On Prior Navigation Knowledge in Multi Sensor Indoor Localisation

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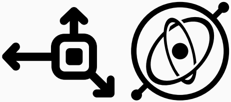
Overview

absolute positioning (x, y, z)

Wi-Fi, iBeacons

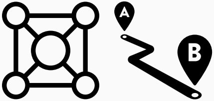


relative positioning (x, y)

accelerometer, gyroscope

relative positioning (z)

barometer



motion prediction (x, y, z)

graph, routing

System

Recursive Density Estimation

- Current State

$$\boldsymbol{q} = (x, y, z, \theta, \hat{\rho}_{\text{rel}})^T, \quad \overbrace{x, y, z \in \mathbb{R}}^{\text{position}}, \quad \overbrace{\theta \in \mathbb{R}}^{\text{heading}}, \quad \overbrace{\hat{\rho}_{\text{rel}} \in \mathbb{R}}^{\text{rel. pressure}}$$

$$\boldsymbol{q}_0 = \text{uniformly distributed}$$

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- Observation

  $$\boldsymbol{o} = (\boldsymbol{s}_{\text{wifi}}, \boldsymbol{s}_{\text{beacons}}, n_{\text{step}}, \Delta\theta, \rho_{\text{rel}})$$

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- $$\underbrace{p(\boldsymbol{q_t} \mid \boldsymbol{o}_{1:t})}_{\text{estimation}} \propto \underbrace{p(\boldsymbol{o_t} \mid \boldsymbol{q_t})}_{\text{evaluation}} \int \underbrace{p(\boldsymbol{q_t} \mid \boldsymbol{q_{t-1}}, \boldsymbol{o_{t-1}})}_{\text{transition}} \underbrace{p(\boldsymbol{q_{t-1}} \mid \boldsymbol{o}_{1:t-1})}_{\text{recursion}} d\boldsymbol{q}_{t-1}$$

Observation

- a location's probability based on the current sensor readings

$$p(\boldsymbol{o}_t \mid \boldsymbol{q}_t) =$$

$$p(\boldsymbol{o}_t \mid \boldsymbol{q}_t)_{\text{wifi}}$$

$$p(\boldsymbol{o}_t \mid \boldsymbol{q}_t)_{\text{beacons}}$$

$$p(\boldsymbol{o}_t \mid \boldsymbol{q}_t)_{\text{baro}}$$

- assuming statistical independence
- *step- and turn detection are used within the transition*

Observation - Wi-Fi/iBeacons

- $p(\boldsymbol{o}_t \mid \boldsymbol{q}_t)_{\text{wifi}} = p(\boldsymbol{s}_{\text{wifi}} \mid \boldsymbol{q}_t) = \prod_{s_{\text{wifi}}} \mathcal{N}(s_i \mid P_r(d_i, \Delta f_i), \sigma^2_{\text{wifi}}),$

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- 3D signal strength prediction

$$P_r(d, \Delta f) = \underbrace{P_0}_{\text{reference}} \quad \underbrace{-10\gamma \cdot \log_{10}(\tfrac{d}{d_0})}_{\text{attenuation per meter}} \quad \underbrace{+\Delta f \lambda}_{\text{floor attenuation}} \quad \underbrace{+X}_{\text{noise}}$$

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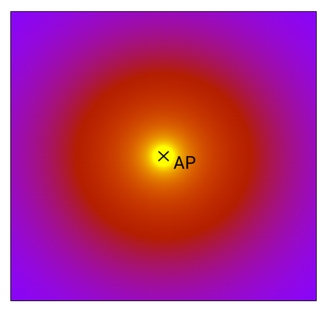

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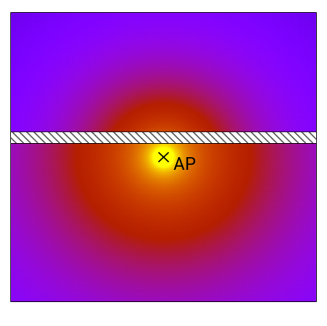

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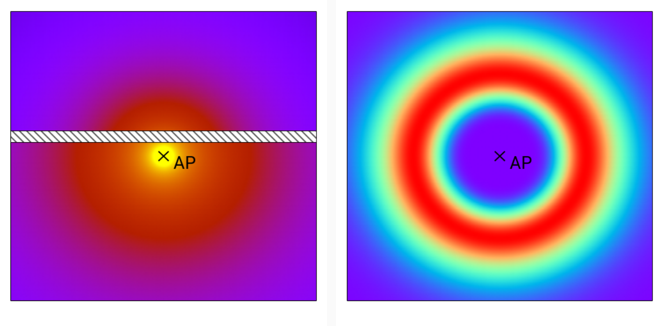

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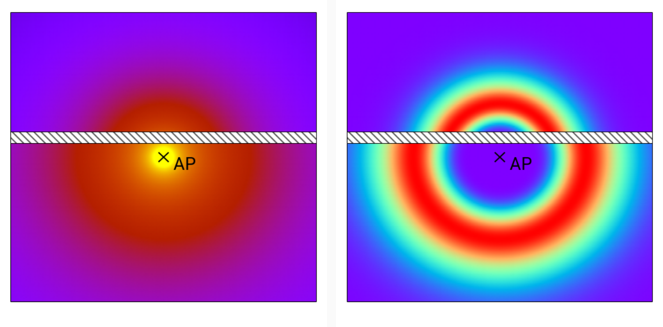

Observation - Barometer

- $p(\boldsymbol{o}_t \mid \boldsymbol{q}_t)_{\text{baro}} = \mathcal{N}(o_t^{\rho_{\text{rel}}} \mid q_t^{\hat{\rho}_{\text{rel}}}, \sigma^2_{\text{baro}})$

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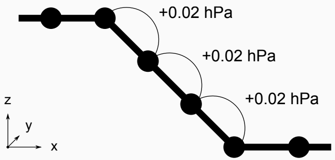
Observation - Barometer

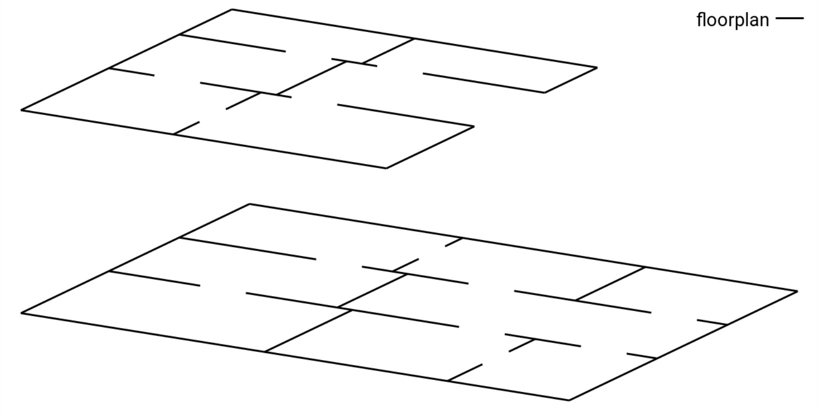
- $p(\boldsymbol{o}_t \mid \boldsymbol{q}_t)_{\text{baro}} = \mathcal{N}(o_t^{\rho_{\text{rel}}} \mid q_t^{\hat{\rho}_{\text{rel}}}, \sigma^2_{\text{baro}})$
- each transition performs a relative pressure prediction:

$$q_t^{\hat{\rho}_{\text{rel}}} = q_{t-1}^{\hat{\rho}_{\text{rel}}} + \Delta z \cdot b, \quad \underbrace{\Delta z = q_{t-1}^{z} - q_t^{z}}_{\text{height change}}, \qquad \underbrace{b \in \mathbb{R}}_{\text{pressure change / meter}}$$



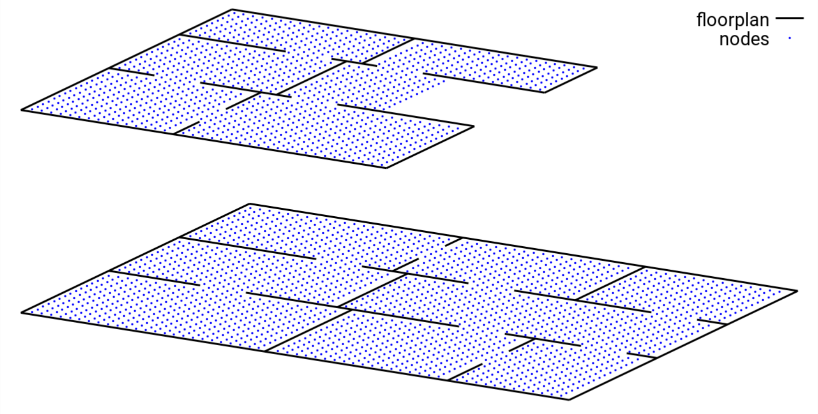
Transition - Floorplan

1) start with the building's floorplan



Transition - Floorplan

2) divide into cells and remove those intersecting with walls



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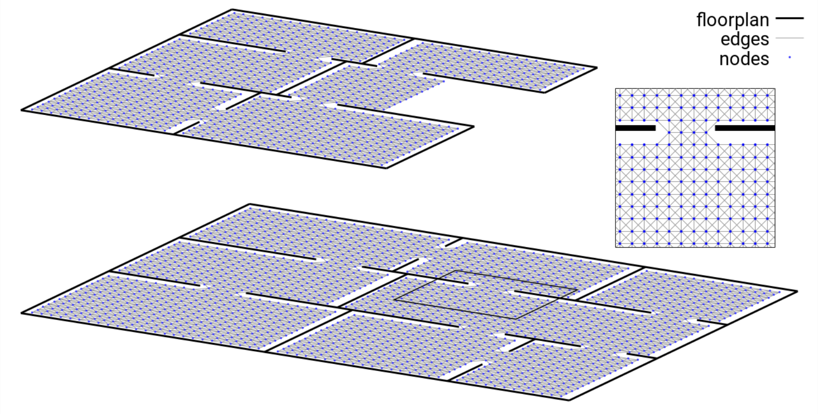
Transition - Floorplan

3) add edges to all (available) adjacent cells



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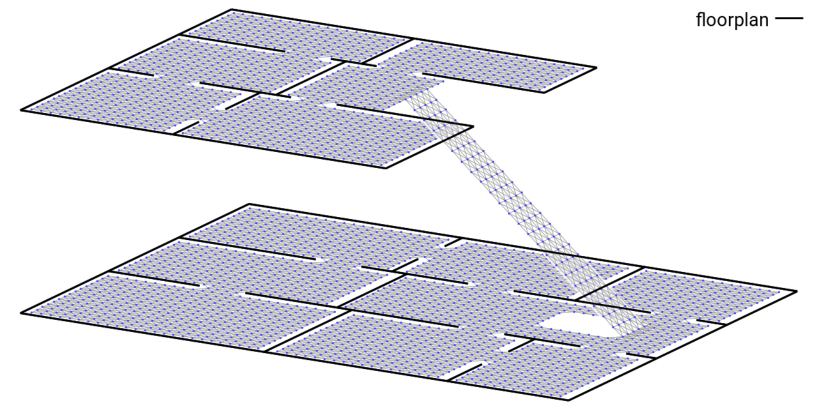
Transition - Floorplan

4) add stairs and remove unreachable cells



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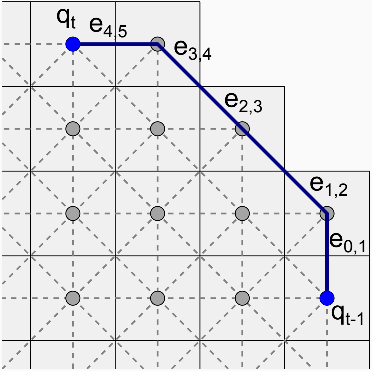
Transition - Random Walk

$p(\boldsymbol{q}_t \mid \boldsymbol{q}_{t-1})$:

1. get node $\boldsymbol{q}_{t-1}$ belongs to
2. draw distance d to walk
3. repeat until d is reached
   3.1 draw edge $e_{i,j}$ according to its probability $p(e_{i,j})$
   3.2 walk along the edge
   3.3 $d = d - \|e_{i,j}\|$



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Transition - Random Walk

- distance to walk

$$d = \underbrace{o_{t-1}^{n_{\text{step}}}}_{\text{steps detected}} \cdot \underbrace{s_{\text{step}}}_{\text{step size}} + \underbrace{\mathcal{N}(0, \sigma_d^2)}_{\text{uncertainty}}$$

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- pedestrian's heading

$$p(e_{i,j})_{\text{turn}} = p(e_{i,j} \mid \theta_{\text{walk}}) = \mathcal{N}(\angle e_{i,j} \mid \theta_{\text{walk}}, \sigma_{\text{dev}}^2)$$

$$\underbrace{\theta_{\text{walk}} = q_t^{\theta}}_{\text{current heading}} = \underbrace{q_{t-1}^{\theta}}_{\text{previous heading}} + \underbrace{o_{t-1}^{\Delta\theta}}_{\text{sensor readings}} + \underbrace{\mathcal{N}(0, \sigma_{\theta_{\text{walk}}}^2)}_{\text{uncertainty}}$$

Transition - Prior Knowledge

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- use this prior knowledge to enhance the movement prediction
  - calculate the shortest path from the desired destination to all other vertices using Dijkstra's algorithm
  - favour nodes approaching the destination over others
  - $p(e_{i,j})_{\text{path}} = p(v_j \mid v_i) = \begin{cases} \kappa & \mathrm{d}(v_j, v_{\text{dest}}) < \mathrm{d}(v_i, v_{\text{dest}}) \\ (1-\kappa) & \text{else} \end{cases}$

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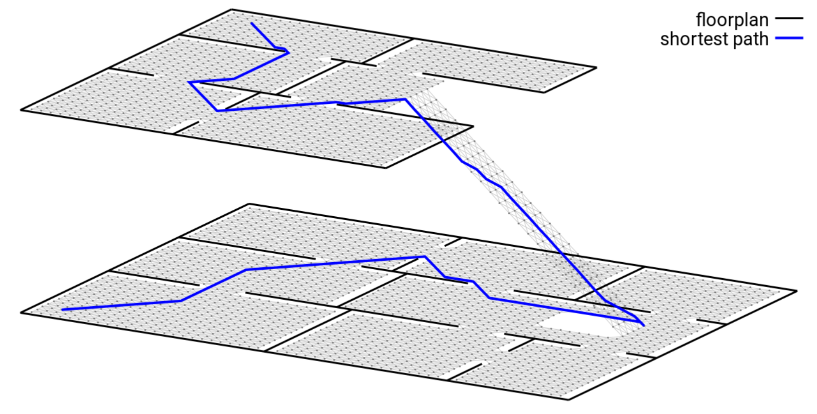
- however: calculated path is very unrealistic and sticks to walls

Transition - Shortest Path

1) using shortest path as-is, produces unlikely-to-walk paths



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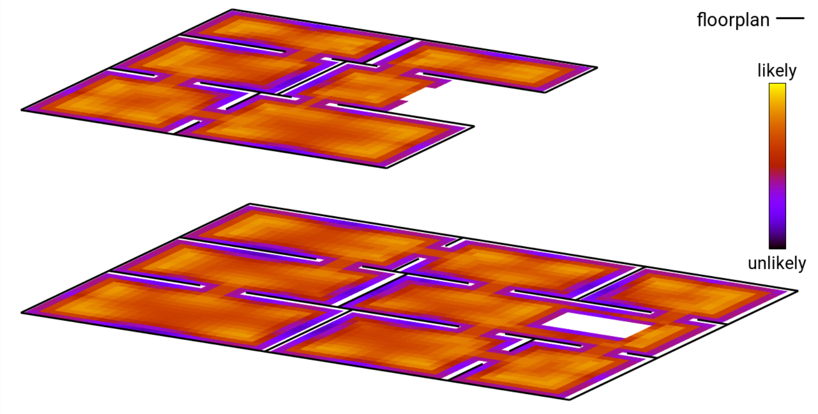
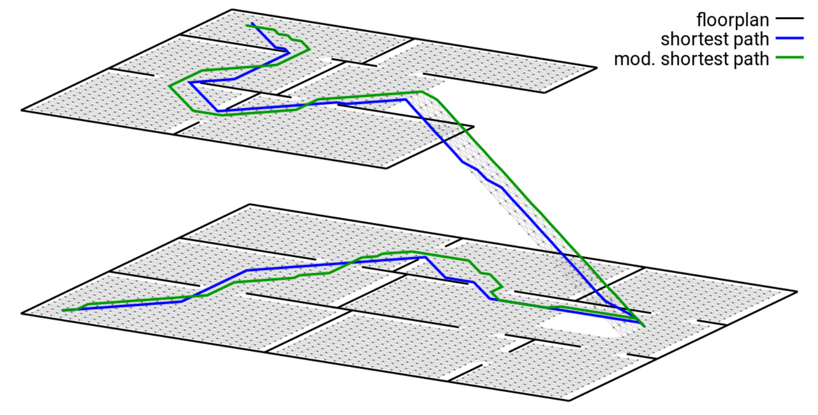
2) determine likelyhood for a vertex to be visited by the pedestrian



Transition - Shortest Path

3) use this likelyhood to adjust Dijkstra's weighting function $\delta(e_{i,h})$



Experiments