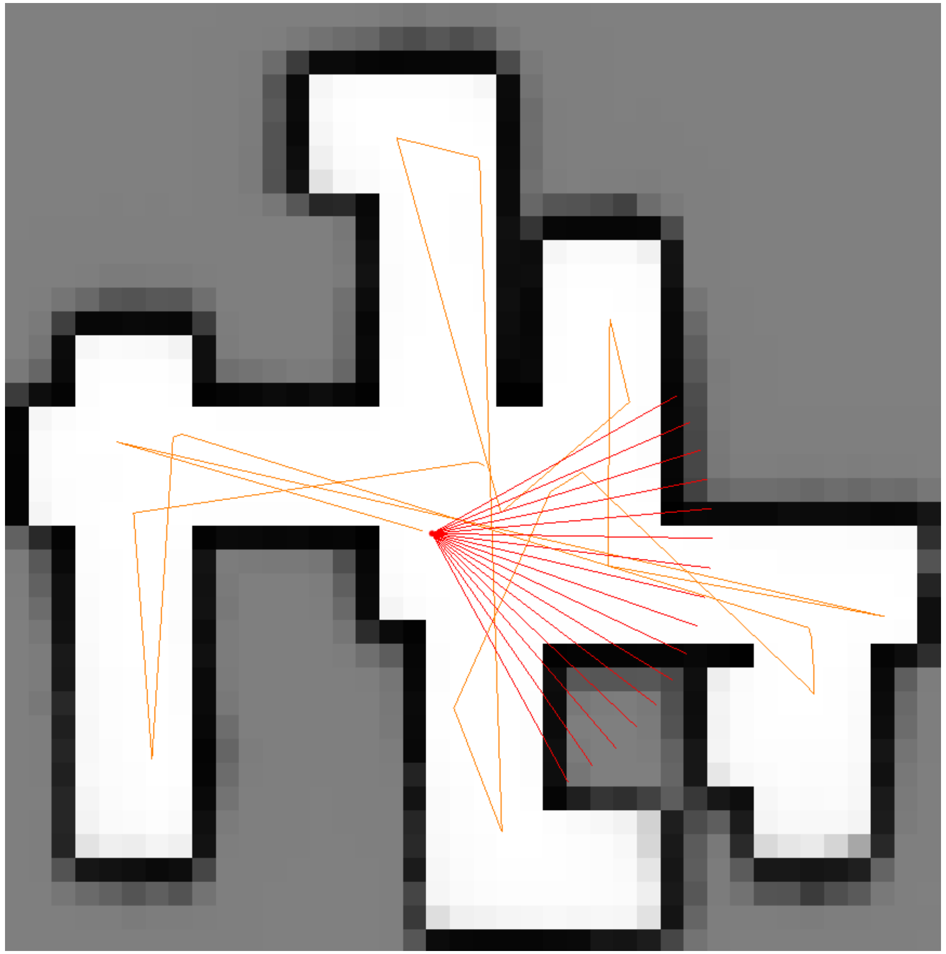
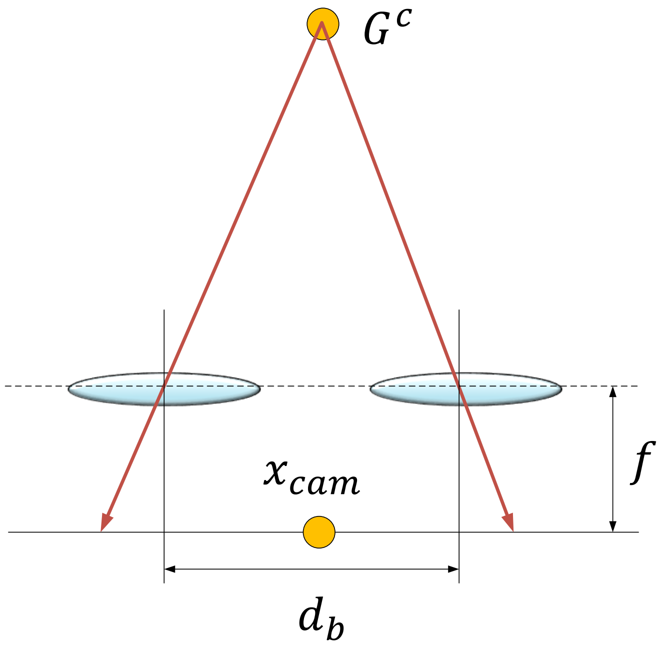
Occupancy Grid Mapping





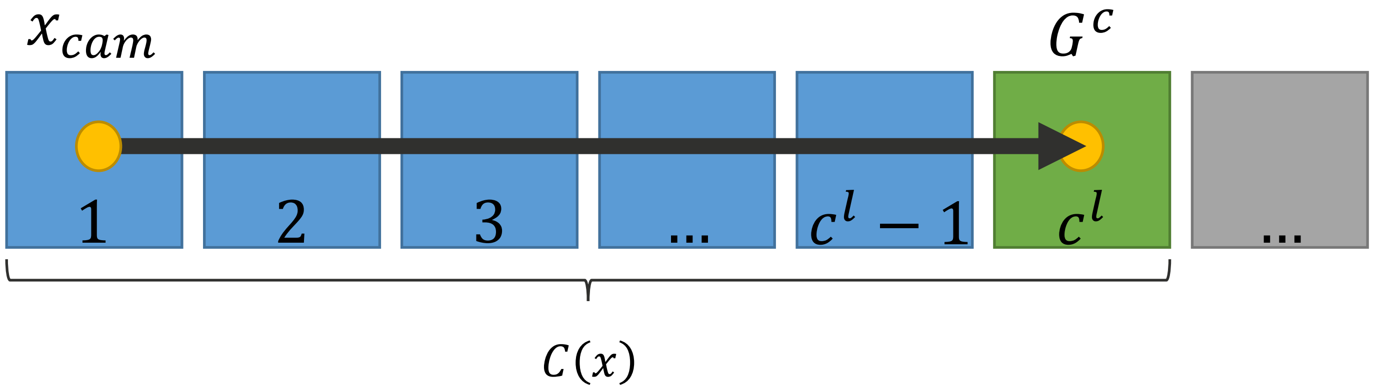
Confidence-rich Mapping



- **Observation model** for stereo camera

$$p(z|x, b^m) = \sum_{c \in C(x)} p(z|x, c, b^m) p(c|b^m)$$

$$= \sum_{c \in C(x)} \mathcal{N}\left(\frac{f \cdot d_b}{||G^c - x_{cam}||}, V\right) \hat{m}^c \prod_{l=1}^{c^l - 1} \left(1 - \hat{m}^{g(l,x)}\right)$$



Confidence-rich Mapping

Belief of voxel i at step k

$$b_k^{m^i} = p\left(m^i \middle| z_{0:k}, x_{0:k}\right) = \sum_{c_k \in \mathbb{C}(x)} p\left(m^i | c_k, z_{0:k}, x_{0:k}\right) p(c_k | z_{0:k}, x_{0:k})$$

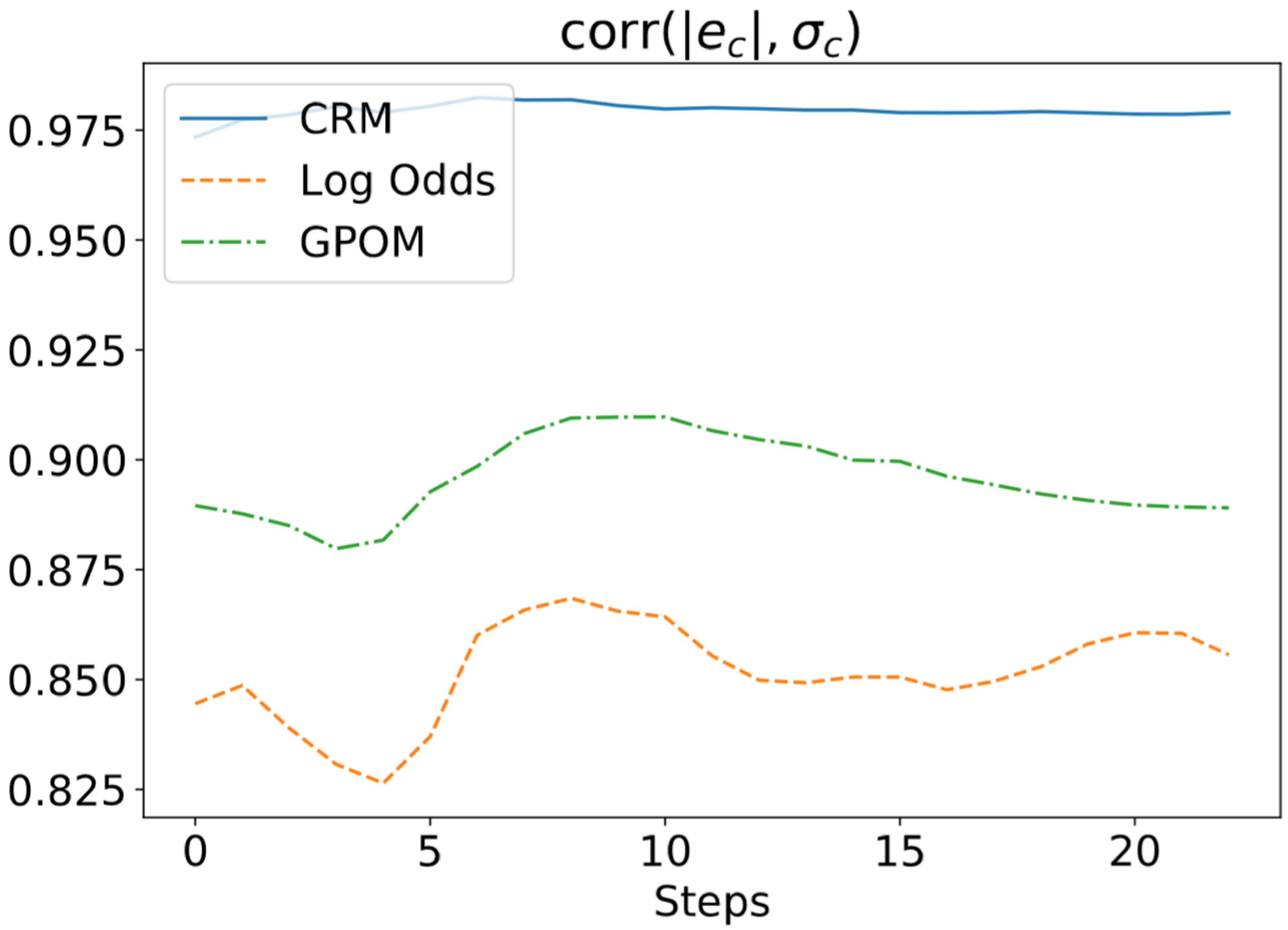
Applying Bayes' rule to $p\left(m^i | c_k, z_{0:k}, x_{0:k}\right) = p\left(m^i | c_k, z_{0:k-1}, x_{0:k}\right)$*:*

$$b_k^{m^i} = \sum_{c_k \in \mathbb{C}(x)} \frac{p\left(c_k \middle| m^i, z_{0:k-1}, x_{0:k}\right)}{p(c_k | z_{0:k-1}, x_{0:k})} b_{k-1}^{m^i}\, p(c_k | z_{0:k}, x_{0:k})$$

Reusing map belief b_{k-1}^m *as sufficient statistic for* $(z_{0:k-1}, x_{0:k-1})$*:*

$$b_k^{m^i} = \sum_{c_k \in \mathbb{C}(x)} \frac{p\left(c_k \middle| m^i, b_{k-1}^m, x_k\right)}{p(c_k | b_{k-1}^m, x_k)} b_{k-1}^{m^i}\, p(c_k | b_{k-1}^m, z_k, x_k)$$

Estimated Confidence vs. True Error



Why Bernoulli-variance is not sufficient?

- Kalman Filter filter update: mean(z_pred) – MLE(z) innovation update:

This difference evaporates over time (the most likely prediction is assumed to be true, so this difference already goes to zero)

The single-parameter Bernoulli distribution does not allow to capture the second moment in order to maintain the variance of measurements in the occupancies.