Experience-Based Prediction of Unknown Environments for Enhanced Belief Space Planning

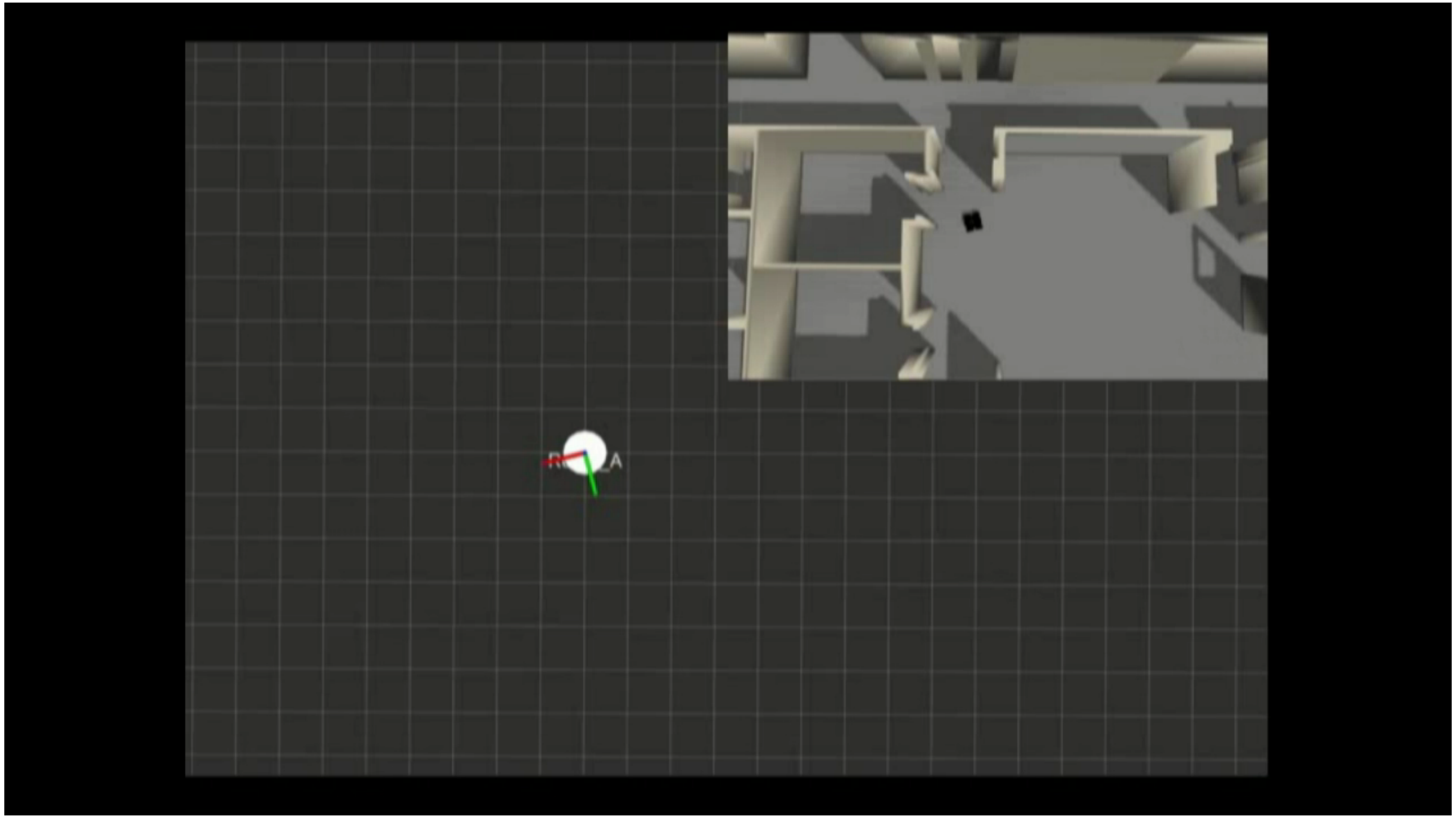
OMRI ASRAF

UNDER THE SUPERVISION OF ASST. PROF. VADIM INDELMAN

DEPARTMENT OF AEROSPACE ENGINEERING | TECHNION Israel Institute of Technology

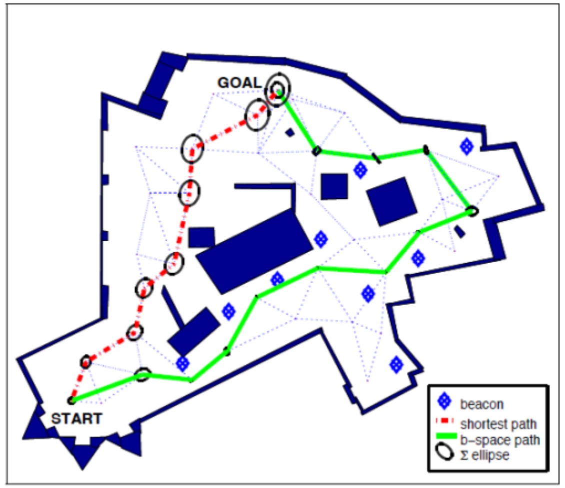
ANPL | Autonomous Navigation and Perception Lab

Introduction – SLAM



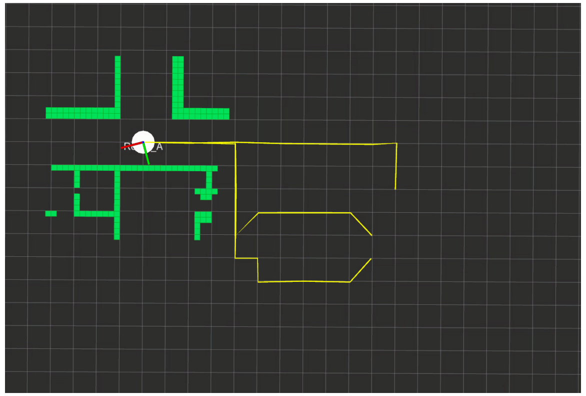
Introduction – Decision Making

- Belief Space Planning (BSP)



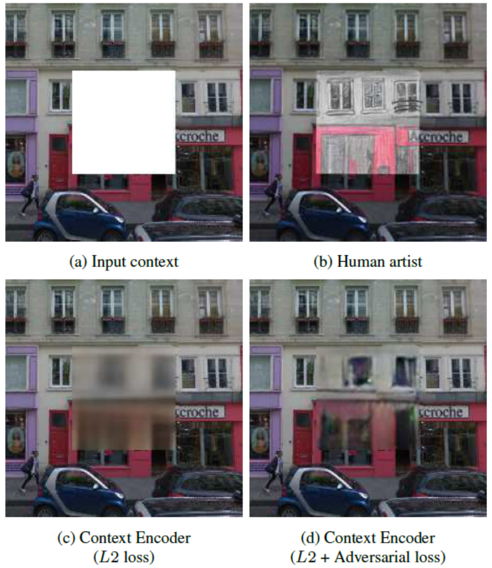
S. Prentice et al., IJRR 2009

- Planning in Unknown Environments



Introduction – Inpainting

- Image completion task
- Addressed by DL based generative models:
  - Variational Autoencoders (VAE)
  - Generative Adversarial Network (GAN)

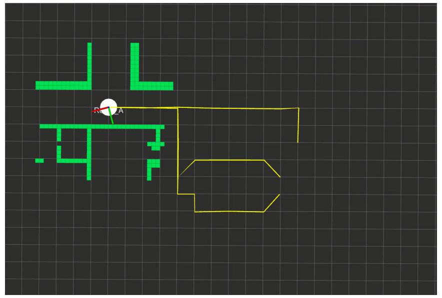


(a) Input context (b) Human artist

(c) Context Encoder ($L2$ loss) (d) Context Encoder ($L2$ + Adversarial loss)

D. Pathak et al., CVPR 2016

- Extended map task



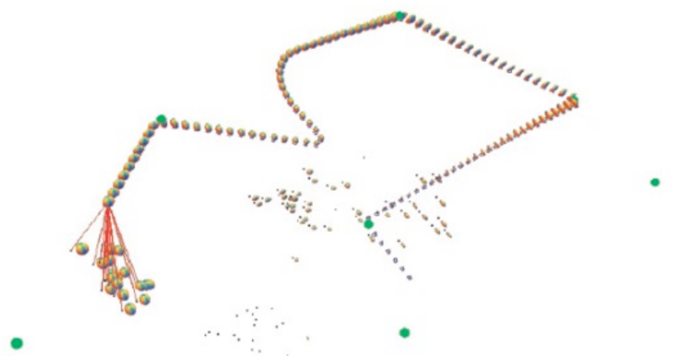
Related Works

- Belief Space Planning in unknown environments

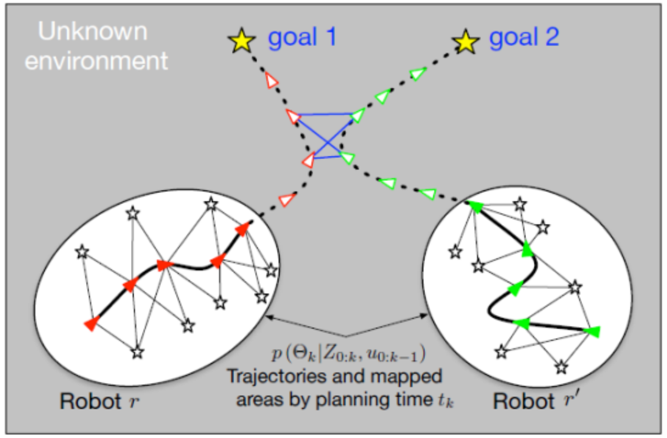
A. Kim et al.: “Active visual SLAM for robotic area coverage: Theory and experiment”, IJRR 2015.

V. Indelman et al.: “Planning in the continuous domain: A generalized belief space approach for autonomous navigation in unknown environments”, IJRR 2015.

V. Indelman: “Cooperative multi-robot belief space planning for autonomous navigation in unknown environments”, ARJ 2017.



V. Indelman et al., IJRR 2015



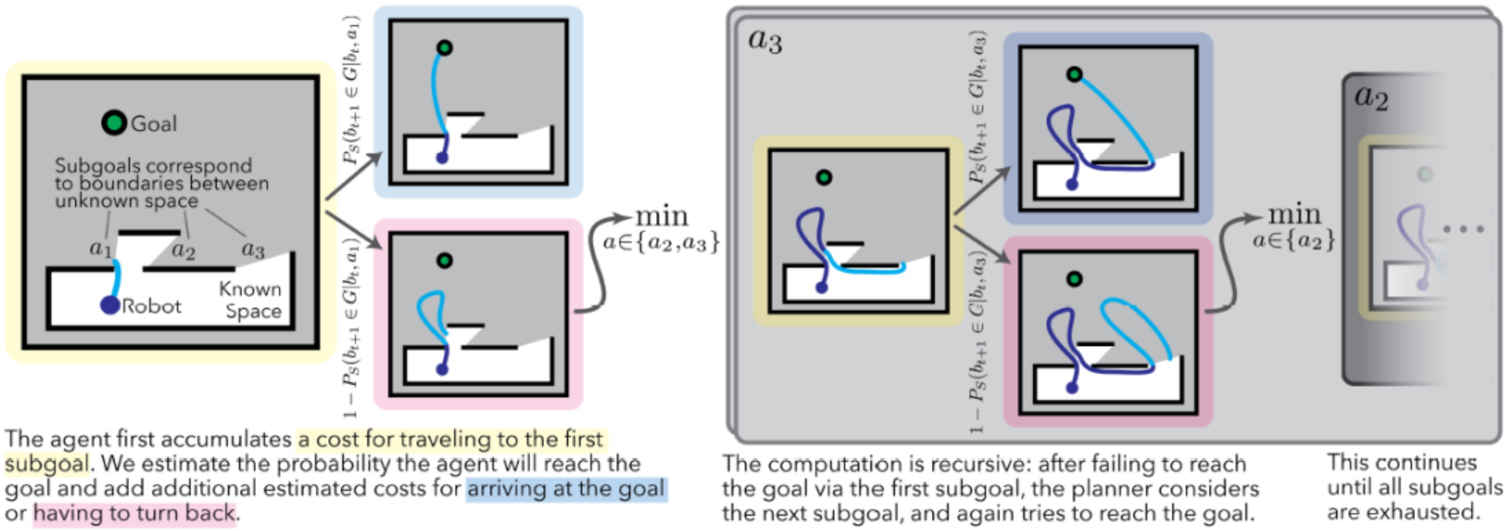
V. Indelman, ARJ 2017

Related Works

- Reinforcement Learning (RL) in POMDP setting

P. Karkus et al.: “Qmdp-net: Deep learning for planning under partial observability”, NIPS 2017.

G. J. Stein et al.: “Learning over subgoals for efficient navigation of structured, unknown environments”, CORL 2018.



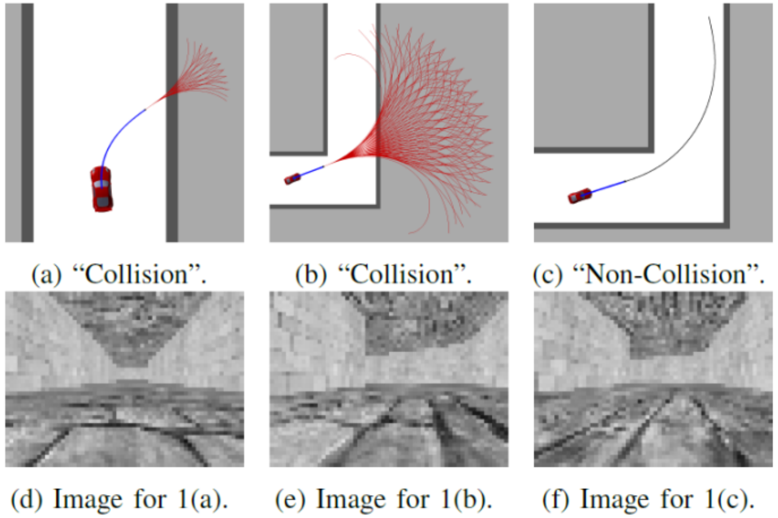
G.J.Stein et al., CORL 2018

Related Works

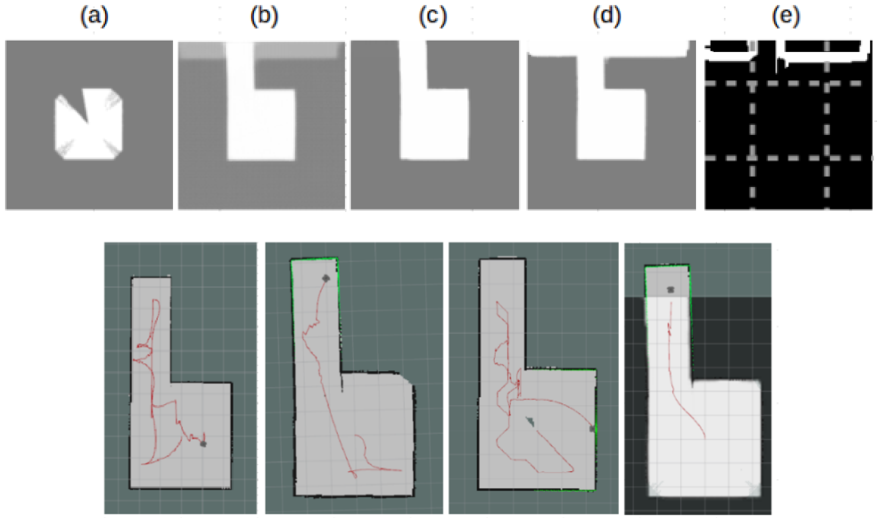
- Experience for Planning in unknown environment

C. Richter and N. Roy: “Safe visual navigation via deep learning and novelty detection”, RSS 2017.

K. Katyal et al.: “Uncertainty-aware occupancy map prediction using generative networks for robot navigation”, ICRA 2019.



C. Richter et al., RSS 2017



K. Katyal et al., ICRA 2019

Problem Statement

- Current BSP methods lack the information necessary to predict future measurements in unknown environments.

- Contributions:

I. predict distribution over an unexplored area for future measurements generation

II. incorporate experience-based prediction within BSP. In particular, with information-theoretic costs.

Problem Formulation - SLAM

- Motion model

$$x_i = f(x_{i-1}, a_{i-1}) + w_i, \qquad w_i \sim \mathcal{N}(0, \Sigma_w)$$

- Observation model of a raw measurement

$$y_i = g(x_i, m_i) + u_i, \qquad u_i \sim \mathcal{N}(0, \Sigma_u)$$

- Observation model of a relative-pose measurement

$$y_{ij}^{rel}(y_i, y_j) = h(x_i, x_j) + v_{ij}, \quad v_{ij} \sim \mathcal{N}(0, \Sigma_v(y_i, y_j))$$

Notations:

x_i - robot state at time i

a_i - action at time i

m_i- environment state(map/landmarks)

y_i - raw measurement at time i

y_{ij}^{rel} - relative pose measurement

Problem Formulation - SLAM

- Robot's state belief

$$b_k \doteq \mathbb{P}(x_{1:k}|y_{1:k}, a_{0:k-1})$$

- Map belief

$$\mathbb{P}(M_k|y_{1:k}, a_{0:k-1})$$

Notations:

$x_{1:k}$ - robot states until current time

M_k - the map observed up to time k

$y_{1:k}$ - measurements up to time k

$a_{0:k-1}$ - actions up to time k

Problem Formulation - BSP

- Future belief

$$b_{k+l} \doteq \mathbb{P}(x_{1:k+l} \mid H_k, a_{k:k+l-1}, y_{k+1:k+l})$$

- Objective function

$$J(b_k, a_{k:k+L-1}) = \sum_{l=1}^{L} \underset{y_{k+1:k+l}}{\mathbb{E}} \{c(b_{k+l}, a_{k+l-1})\}$$

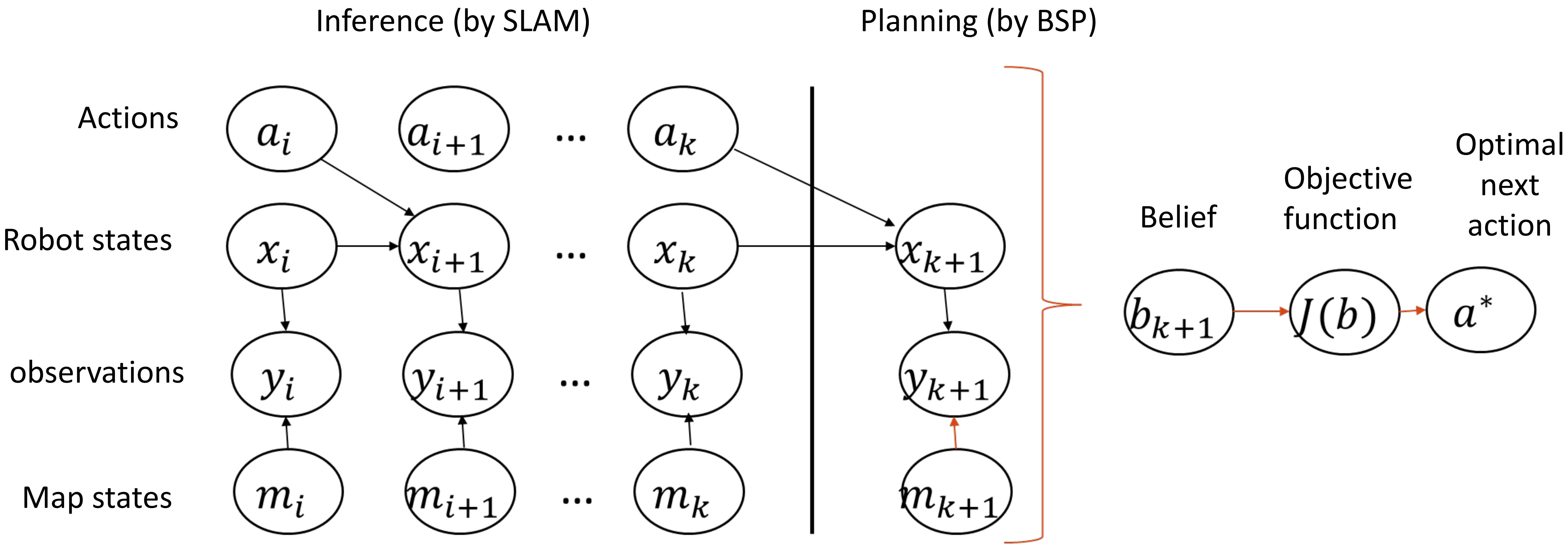
- Optimal action

$$a^*_{k:k+L-1} = \arg \min_{a_{k:k+L-1}} J(b_k, a_{k:k+L-1})$$

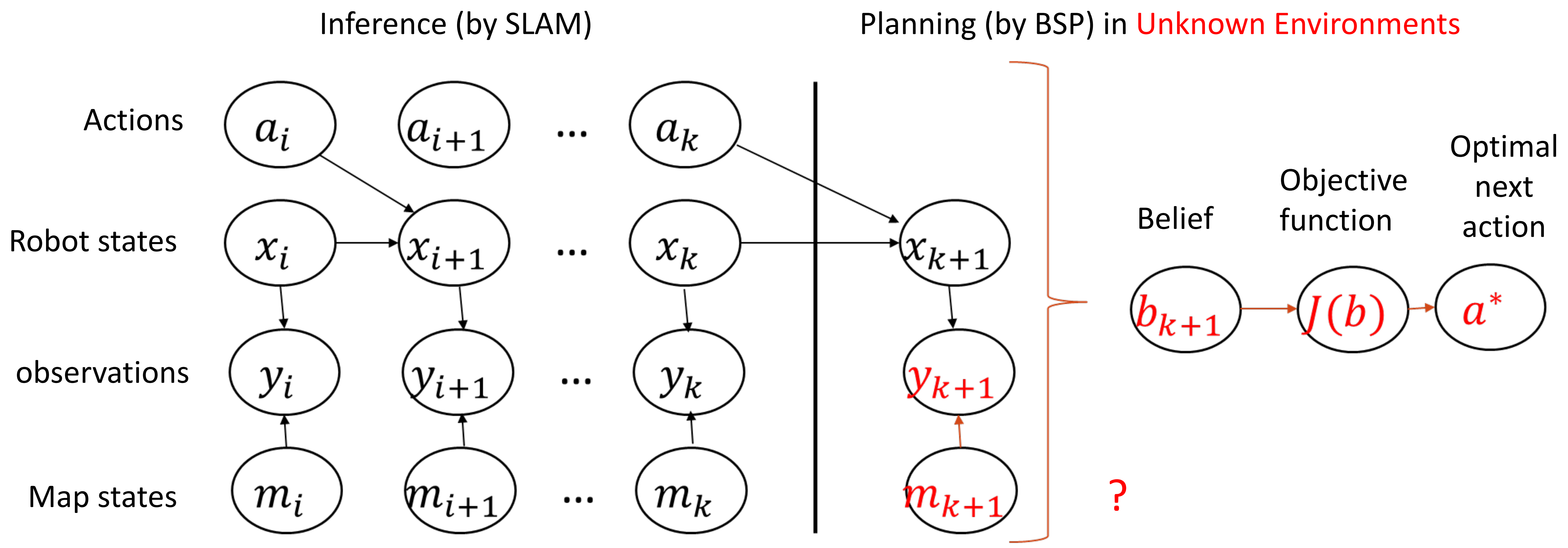
Notations:

$x_{1:k}$ - robot states until current time
M_k - the map observed up to time k
$y_{1:k}$ - measurements up to time k
$a_{0:k-1}$ - actions up to time k
$H_k = \{y_{1:k}, a_{0:k-1}\}$ - history

Problem Formulation



Problem Formulation



Approach

- Incorporation of experience D within BSP objective function

$$J(b_k, a_k) = \int \mathbb{P}(y_{k+1}|H_k, a_k, D)c(b_{k+1}, a_k)dy_{k+1}$$

- Future measurement generated given a map distribution

$$\mathbb{P}(y_{k+1}|H_k, a_k, D) \approx \int_{m_{k+1}} \underbrace{\mathbb{P}(y_{k+1}|\hat{x}^-_{k+1}, m_{k+1})}_{\text{Observation model}} \underbrace{\mathbb{P}(m_{k+1}|H^-_{k+1}, D)}_{?} dm_{k+1}$$

Notations:

$x_{1:k}$ - robot states until current time
M_k - the map observed up to time k
$m_i \subseteq M_i$ - sub map around x_i
$y_{1:k}$ - measurements up to time k
$a_{0:k-1}$ - actions up to time k
$H_k = \{y_{1:k}, a_{0:k-1}\}$ – history
D - experience

Approach

- Future measurement generated given a map distribution

$$\mathbb{P}(y_{k+1}|H_k, a_k, D) \approx \int_{m_{k+1}} \underbrace{\mathbb{P}(y_{k+1}|\hat{x}^-_{k+1}, m_{k+1})}_{\text{Observation model}} \underbrace{\mathbb{P}(m_{k+1}|H^-_{k+1}, D)}_{?} dm_{k+1}$$

- Experience-based prediction of map distribution

$$\mathbb{P}(m_{k+1}|H_k, a_k, D) \approx \mathbb{P}(m_{k+1}|\hat{M}_k, a_k, D)$$

$$\approx \mathbb{P}(m_{k+1} \mid \hat{m}_k, a_k, D)$$

Notations:

$x_{1:k}$ - robot states until current time
M_k - the map observed up to time k
$m_i \subseteq M_i$ - sub map around x_i
$y_{1:k}$ - measurements up to time k
$a_{0:k-1}$ - actions up to time k
$H_k = \{y_{1:k}, a_{0:k-1}\}$ – history
D - experience

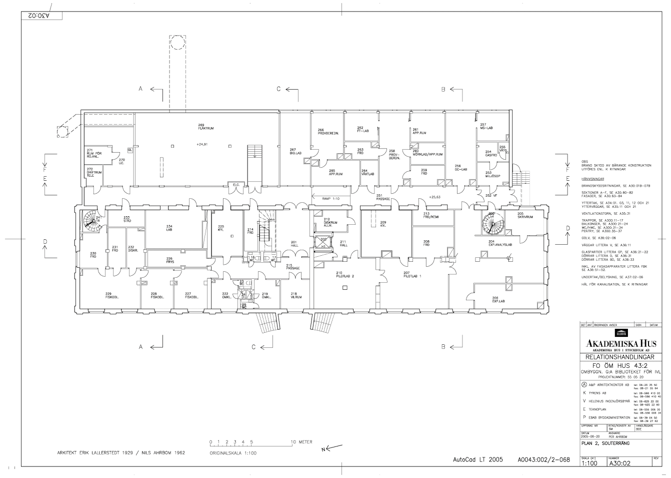
Approach – Map Prediction

- Purpose – learn the future map distribution offline

$$\mathbb{P}(m'|m, a)$$

- Data Set - floor plans (KTH)

$$D \doteq \{(m, a, m')\}$$



m a m'

1m Left

Approach – Map Prediction

- CVAE architecture
- Encoder

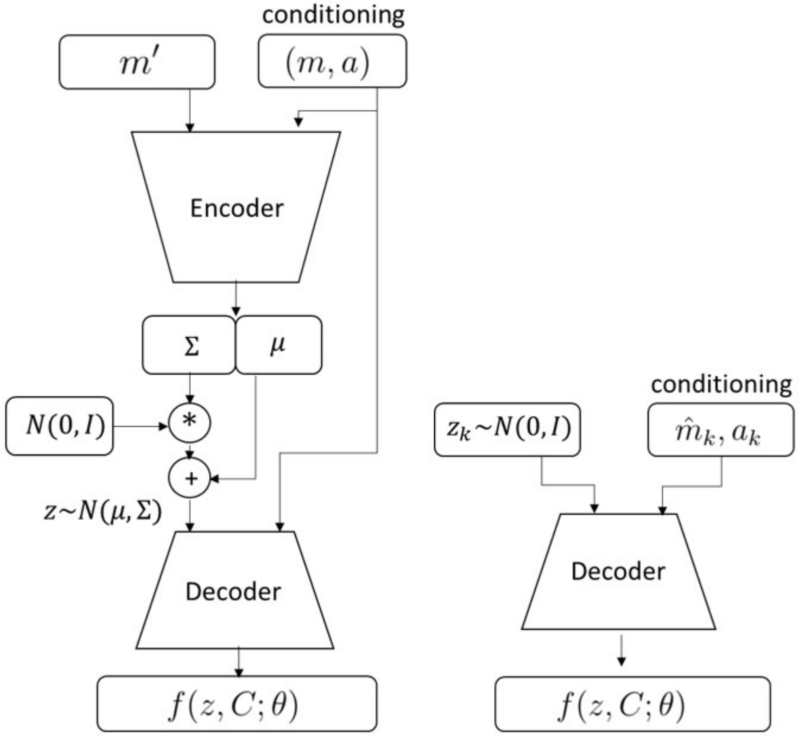
$$\mathbb{Q}(z \mid m', C; \phi) = \mathcal{N}(\mu(m', C; \phi), \Sigma(m', C; \phi))$$

- Decoder

$$\mathbb{P}(m' | z, C; \theta) = \mathcal{N}(f(z, C; \theta), \sigma^2 * I)$$

- Loss function

$$\|m' - f(z, C; \theta)\|^2 + \mathrm{KL}[\mathcal{N}(\mu(m', C; \phi), \Sigma(m', C; \phi)) \,||\, \mathcal{N}(0, I)]$$



(a) CVAE Training (b) Deployment

Approach (Reminder)

- Incorporation of experience D within BSP objective function

$$J(b_k, a_k) = \int \mathbb{P}(y_{k+1}|H_k, a_k, D)c(b_{k+1}, a_k)dy_{k+1}$$

- Future measurement generated given a map distribution

$$\mathbb{P}(y_{k+1}|H_k, a_k, D) \approx \int_{m_{k+1}} \mathbb{P}(y_{k+1}|\hat{x}^-_{k+1}, m_{k+1})\mathbb{P}(m_{k+1}|H^-_{k+1}, D)dm_{k+1}$$

- Experience-based prediction of map distribution

$$\mathbb{P}(m_{k+1}|H_k, a_k, D) \approx \mathbb{P}(m_{k+1}|\hat{M}_k, a_k, D)$$

$$\approx \mathbb{P}(m_{k+1} \mid \hat{m}_k, a_k, D)$$

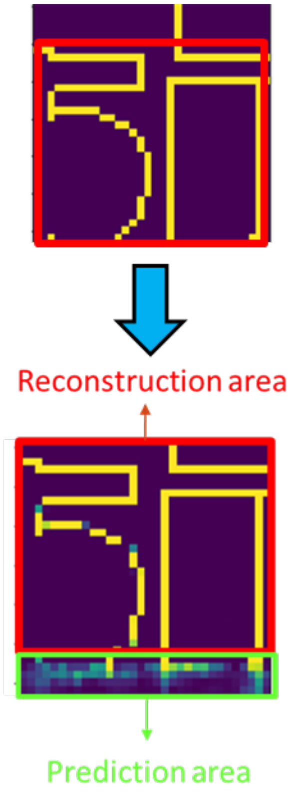
Notations:

$x_{1:k}$ - robot states until current time
M_k - the map observed up to time k
$m_i \subseteq M_i$ - sub map around x_i
$y_{1:k}$ - measurements up to time k
$a_{0:k-1}$ - actions up to time k
$H_k = \{y_{1:k}, a_{0:k-1}\}$ – history
D - experience

Approach – Novelty detection

- Is the experience relevant and reliable for the current task?
- In our method we measure the reconstruction error (RE) in the copy operation of the overlap area (OA) between the conditional input and the map prediction:

$$RE(m_k) = \|\{m_k\}^{OA} - \{f(z, m_k, a_k; \theta^*)\}^{OA}\|^2$$



- If $RE(m_k) > \text{threshold}$, a standard BSP method will be used instead.

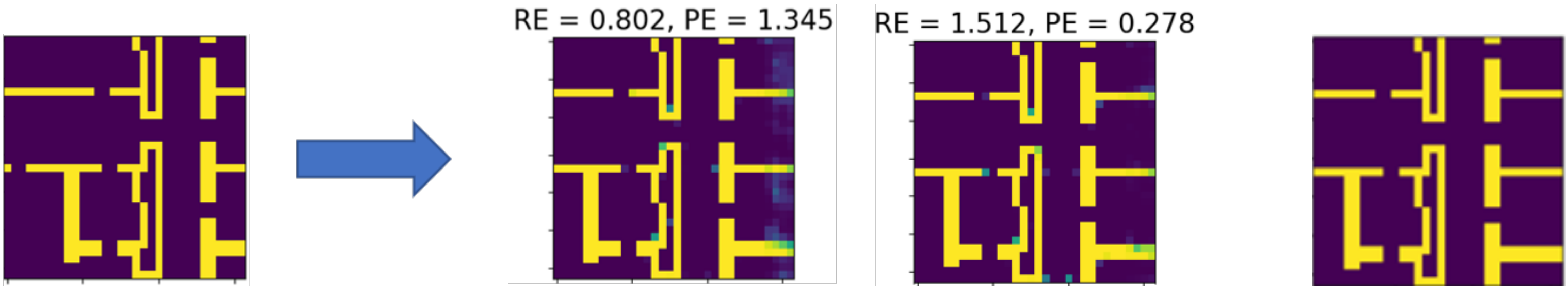
Results – Map Prediction

- Example 1 - most predictions are correct (low prediction error (PE))

Conditioning

$m' \sim \mathbb{P}(m' | z, m, a; \theta)$

Map | Action | Worst sample | Best sample | Ground truth



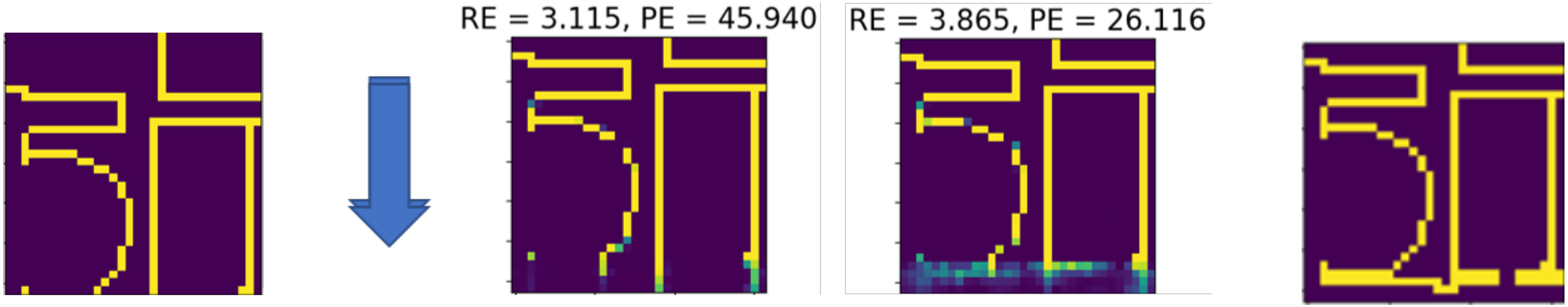
Results – Map Prediction

- Example 2 - most predictions are wrong because of an unfamiliar input (high PE and high RE).

Conditioning

$$m' \sim \mathbb{P}(m' | z, m, a; \theta)$$

Map | Action | Worst sample | Best sample | Ground truth



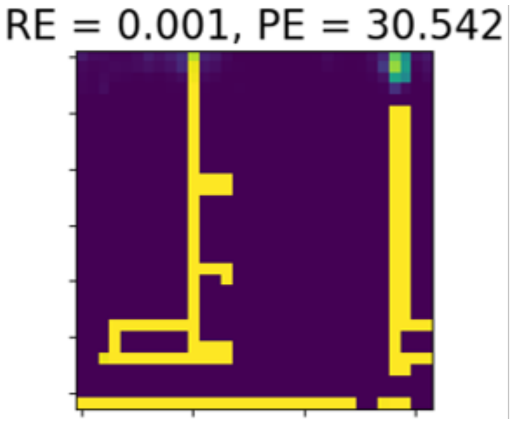
Results – Map Prediction

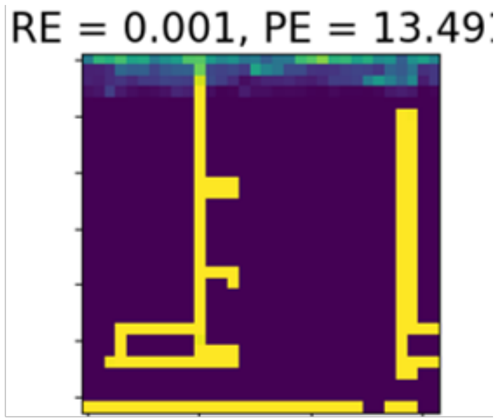
- Example 3 - most predictions are wrong because of uncommon ground truth map (high PE and low RE)

Conditioning

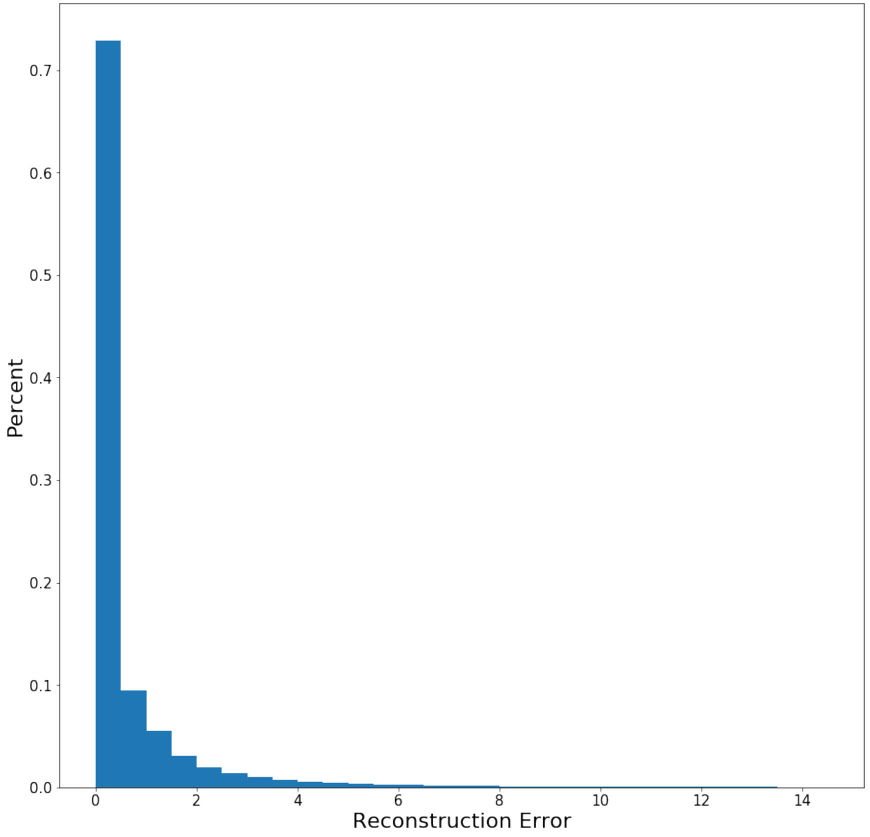
$$m' \sim \mathbb{P}(m' | z, m, a; \theta)$$

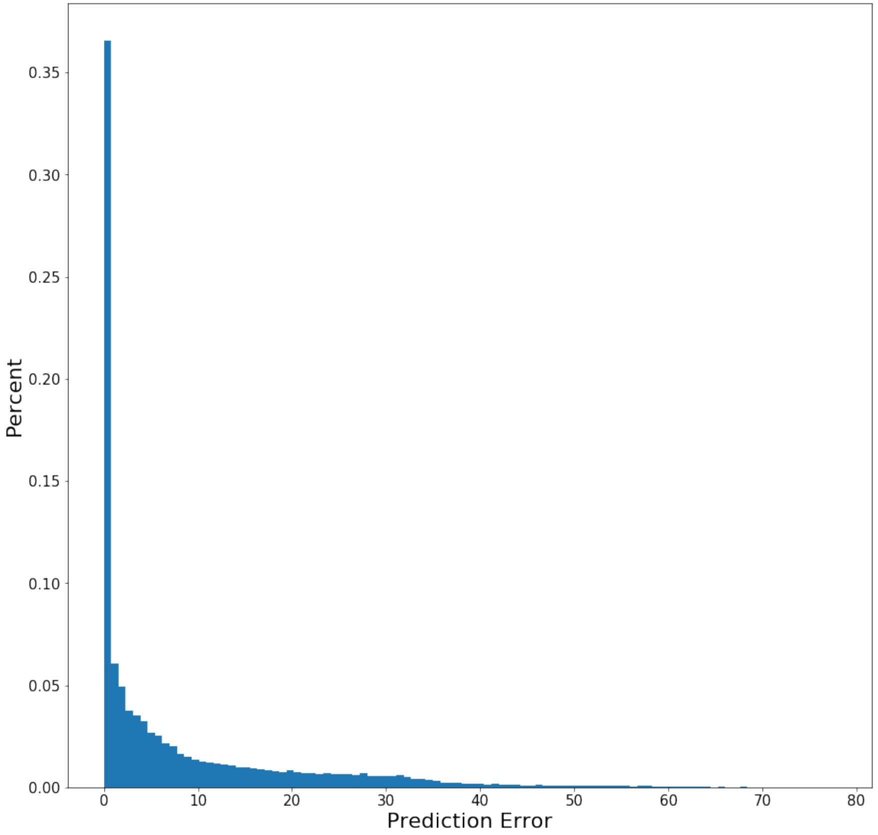
Map | Action | Worst sample | Best sample | Ground truth

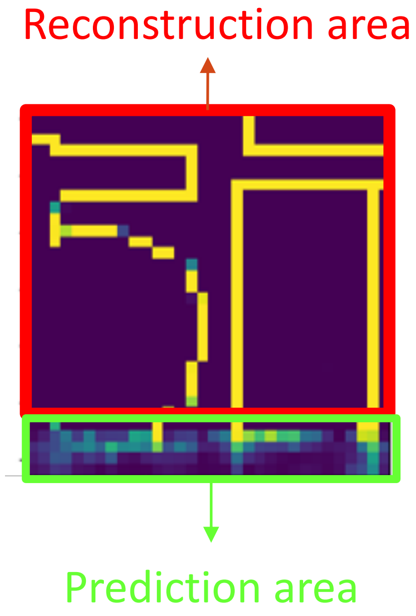




Results – Map Prediction







Reconstruction and prediction error of the test set

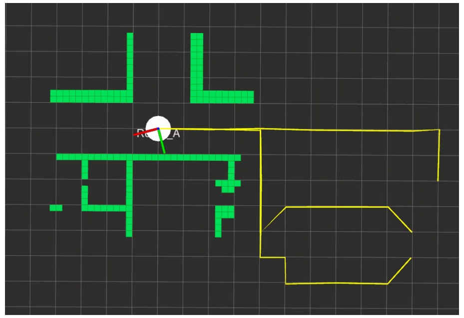
BSP with Experience-Based Prediction

Algorithm 1 BSP with Experience-Based Prediction

Inputs:
b_k: state belief at current time
$\mathbb{P}(M_k|H_k)$: map belief at current time
$a_{k:k+L-1}$: a candidate L look-ahead steps action sequence
$f(.;\theta^*)$: trained decoder
Outputs:
$J(b_k, a_{k:k+L-1})$: computed objective function for a given action sequence $a_{k:k+L-1}$

$\hat{M}_k \Leftarrow \mathbb{P}(M_k|H_k)$ ▷ Get maximum likelihood estimate of map belief
$\hat{m}_k \subseteq \hat{M}_k$ ▷ Get current sub-map estimate from $\hat{M}_k$
for $i = 1 : N$ **do**
  $m^i_k = \hat{m}_k$
  for $j = 1 : L$ **do**
    $\hat{x}^-_{k+j} \Leftarrow \mathbb{P}(x_{k+j}|H_k, a_{k:k+j-1})$ ▷ Get ML estimate without future observations
    $z^i \sim \mathcal{N}(0, I)$
    $m^i_{k+j} \sim \mathcal{N}(f(z^i, m^i_{k+j-1}, a_{k+j-1}; \theta^*), \sigma^2 * I)$ ▷ Predict sub-map (Eq. (29))
    $y^i_{k+j} \sim \mathbb{P}(y_{k+j} \mid m^i_{k+j}, \hat{x}^-_{k+j})$ ▷ Generate future observation (Eq. (18))
    Calculate b^i_{k+j} ▷ Calculate future belief using y^i_{k+j} (Eq. (9))
    Calculate cost/reward $c(b^i_{k+j})$
    $J(b_k, a_{k:k+L-1}) = J(b_k, a_{k:k+L-1}) + c(b^i_{k+j})$ ▷ Accumulate costs
  end for
end for
$J(b_k, a_{k:k+L-1}) = \frac{1}{N} J(b_k, a_{k:k+L-1})$ ▷ Normalize to get empirical expectation
return $J(b_k, a_{k:k+L-1})$

Inputs:
State belief
Map belief
Candidate action
Trained decoder



Output:
computed objective function

$$J(b_k, a_{k:k+L-1}) = \sum_{l=1}^{L} \mathop{\mathbb{E}}_{y_{k+1:k+l}} \{c(b_{k+l}, a_{k+l-1})\}$$

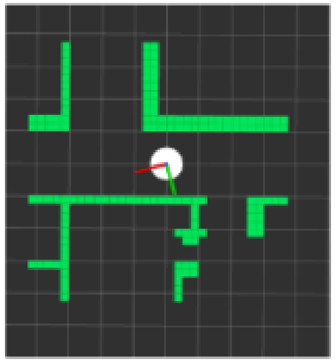
BSP with Experience-Based Prediction

Algorithm 1 BSP with Experience-Based Prediction

1: **Inputs:**
2: b_k: state belief at current time
3: $\mathbb{P}(M_k|H_k)$: map belief at current time
4: $a_{k:k+L-1}$: a candidate L look-ahead steps action sequence
5: $f(.;\theta^*)$: trained decoder
6: **Outputs:**
7: $J(b_k, a_{k:k+L-1})$: computed objective function for a given action sequence $a_{k:k+L-1}$
8:
9: $\hat{M}_k \Leftarrow \mathbb{P}(M_k|H_k)$ ▷ Get maximum likelihood estimate of map belief
10: $\hat{m}_k \subseteq \hat{M}_k$ ▷ Get current sub-map estimate from $\hat{M}_k$
11: **for** $i = 1 : N$ **do**
12: $\quad m_k^i = \hat{m}_k$
13: $\quad$ **for** $j = 1 : L$ **do**
14: $\quad\quad \hat{x}_{k+j}^- \Leftarrow \mathbb{P}(x_{k+j}|H_k, a_{k:k+j-1})$ ▷ Get ML estimate without future observations
15: $\quad\quad z^i \sim \mathcal{N}(0, I)$
16: $\quad\quad m_{k+j}^i \sim \mathcal{N}(f(z^i, m_{k+j-1}^i, a_{k+j-1}; \theta^*), \sigma^2 * I)$ ▷ Predict sub-map (Eq. (29))
17: $\quad\quad y_{k+j}^i \sim \mathbb{P}(y_{k+j} \mid m_{k+j}^i, \hat{x}_{k+j}^-)$ ▷ Generate future observation (Eq. (18))
18: $\quad\quad$ Calculate b_{k+j}^i ▷ Calculate future belief using y_{k+j}^i (Eq. (9))
19: $\quad\quad$ Calculate cost/reward $c(b_{k+j}^i)$
20: $\quad\quad J(b_k, a_{k:k+L-1}) = J(b_k, a_{k:k+L-1}) + c(b_{k+j}^i)$ ▷ Accumulate costs
21: $\quad$ **end for**
22: **end for**
23: $J(b_k, a_{k:k+L-1}) = \frac{1}{N} J(b_k, a_{k:k+L-1})$ ▷ Normalize to get empirical expectation
24: **return** $J(b_k, a_{k:k+L-1})$

Get current sub-map

9: $\hat{M}_k \Leftarrow \mathbb{P}(M_k|H_k)$
10: $\hat{m}_k \subseteq \hat{M}_k$



Double loop and initialization

11: **for** $i = 1 : N$ **do**
12: $\quad m_k^i = \hat{m}_k$
13: $\quad$ **for** $j = 1 : L$ **do**

BSP with Experience-Based Prediction

Algorithm 1 BSP with Experience-Based Prediction

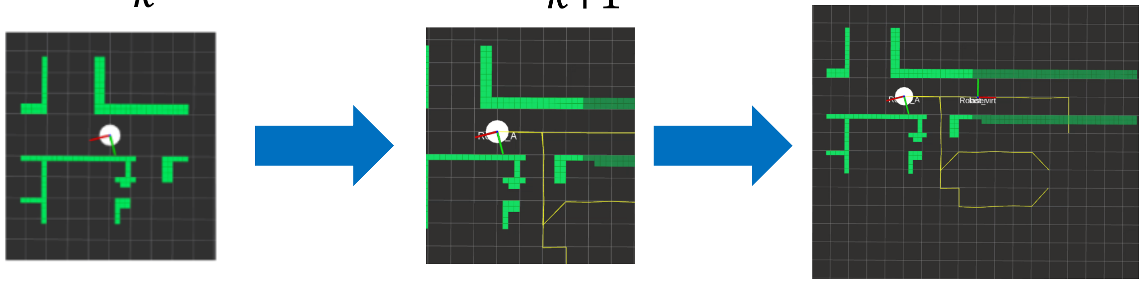
1: **Inputs:**
2: b_k: state belief at current time
3: $\mathbb{P}(M_k|H_k)$: map belief at current time
4: $a_{k:k+L-1}$: a candidate L look-ahead steps action sequence
5: $f(.;\theta^*)$: trained decoder
6: **Outputs:**
7: $J(b_k, a_{k:k+L-1})$: computed objective function for a given action sequence $a_{k:k+L-1}$
8:
9: $\hat{M}_k \Leftarrow \mathbb{P}(M_k|H_k)$ ▷ Get maximum likelihood estimate of map belief
10: $\hat{m}_k \subseteq \hat{M}_k$ ▷ Get current sub-map estimate from $\hat{M}_k$
11: **for** $i = 1 : N$ **do**
12: $\quad m^i_k = \hat{m}_k$
13: $\quad$ **for** $j = 1 : L$ **do**
14: $\quad\quad \hat{x}^-_{k+j} \Leftarrow \mathbb{P}(x_{k+j}|H_k, a_{k:k+j-1})$ ▷ Get ML estimate without future observations
15: $\quad\quad z^i \sim \mathcal{N}(0, I)$
16: $\quad\quad m^i_{k+j} \sim \mathcal{N}(f(z^i, m^i_{k+j-1}, a_{k+j-1}; \theta^*), \sigma^2 * I)$ ▷ Predict sub-map (Eq. (29))
17: $\quad\quad y^i_{k+j} \sim \mathbb{P}(y_{k+j} \mid m^i_{k+j}, \hat{x}^-_{k+j})$ ▷ Generate future observation (Eq. (18))
18: $\quad\quad$ Calculate b^i_{k+j} ▷ Calculate future belief using y^i_{k+j} (Eq. (9))
19: $\quad\quad$ Calculate cost/reward $c(b^i_{k+j})$
20: $\quad\quad J(b_k, a_{k:k+L-1}) = J(b_k, a_{k:k+L-1}) + c(b^i_{k+j})$ ▷ Accumulate costs
21: $\quad$ **end for**
22: **end for**
23: $J(b_k, a_{k:k+L-1}) = \frac{1}{N} J(b_k, a_{k:k+L-1})$ ▷ Normalize to get empirical expectation
24: **return** $J(b_k, a_{k:k+L-1})$

Prediction of next sub-map

15: $z^i \sim \mathcal{N}(0, I)$

16: $m^i_{k+j} \sim \mathcal{N}(f(z^i, m^i_{k+j-1}, a_{k+j-1}; \theta^*), \sigma^2 * I)$

m^i_k $\quad$ m^i_{k+1} $\quad$ $\{m^i_{k:k+L-1}\}$



Conditional map in light green, predicted map in dark green.

BSP with Experience-Based Prediction

Algorithm 1 BSP with Experience-Based Prediction

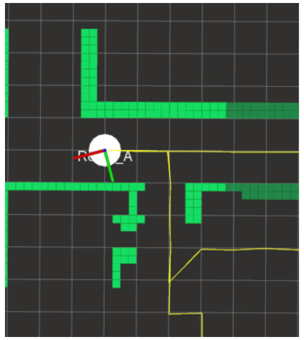
1: **Inputs:**
2: b_k: state belief at current time
3: $\mathbb{P}(M_k|H_k)$: map belief at current time
4: $a_{k:k+L-1}$: a candidate L look-ahead steps action sequence
5: $f(.;\theta^*)$: trained decoder
6: **Outputs:**
7: $J(b_k, a_{k:k+L-1})$: computed objective function for a given action sequence $a_{k:k+L-1}$
8:
9: $\hat{M}_k \Leftarrow \mathbb{P}(M_k|H_k)$ ▷ Get maximum likelihood estimate of map belief
10: $\hat{m}_k \subseteq \hat{M}_k$ ▷ Get current sub-map estimate from $\hat{M}_k$
11: **for** $i = 1 : N$ **do**
12: $\quad m_k^i = \hat{m}_k$
13: $\quad$ **for** $j = 1 : L$ **do**
14: $\quad\quad \hat{x}_{k+j}^- \Leftarrow \mathbb{P}(x_{k+j}|H_k, a_{k:k+j-1})$ ▷ Get ML estimate without future observations
15: $\quad\quad z^i \sim \mathcal{N}(0, I)$
16: $\quad\quad m_{k+j}^i \sim \mathcal{N}(f(z^i, m_{k+j-1}^i, a_{k+j-1}; \theta^*), \sigma^2 * I)$ ▷ Predict sub-map (Eq. (29))
17: $\quad\quad y_{k+j}^i \sim \mathbb{P}(y_{k+j} \mid m_{k+j}^i, \hat{x}_{k+j}^-)$ ▷ Generate future observation (Eq. (18))
18: $\quad\quad$ Calculate b_{k+j}^i ▷ Calculate future belief using y_{k+j}^i (Eq. (9))
19: $\quad\quad$ Calculate cost/reward $c(b_{k+j}^i)$
20: $\quad\quad J(b_k, a_{k:k+L-1}) = J(b_k, a_{k:k+L-1}) + c(b_{k+j}^i)$ ▷ Accumulate costs
21: $\quad$ **end for**
22: **end for**
23: $J(b_k, a_{k:k+L-1}) = \frac{1}{N} J(b_k, a_{k:k+L-1})$ ▷ Normalize to get empirical expectation
24: **return** $J(b_k, a_{k:k+L-1})$

Generation of future observation

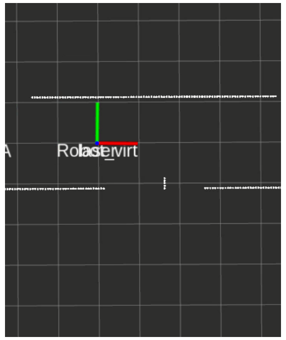
14: $\hat{x}_{k+j}^- \Leftarrow \mathbb{P}(x_{k+j}|H_k, a_{k:k+j-1})$

17: $y_{k+j}^i \sim \mathbb{P}(y_{k+j} \mid m_{k+j}^i, \hat{x}_{k+j}^-)$

m_{k+1}^i



y_{k+1}^i



BSP with Experience-Based Prediction

Algorithm 1 BSP with Experience-Based Prediction

Inputs:
b_k: state belief at current time
$\mathbb{P}(M_k|H_k)$: map belief at current time
$a_{k:k+L-1}$: a candidate L look-ahead steps action sequence
$f(.;\theta^*)$: trained decoder
Outputs:
$J(b_k, a_{k:k+L-1})$: computed objective function for a given action sequence $a_{k:k+L-1}$

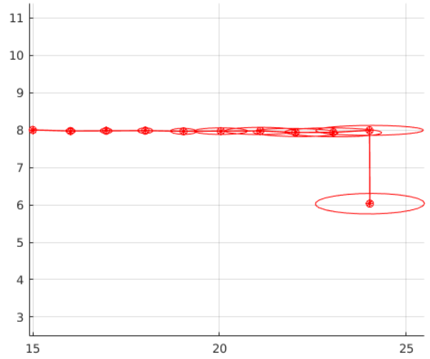
$\hat{M}_k \Leftarrow \mathbb{P}(M_k|H_k)$ ▷ Get maximum likelihood estimate of map belief
$\hat{m}_k \subseteq \hat{M}_k$ ▷ Get current sub-map estimate from $\hat{M}_k$
for $i = 1 : N$ **do**
    $m^i_k = \hat{m}_k$
    for $j = 1 : L$ **do**
        $\hat{x}^-_{k+j} \Leftarrow \mathbb{P}(x_{k+j}|H_k, a_{k:k+j-1})$ ▷ Get ML estimate without future observations
        $z^i \sim \mathcal{N}(0, I)$
        $m^i_{k+j} \sim \mathcal{N}(f(z^i, m^i_{k+j-1}, a_{k+j-1}; \theta^*), \sigma^2 * I)$ ▷ Predict sub-map (Eq. (29))
        $y^i_{k+j} \sim \mathbb{P}(y_{k+j} \mid m^i_{k+j}, \hat{x}^-_{k+j})$ ▷ Generate future observation (Eq. (18))
        Calculate b^i_{k+j} ▷ Calculate future belief using y^i_{k+j} (Eq. (9))
        Calculate cost/reward $c(b^i_{k+j})$
        $J(b_k, a_{k:k+L-1}) = J(b_k, a_{k:k+L-1}) + c(b^i_{k+j})$ ▷ Accumulate costs
    end for
end for
$J(b_k, a_{k:k+L-1}) = \frac{1}{N} J(b_k, a_{k:k+L-1})$ ▷ Normalize to get empirical expectation
return $J(b_k, a_{k:k+L-1})$

Calculation of future belief using the generated observation

$$b_{k+l} \doteq \mathbb{P}(x_{1:k+l} \mid H_k, a_{k:k+l-1}, y_{k+1:k+l})$$

Calculation of the cost function

$$c(b^i_{k+j}) = \sqrt{Trace(\Sigma_{k+L})}$$



BSP with Experience-Based Prediction

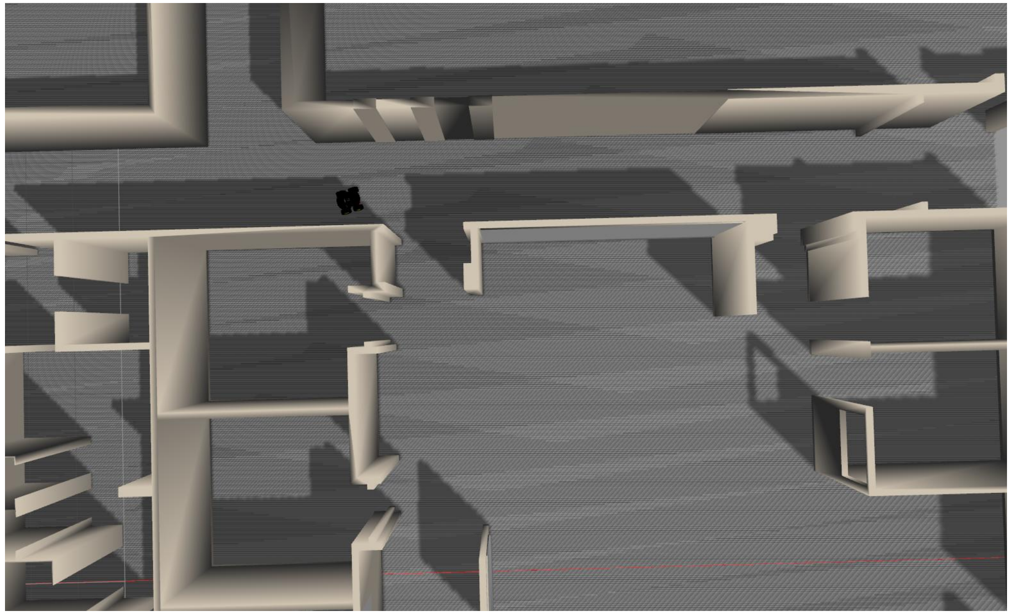
Algorithm 1 BSP with Experience-Based Prediction

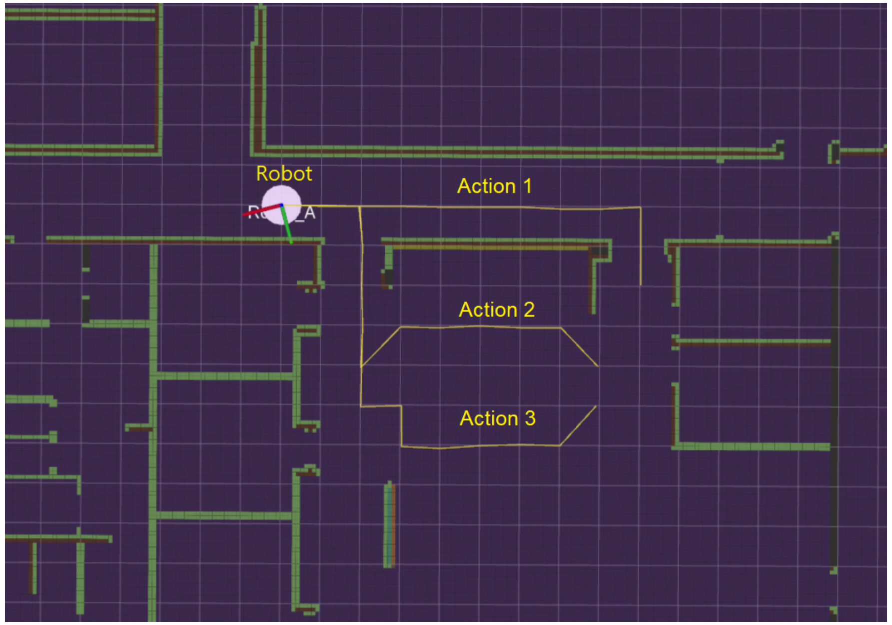
```
Inputs:
  b_k: state belief at current time
  P(M_k|H_k): map belief at current time
  a_{k:k+L-1}: a candidate L look-ahead steps action sequence
  f(.; θ*): trained decoder
Outputs:
  J(b_k, a_{k:k+L-1}): computed objective function for a given action sequence a_{k:k+L-1}

M̂_k ⇐ P(M_k|H_k)                                ▷ Get maximum likelihood estimate of map belief
m̂_k ⊆ M̂_k                                       ▷ Get current sub-map estimate from M̂_k
for i = 1 : N do
    m^i_k = m̂_k
    for j = 1 : L do
        x̂^-_{k+j} ⇐ P(x_{k+j}|H_k, a_{k:k+j-1})   ▷ Get ML estimate without future observations
        z^i ~ N(0, I)
        m^i_{k+j} ~ N(f(z^i, m^i_{k+j-1}, a_{k+j-1}; θ*), σ^2 * I)   ▷ Predict sub-map (Eq. (29))
        y^i_{k+j} ~ P(y_{k+j} | m^i_{k+j}, x̂^-_{k+j})   ▷ Generate future observation (Eq. (18))
        Calculate b^i_{k+j}                     ▷ Calculate future belief using y^i_{k+j} (Eq. (9))
        Calculate cost/reward c(b^i_{k+j})
        J(b_k, a_{k:k+L-1}) = J(b_k, a_{k:k+L-1}) + c(b^i_{k+j})   ▷ Accumulate costs
    end for
end for
J(b_k, a_{k:k+L-1}) = (1/N) J(b_k, a_{k:k+L-1})   ▷ Normalize to get empirical expectation
return J(b_k, a_{k:k+L-1})
```

Calculation of the objective function

$$J(b_k, a_{k:k+L-1}) \doteq \frac{1}{N}\sum_{i=1}^{N}\sqrt{Trace(\Sigma^i_{k+L})}$$

BSP Simulation Results





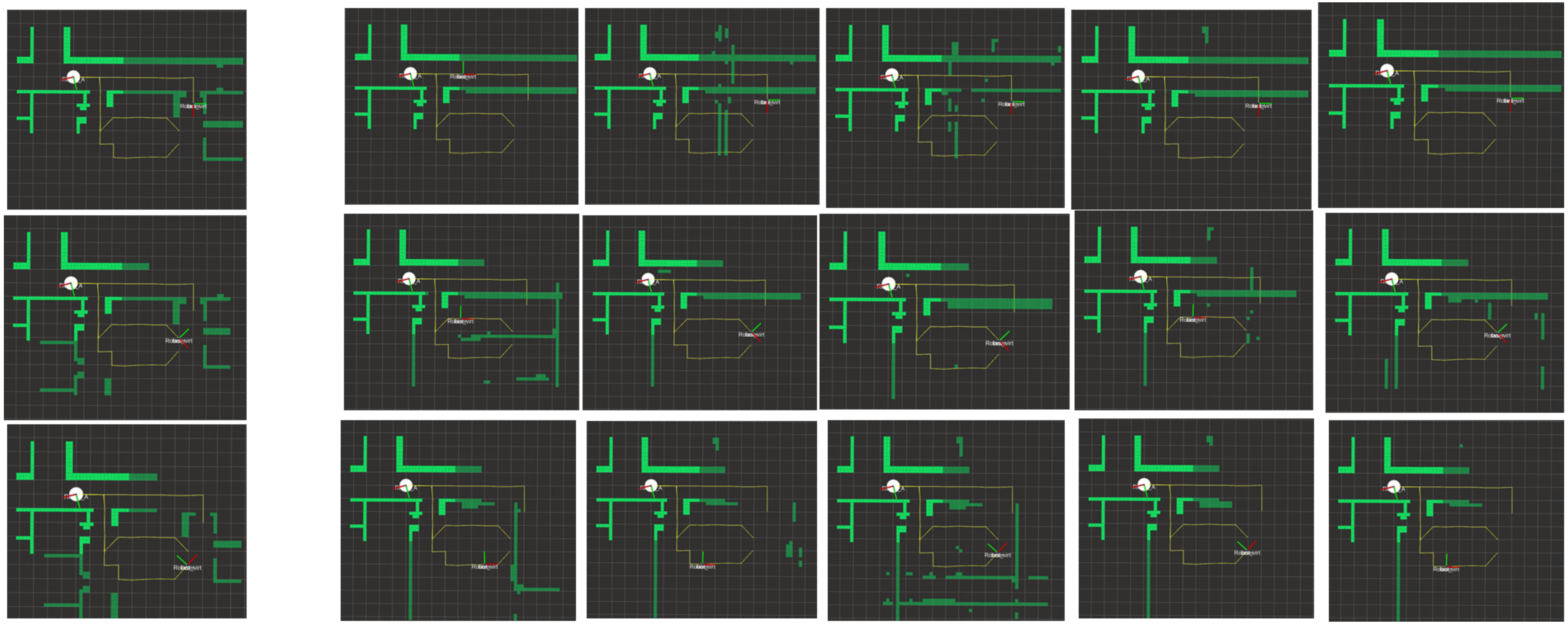
BSP Simulation Results

Ground truth | Samples

Action 1

Action 2

Action 3



Conditional map in light green, predicted map in dark green.

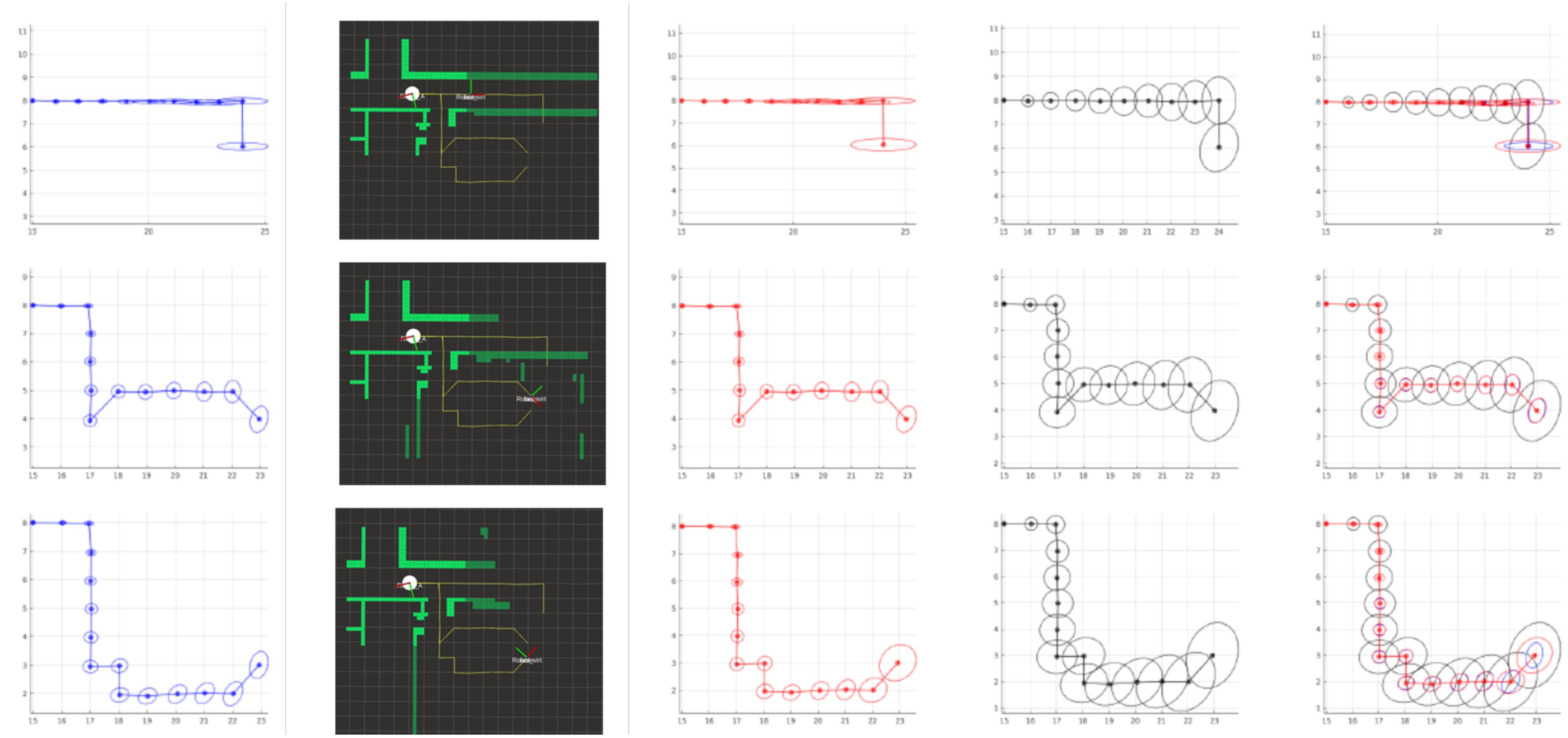
BSP Simulation Results

Ground truth | Samples | Our approach | baseline | comparison

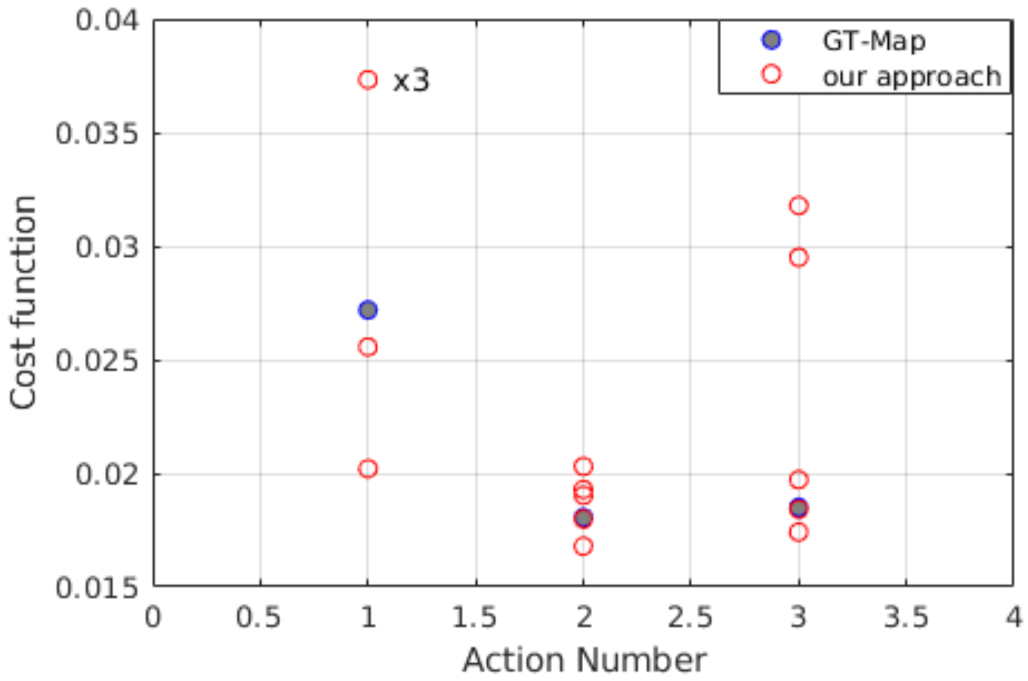
Action 1

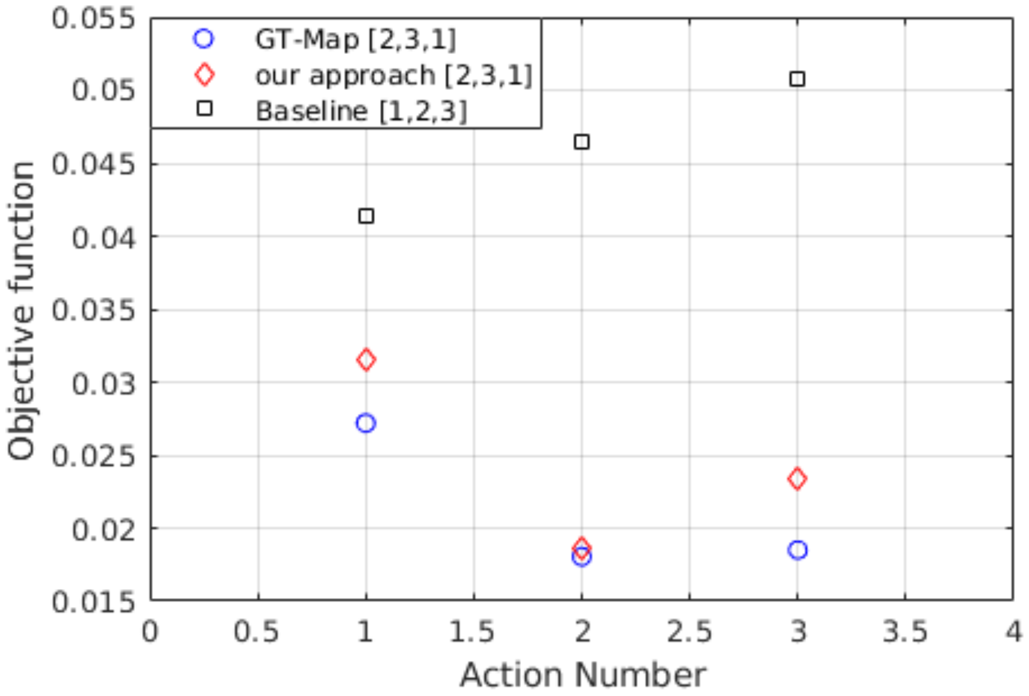
Action 2

Action 3



BSP Simulation Results

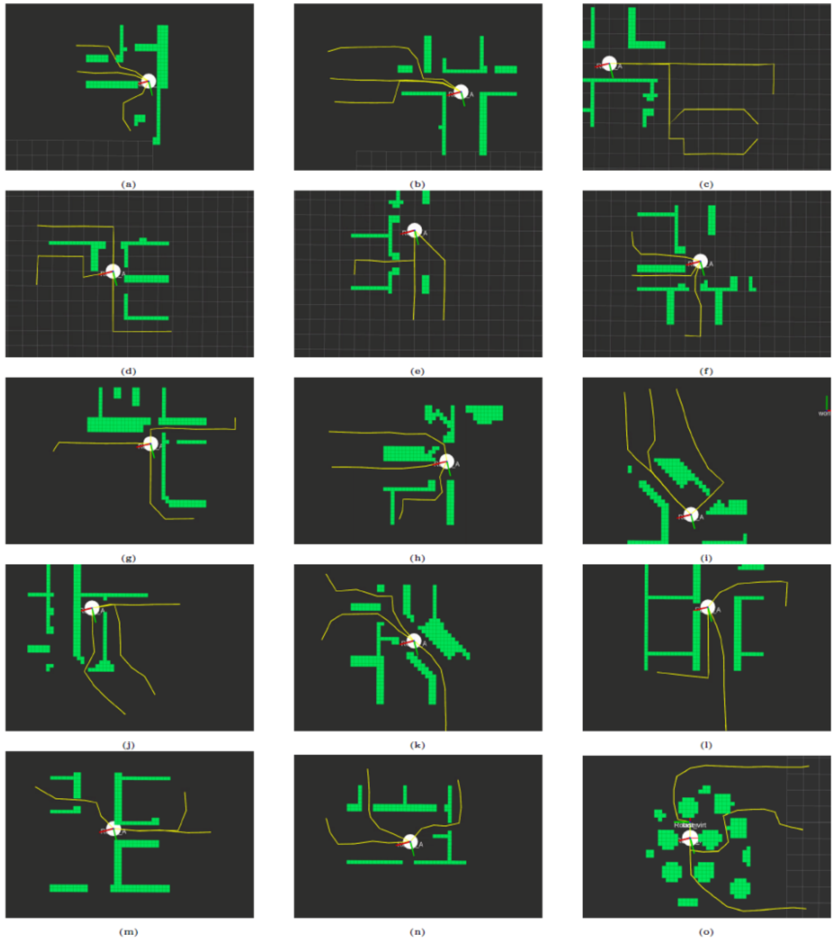




BSP Simulation Results

- The table reports for each method the number of action ordering mistakes with respect to BSP with ground truth map, and the uncertainty cost error.

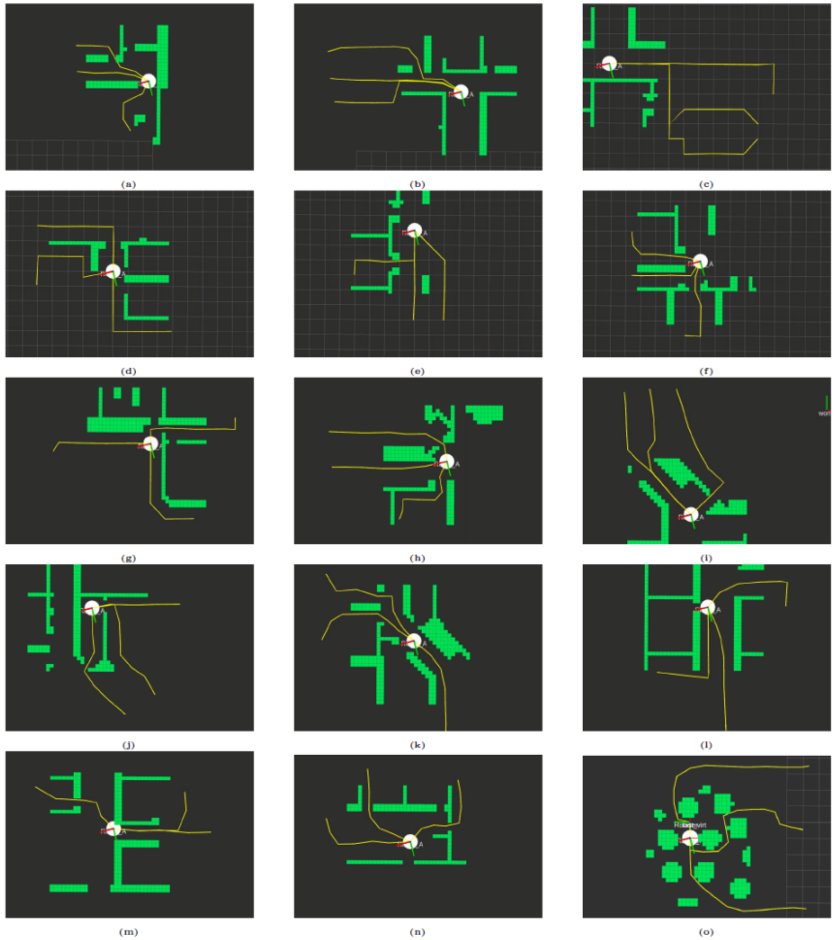
Scenarios	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Avg
Our approach																
Mistakes	0	2	**0**	**1**	**0**	**0**	0	**0**	**0**	2	**0**	**0**	1	**0**	-	**0.43**
Error[%]	0	40	**0**	**0**	**0**	**0**	0	**0**	0	**4**	0	0	**0**	0	-	**2.9**
RE	0.3	1.1	1.4	0.6	0.8	0.1	1.1	2.2	2	1.6	3.8	1.4	1	0	10.4	-
Baseline																
Mistakes	0	**1**	2	2	1	2	0	1	1	2	1	1	1	1	0	1.07
Error[%]	0	**1**	49	6	10	41	0	20	0	12	0	0	16	0	0	10.3



BSP Simulation Results

- Using the novelty detection method we recognized unfamiliar environments and avoided using our approach in these cases (e.g. Sc. 15).

Scenarios	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Avg
Our approach																
Mistakes	0	2	**0**	**1**	**0**	**0**	0	**0**	**0**	2	**0**	**0**	1	**0**	-	**0.43**
Error[%]	0	40	**0**	**0**	**0**	**0**	0	**0**	0	**4**	0	0	**0**	0	-	**2.9**
RE	0.3	1.1	1.4	0.6	0.8	0.1	1.1	2.2	2	1.6	3.8	1.4	1	0	10.4	-
Baseline																
Mistakes	0	**1**	2	2	1	2	0	1	1	2	1	1	1	1	0	1.07
Error[%]	0	**1**	49	6	10	41	0	20	0	12	0	0	16	0	0	10.3



Sc. 15

Summary

- Development of an algorithm that calculates a predicted distribution over an unexplored area using a deep learning method
- Incorporation of this distribution within BSP (considering information-theoretic costs)
- Novelty detection for map prediction
- Gazebo simulation compared our approach to existing BSP approaches - results indicate the potential of our approach to improve decision making in unknown environments

Conclusions and Future Work

- Good interpretability
- Low sensitivity to prediction mistakes

- Evaluation of path feasibility; improvement of map prediction accuracy is needed.
- Future work may extend our novelty detection method to cases with familiar inputs that still provide wrong predictions.

Thank you for listening. Questions?

ASROMRI@GMAIL.COM