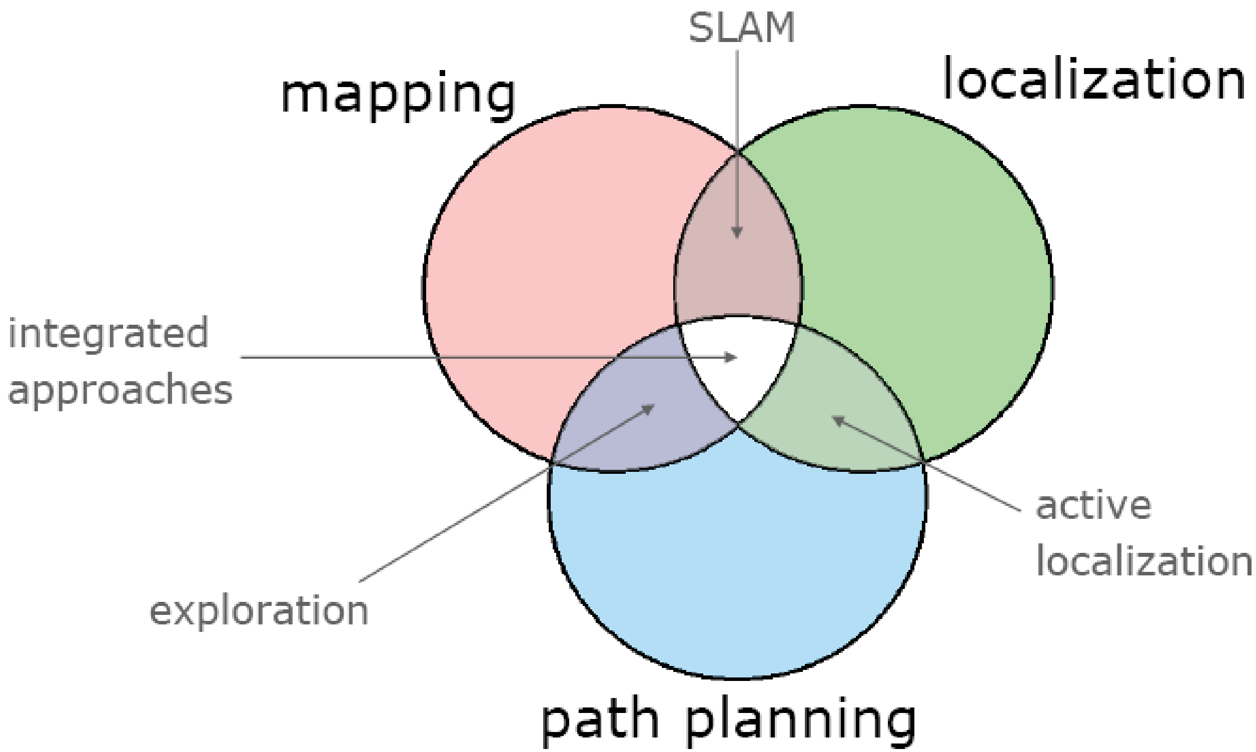
Robotica Probabilistica

Information Gain-Based Exploration

Task dei Robot Mobili



Esplorazione e SLAM

- SLAM is typically passive, because it consumes incoming sensor data
- Exploration actively guides the robot to cover the environment with its sensors
- Exploration in combination with SLAM: Acting under pose and map uncertainty
- Uncertainty should/needs to be taken into account when selecting an action

Filtri Particellari

- Each particle represents a possible trajectory of the robot
- Each particle
  - maintains its own map and
  - updates it upon “mapping with known poses”
- Each particle survives with a probability proportional to the likelihood of the observations relative to its own map

Fattorizzazione

poses map observations & odometry

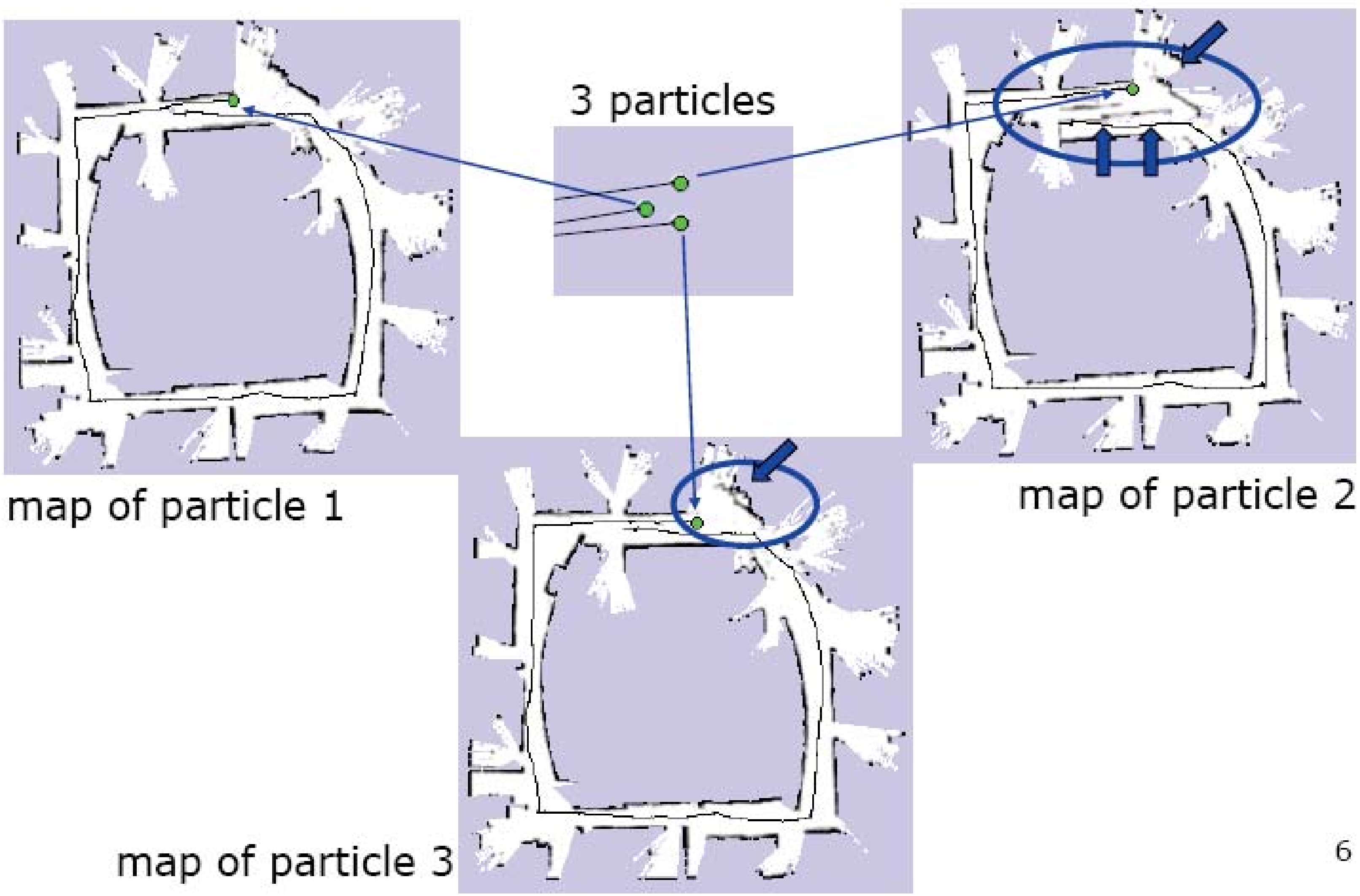
$$p(x, m \mid z, u)$$

$$= \quad p(m \mid x, z, \cancel{u})\, p(x \mid z, u)$$

Mapping with known poses

Particle filter representing trajectory hypotheses

Filtri Particellari



FastSLAM

- **30 particles**
- $250 \times 250 m^2$
- 1.75 km (odometry)
- 20cm resolution during scan matching
- 30cm resolution in final map

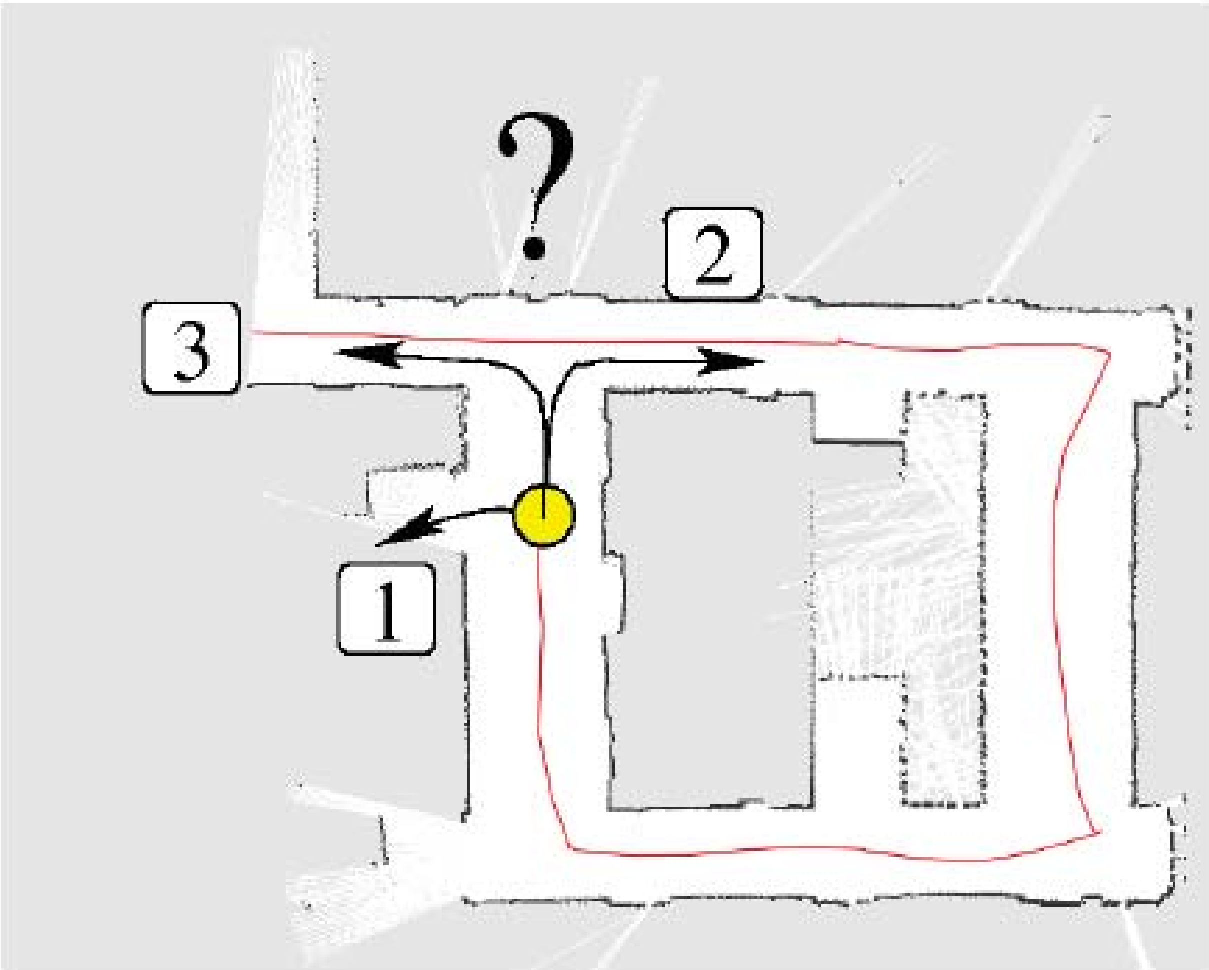
Esplorazione

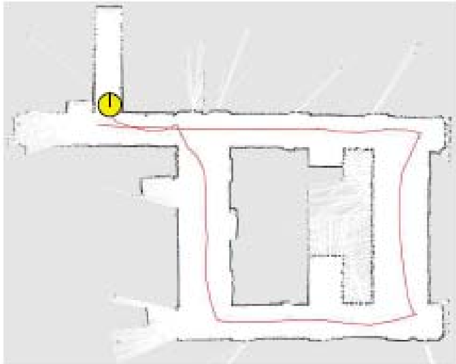
- The approaches seen so far are purely passive

- By reasoning about control, the mapping process can be made much more effective

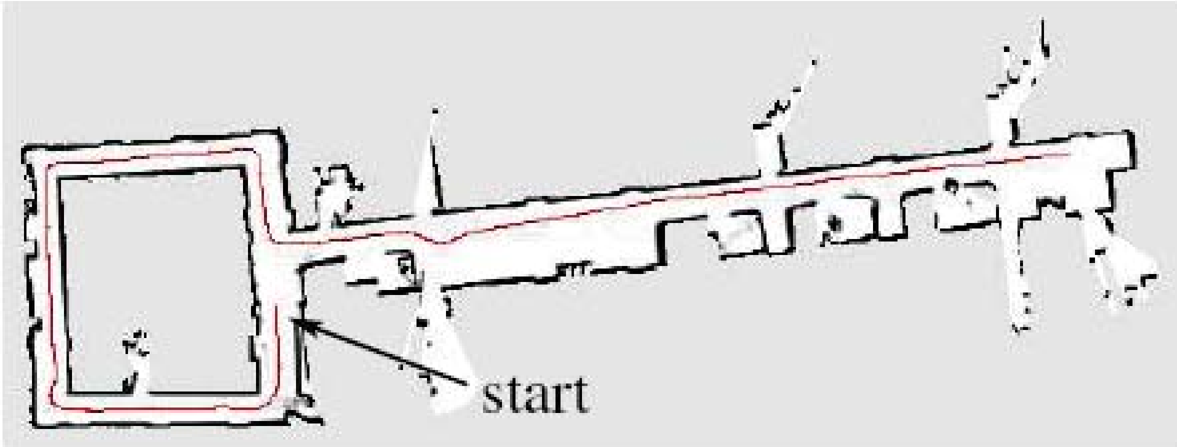
- Question: **Where to move next?**

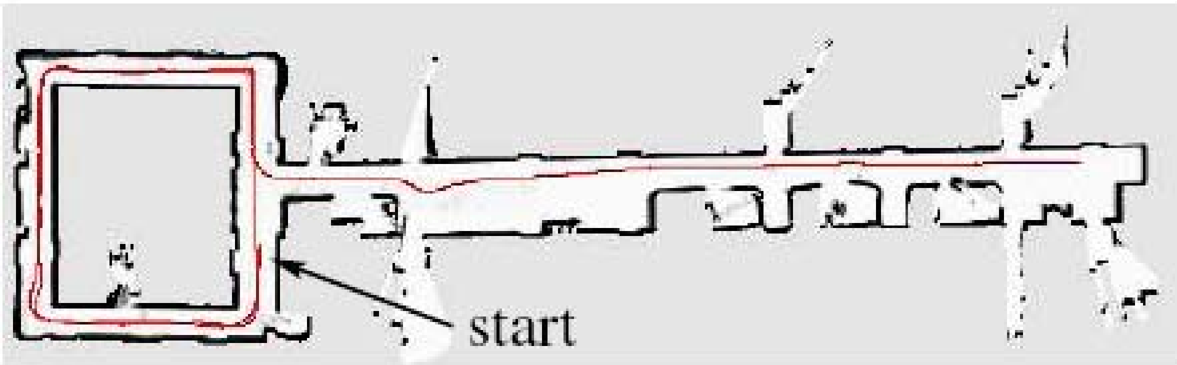
Esplorazione





Esplorazione vs SLAM





La strategia di esplorazione determina la qualità della mappa

Approccio Decision-Teoretico

- Learn the map using a Rao-Blackwellized particle filter
- Consider a set of potential actions
- Apply an exploration approach that minimizes the overall uncertainty

Utility = uncertainty reduction - cost

Incertezza Posterior

- Entropy is a general measure for the uncertainty of a posterior

$$
\begin{aligned}
H(p(x)) &= -\int_x p(x)\log p(x)\,dx \\
&= E_x[-\log(p(x))]
\end{aligned}
$$

- Information Gain = Uncertainty Reduction

$$
I(t+1 \mid t) = H(p(x_t)) - H(p(x_{t+1}))
$$

Calcolo Entropia

$$
\begin{aligned}
& H(p(x,y)) \\
&\quad = \quad E_{x,y}[-\log p(x,y)] \\
&\quad = \quad E_{x,y}[-\log(p(x)\; p(y \mid x))] \\
&\quad = \quad E_{x,y}[-\log p(x)] + E_{x,y}[-\log p(y \mid x)] \\
&\quad = \quad H(p(x)) + \int_{x,y} -p(x,y) \log p(y \mid x)\; dx\; dy \\
&\quad = \quad H(p(x)) + \int_{x,y} -p(y \mid x) p(x) \log p(y \mid x)\; dx\; dy \\
&\quad = \quad H(p(x)) + \int_{x} p(x) \int_{y} -p(y \mid x) \log p(y \mid x)\; dy\; dx \\
&\quad = \quad H(p(x)) + \int_{x} p(x) H(p(y \mid x))\; dx
\end{aligned}
$$

Calcolo incertezza della Mappa e della Posa

$$H(p(x_{1:t}, m \mid d_t)) = H(p(x_{1:t} \mid d_t)) + \int_{x_{1:t}} p(x_{1:t} \mid d_t) H(p(m \mid x_{1:t}, d_t))\, dx_{1:t}$$

Data la rappresentazione approssimata

$$H(p(m, x_{1:t} \mid d_t)) \approx H(p(x_{1:t} \mid d_t)) + \sum_{i=1}^{\#particles} \omega_t^{[i]} H(p(m^{[i]} \mid x_{1:t}^{[i]}, d_t))$$

Incertezza percorso + incertezza mappa

Incertezza del posterior nelle Grid Map

Ogni cella è una variabile aleatoria binaria

Occupancy Grid map m:

$$H(p(m)) = -\sum_{c \in m} p(c) \log p(c) + (1 - p(c)) \log(1 - p(c))$$

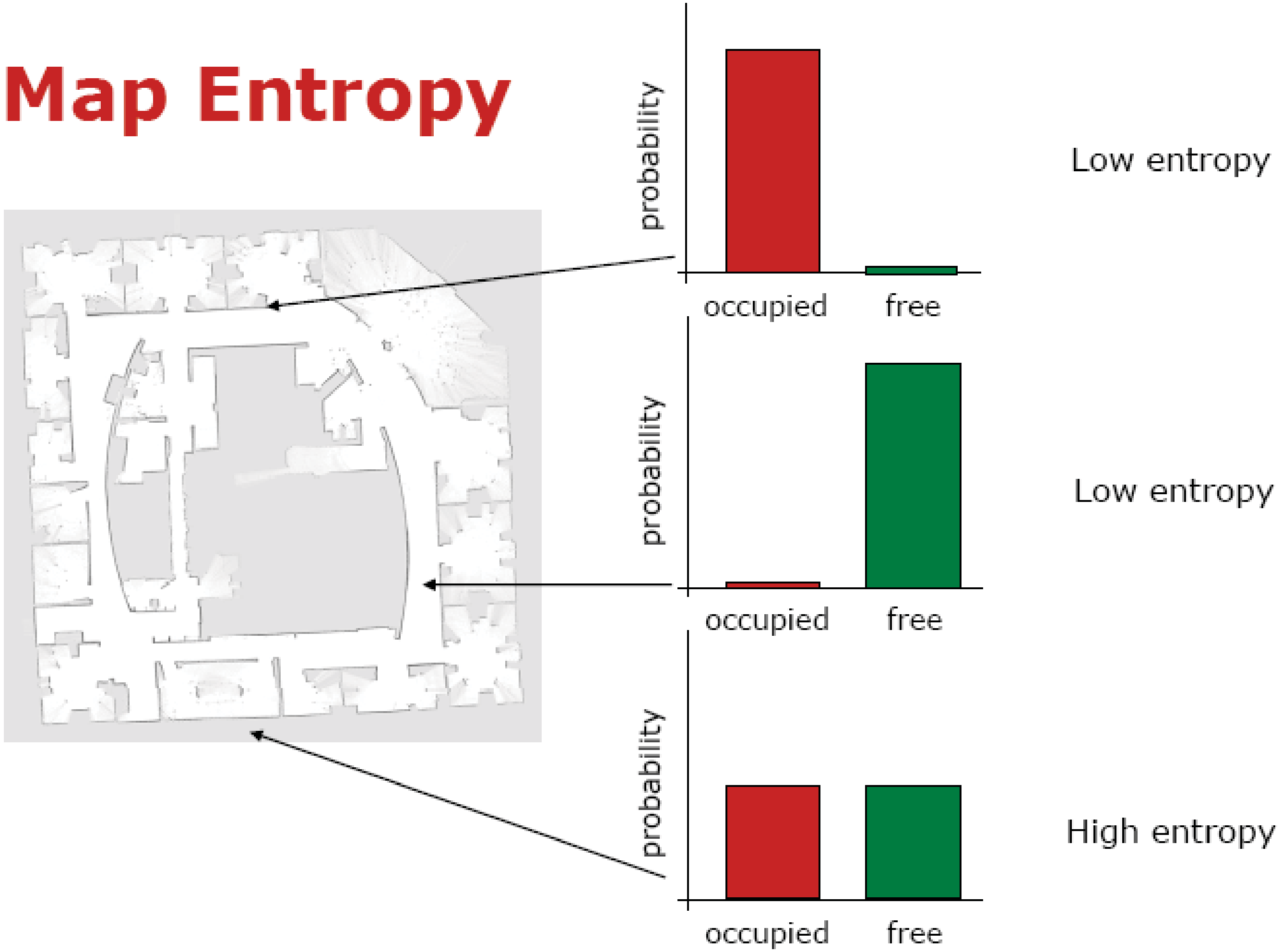
map uncertainty

grid cells

probability that the cell is occupied

Entropia della Mappa

Map Entropy



The overall entropy is the sum of the individual entropy values

Incertezza sulla traiettoria

- Ogni posa dipende dalle pose precedenti 0:t-1
- Approssimazione con incertezza media sul percorso: $H(p(x_{1:t}|d_t))$
- Posterior su traiettoria rappresentato come gaussiana

Incertezza sulla traiettoria

1. High-dimensional Gaussian

$$H(\mathcal{G}(\mu, \Sigma)) \;=\; \log((2\pi e)^{(n/2)}|\Sigma|)$$

   reduced rank for sparse particle sets

2. Grid-based approximation

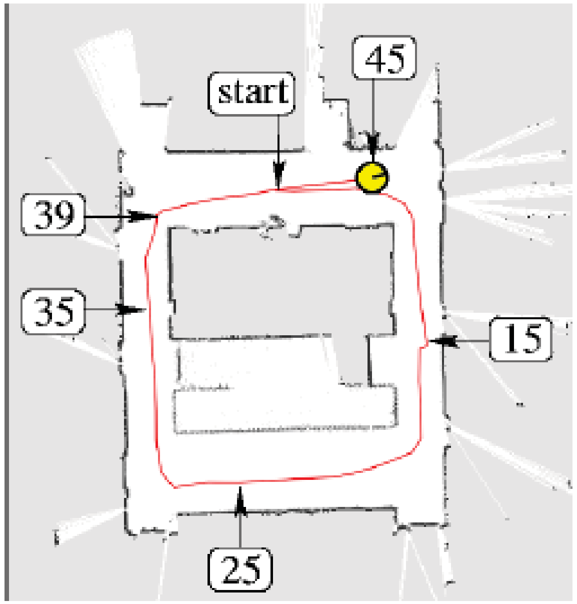
$$H(p(x \mid d)) \;\rightsquigarrow\; const.$$

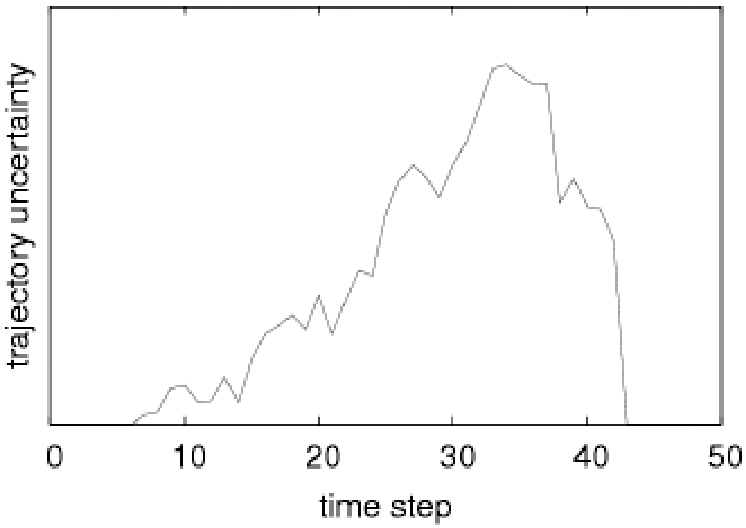
   for sparse particle clouds

Approssimazione incertezza sulla traiettoria

Average pose entropy over time:

$$H(p(x_{1:t} \mid d)) \approx \frac{1}{t} \sum_{t'=1}^{t} H(p(x_{t'} \mid d))$$





Guadagno di informazione con l'esecuzione delle azioni

- The reduction of entropy in the model

observations to be obtained

action

$$I(\hat{z}, a) =$$

$$H(p(m, x \mid d)) -$$

$$H(p(m, x, \hat{x} \mid d, a, \hat{z}))$$

H before action is carried out

H after action is carried out

new poses introduced by action

Guadagno di informazione atteso

- To compute the information gain one needs to know the observations obtained when carrying out an action

- This quantity is not known! Reason about potential measurements

$$E[I(a)] \;=\; \int_{\hat{z}} p(\hat{z} \mid a, d) \cdot I(\hat{z}, a) \, d\hat{z}$$

Sequenze di Misure

- The filter represents a posterior about possible maps
- Use these maps to reason about possible observation
- Simulate laser measurements in the maps of the particles

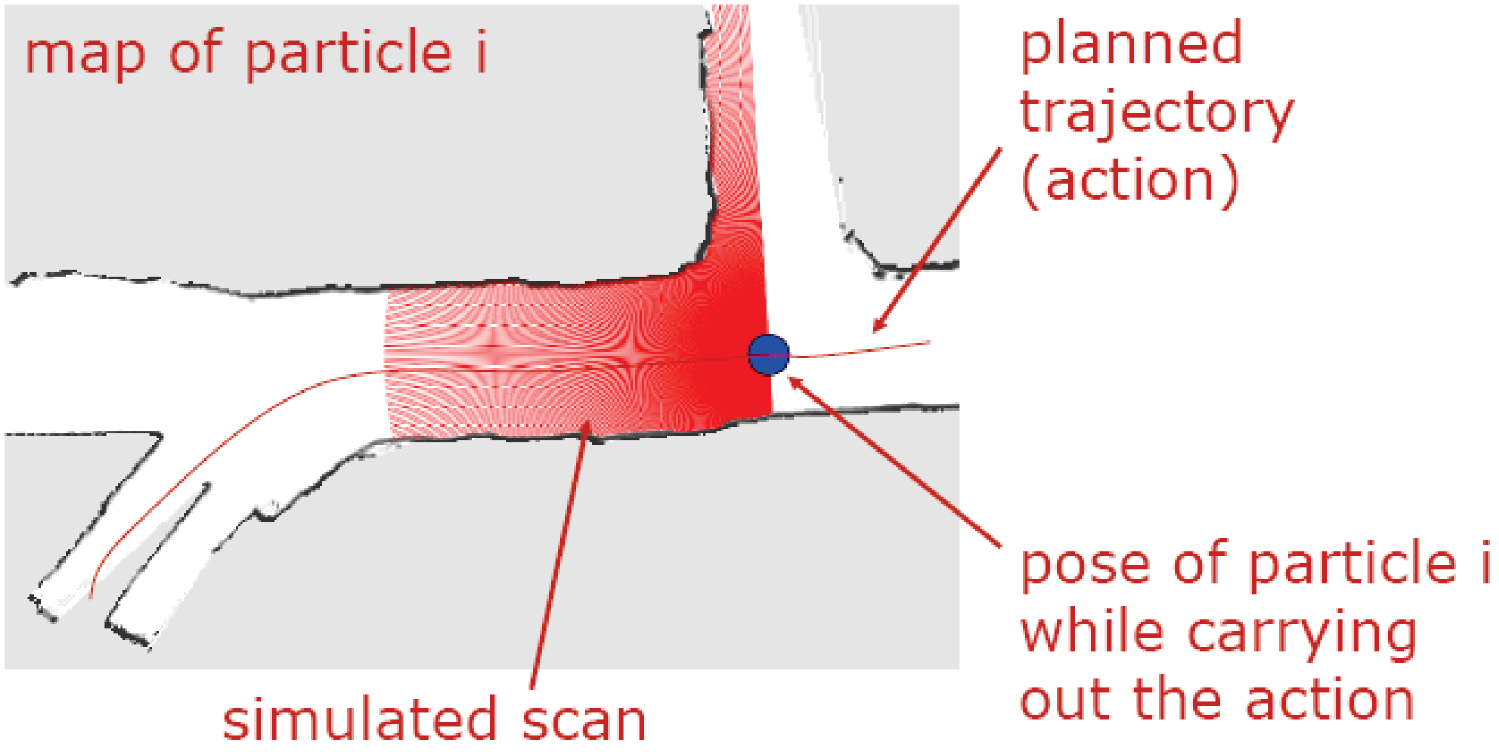
$$E[I(a)] \;=\; \int_{\hat{z}} p(\hat{z} \mid a, d) \cdot I(\hat{z}, a)\, d\hat{z}$$

measurement sequences simulated in the maps

likelihood (particle weight)

Sequenze di Misura

- Ray-casting in the map of each particle to generate observation sequences



$$p(\hat{z} \mid a_t, d_t) \approx \sum_{i=1}^{\#particles} p(\hat{z} \mid a_t, m^{[i]}, x_{1:t}^{[i]}, d_t)$$
$$\cdot\, \omega_t^{[i]} p(m^{[i]} \mid x_{1:t}^{[i]}, d_t)$$

Utilità

- To take into account the cost of an action, we compute a utility

$$U(a) \;=\; I(a) - \alpha \cdot cost(a)$$

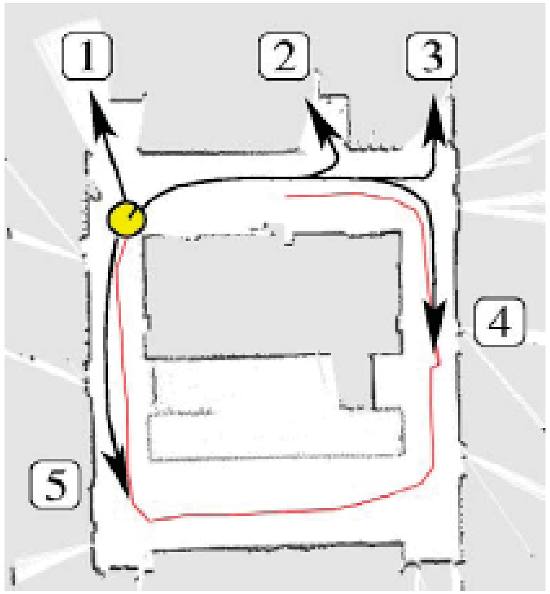
- Select the action with the highest expected utility

$$a^* \;=\; \underset{a}{\operatorname{argmax}}\{E[U(a)]\}$$

Azioni specifiche

To efficiently sample actions we consider

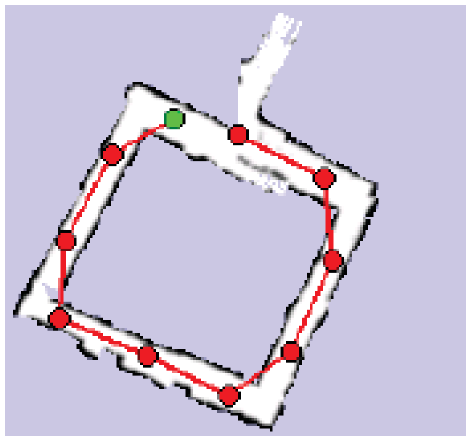
- **exploratory actions (1-3)**
- **loop closing actions (4)** and
- **place revisiting actions (5)**



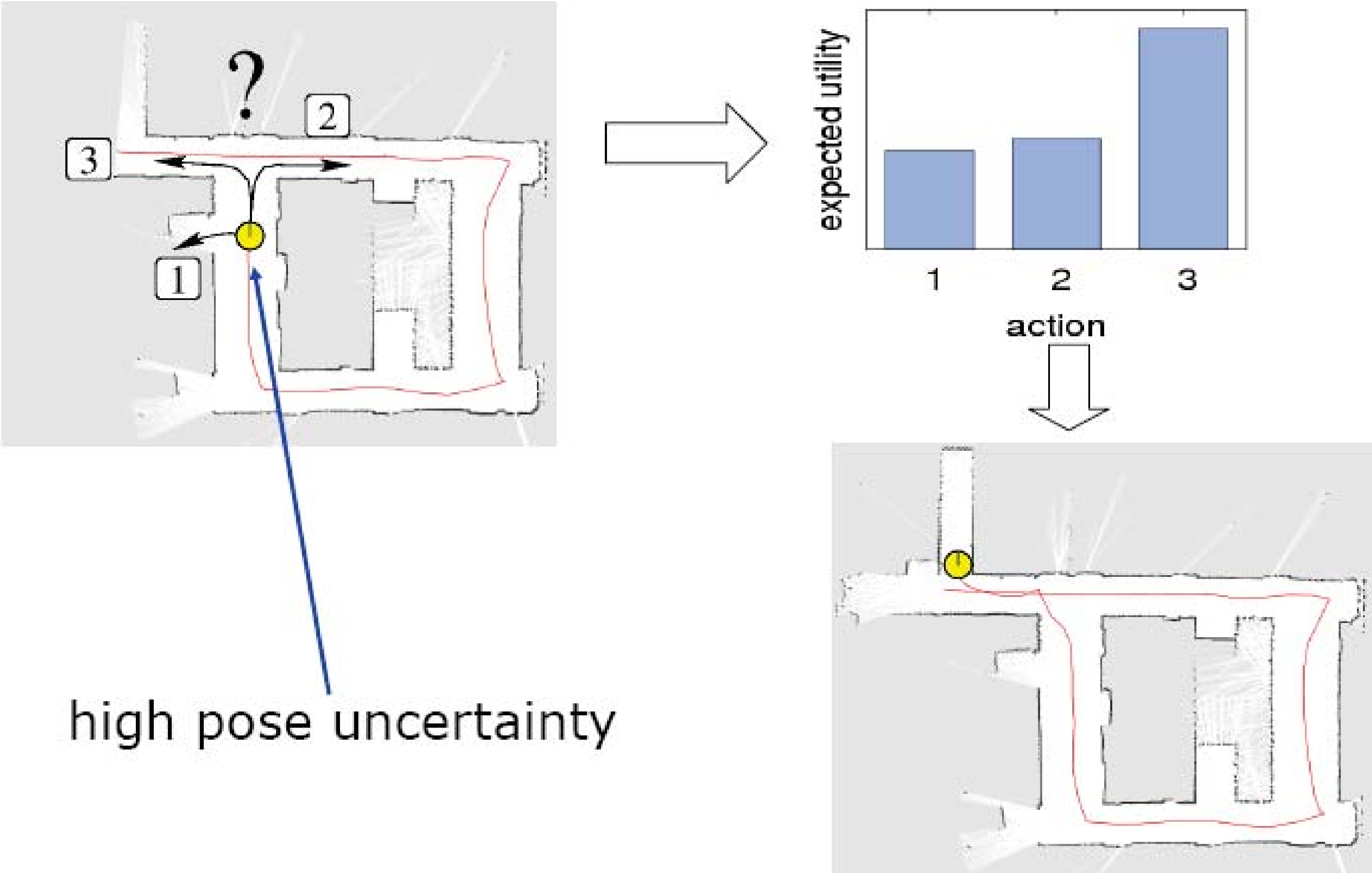
Doppia Rappresentazione per la rilevazione di cicli

- **Trajectory graph** ("topological map") stores the **path traversed by the robot**
- **Occupancy grid** map represents the **space covered by the sensors**

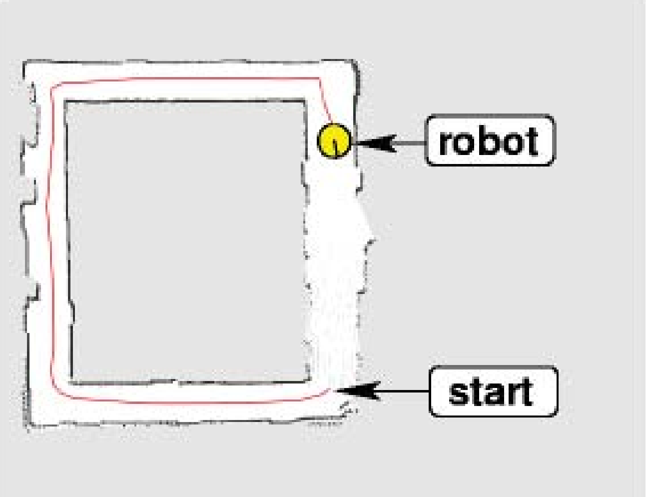
- **Loops** correspond to **long paths in the trajectory graph** and **short paths in the grid map**

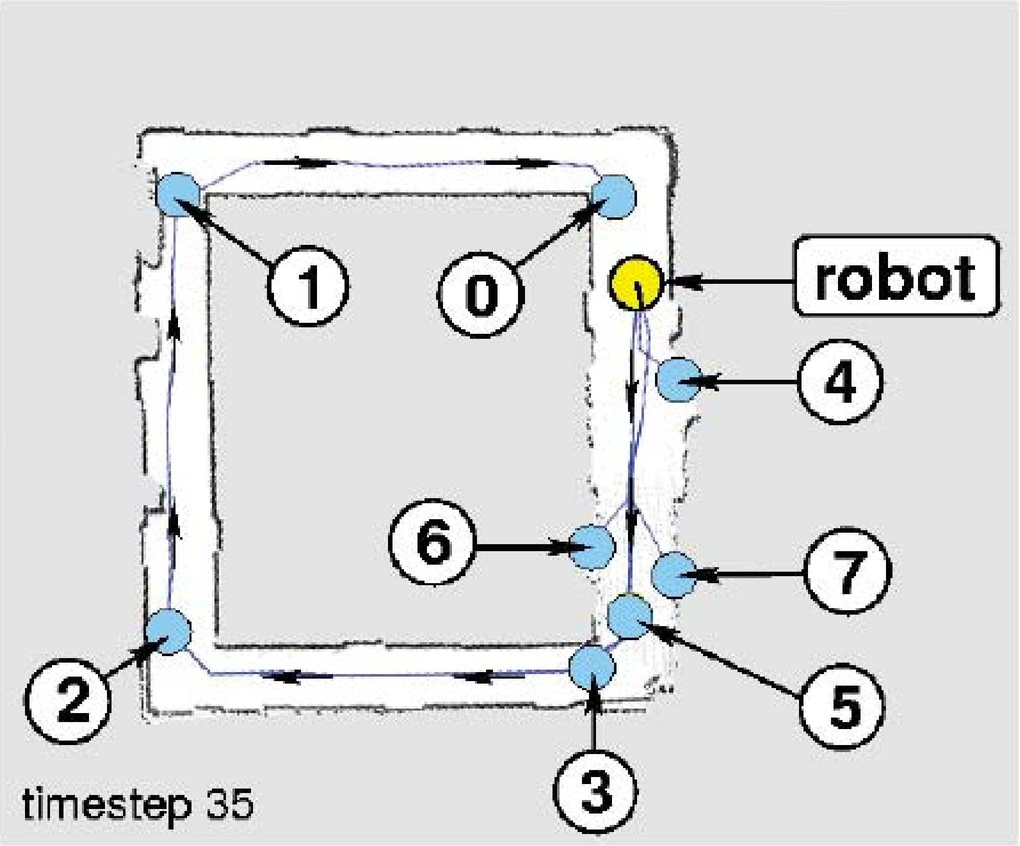


Esempio

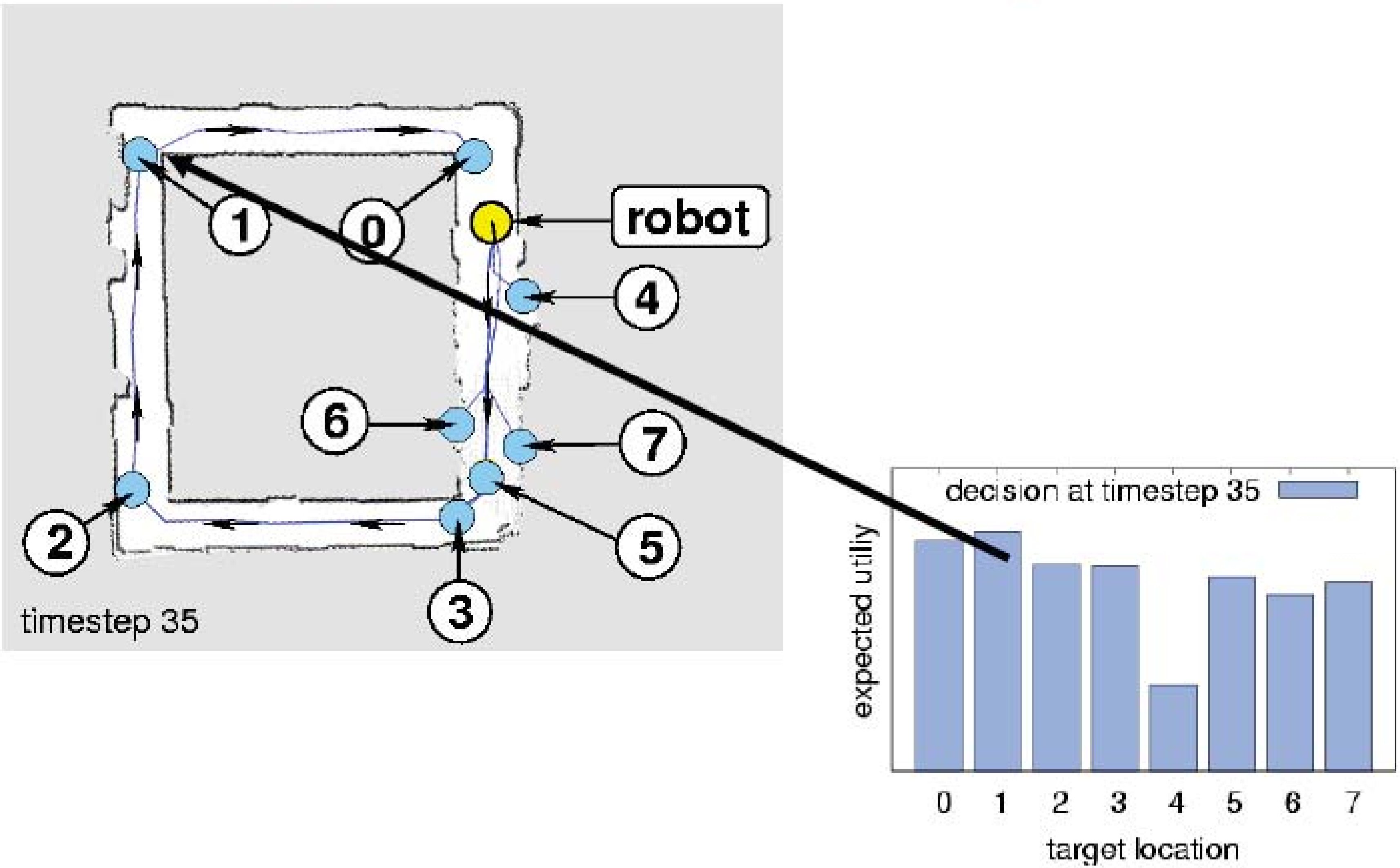


Possibili Target

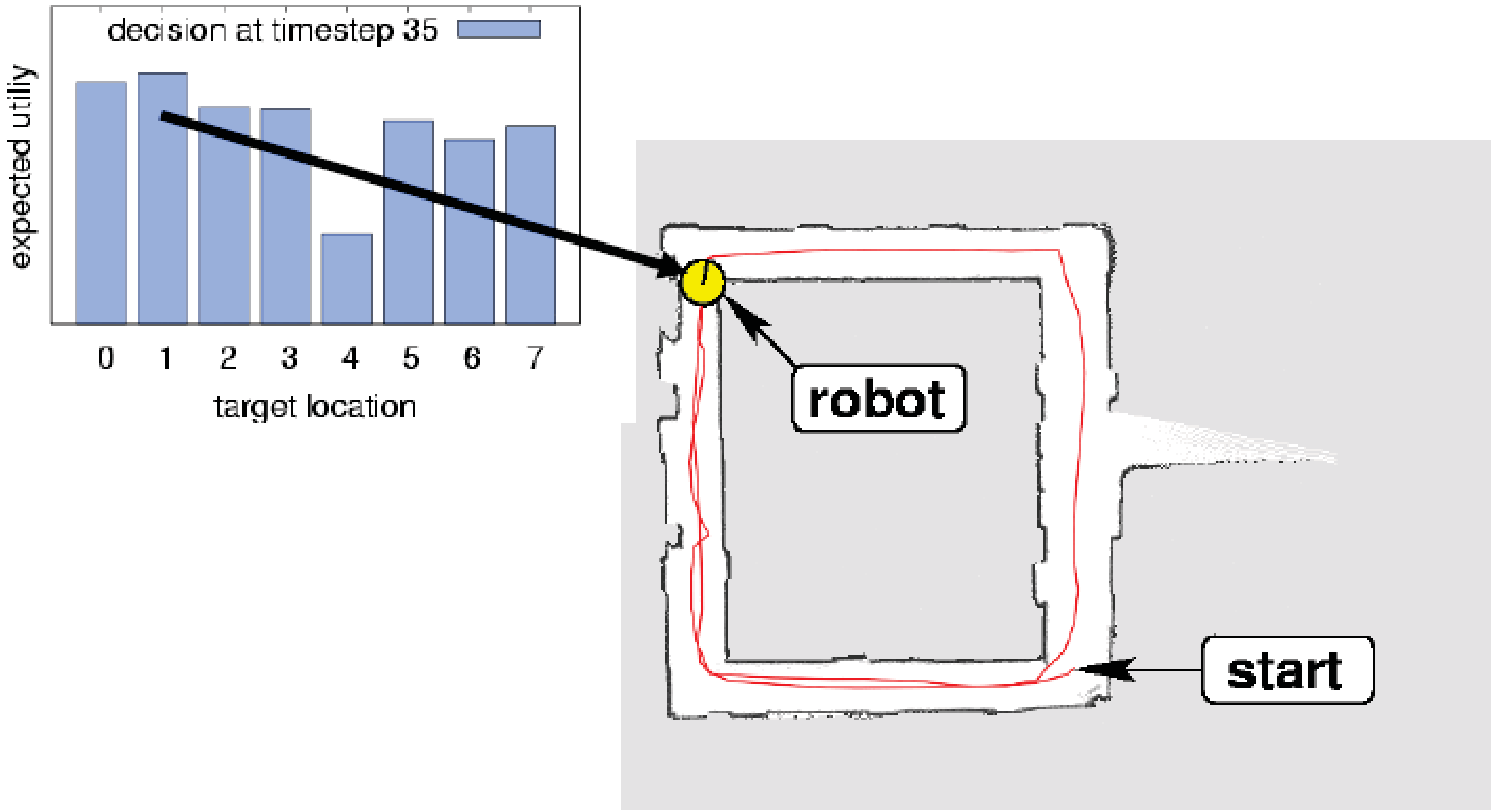




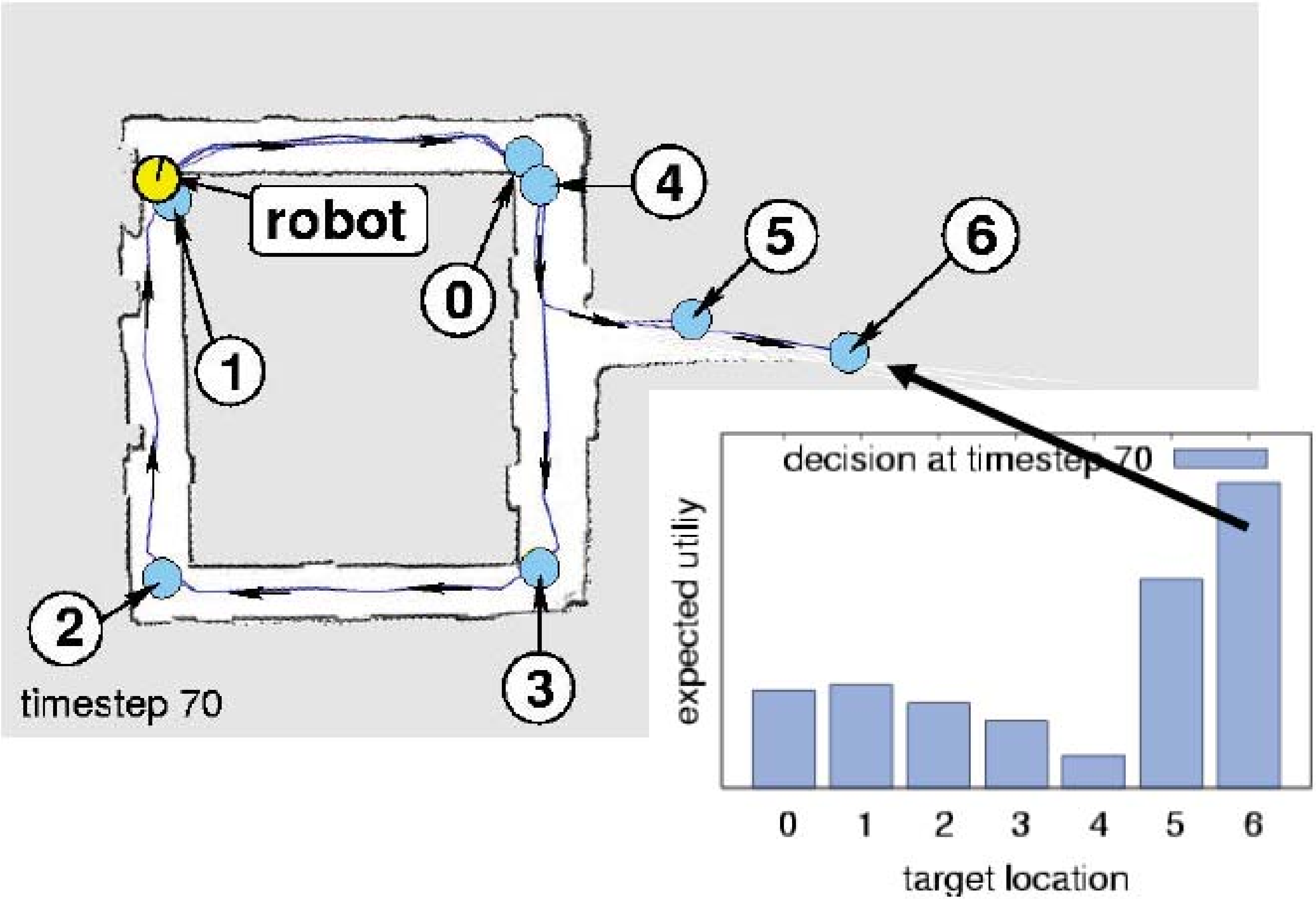
Valutazione dei Target



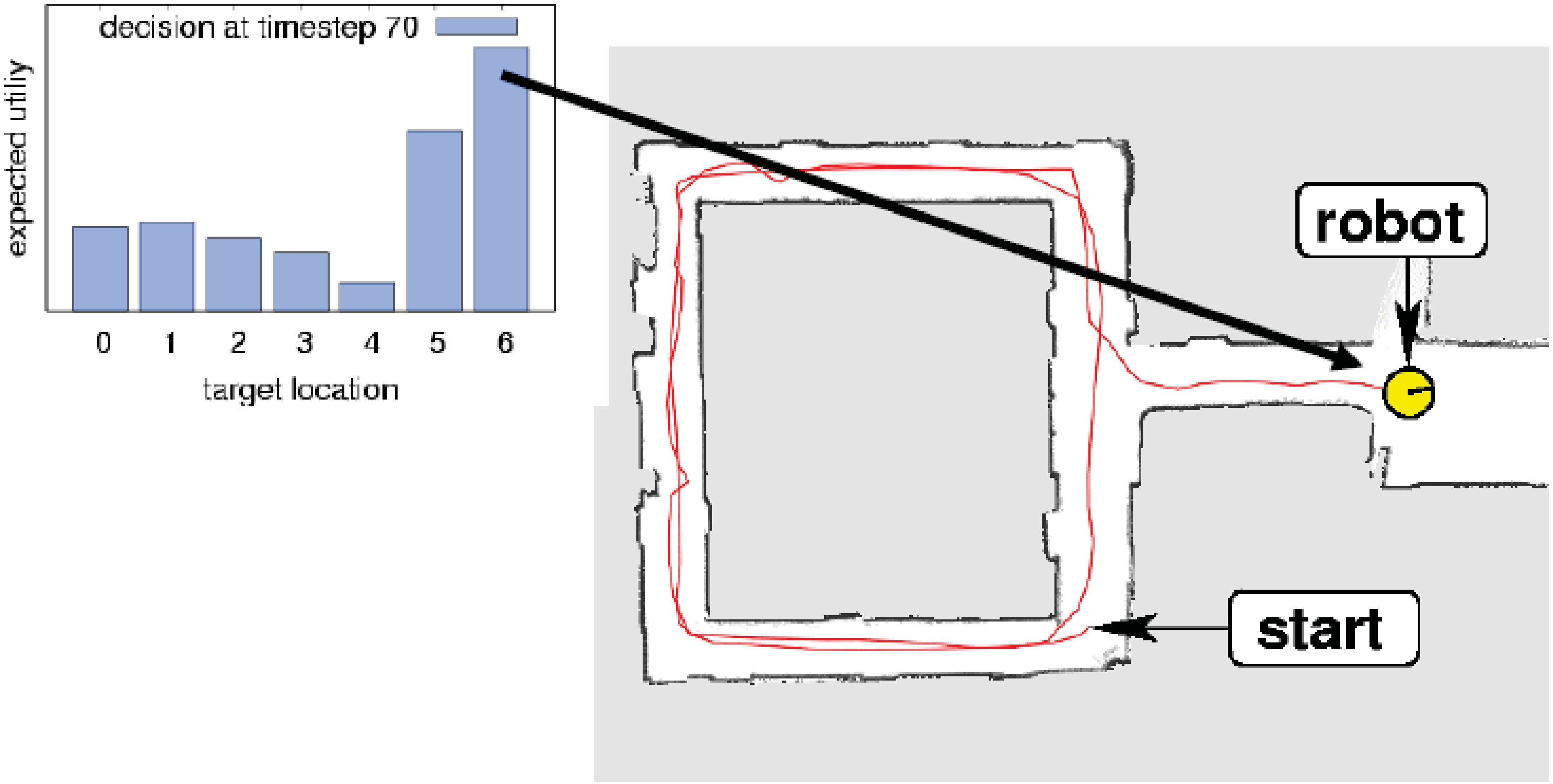
Spostamento sul Target



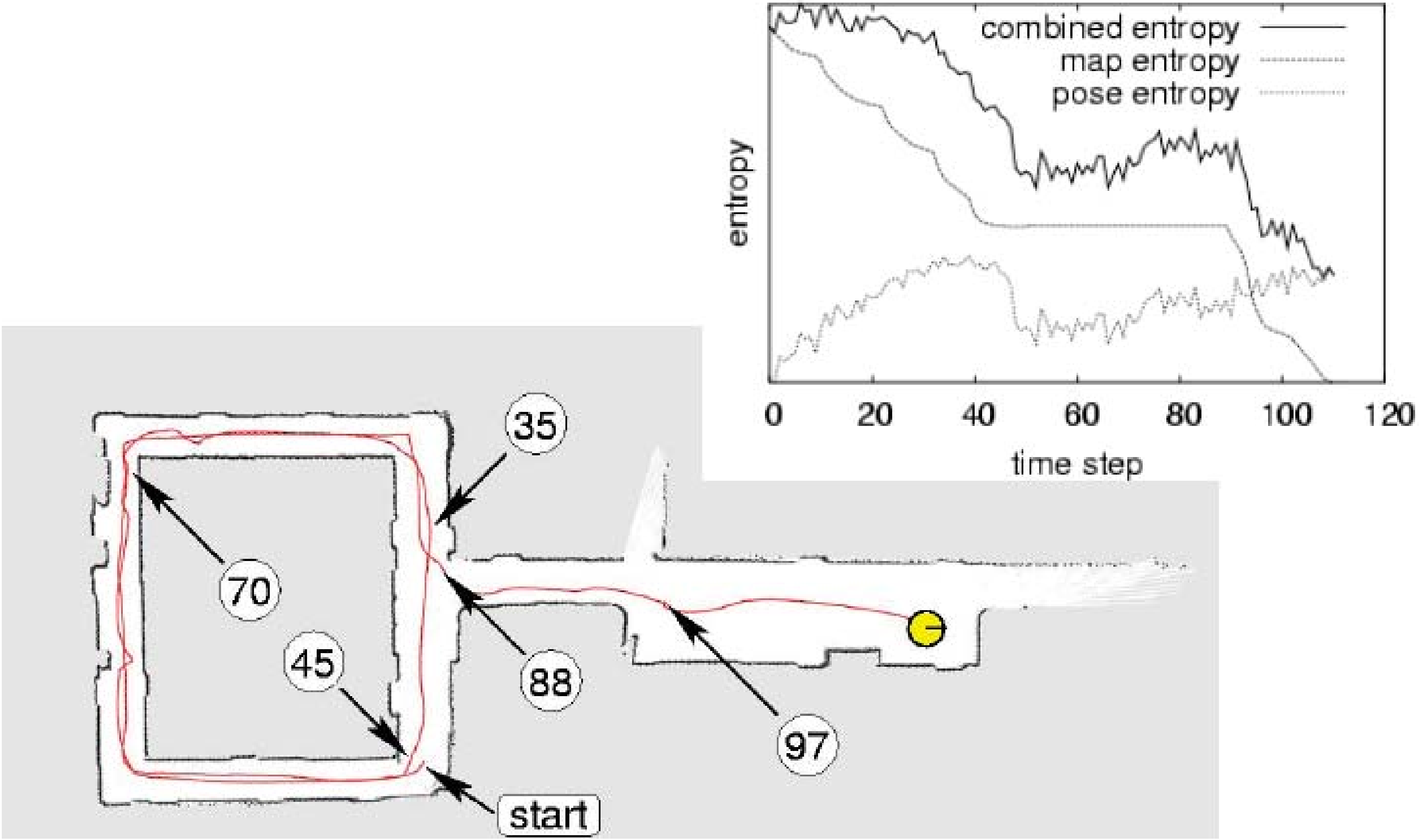
Valutazione dei Target



Movimento Robot

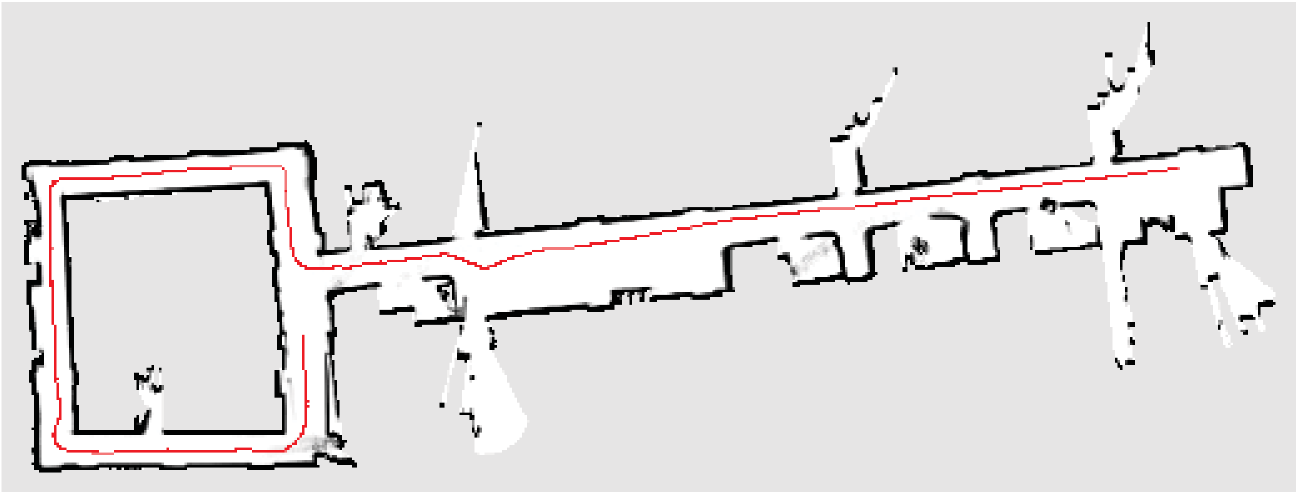


Evoluzione dell'entropia



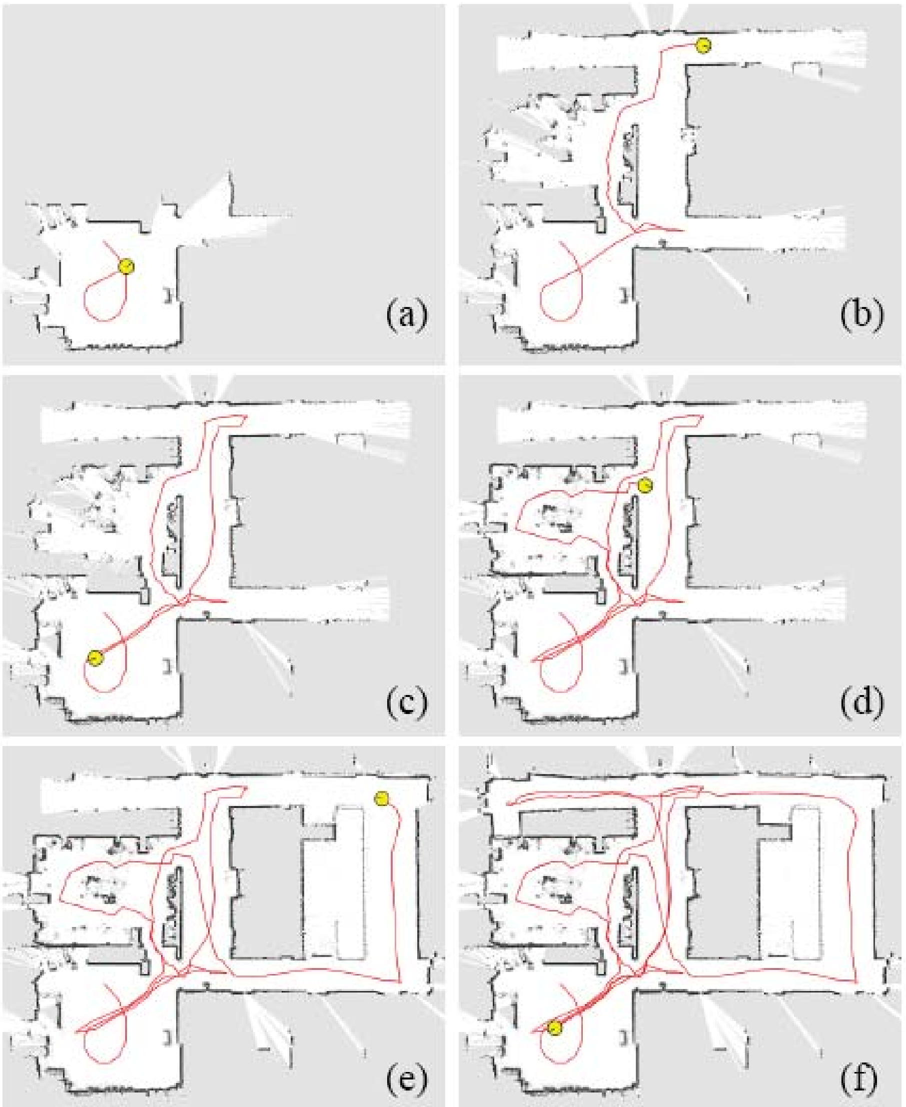
Confronto

Map uncertainty only:



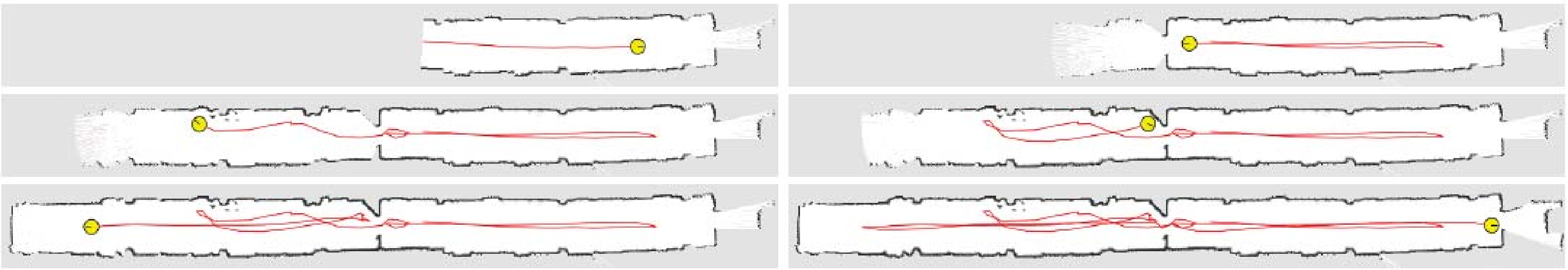
After loop closing action:

Esplorazione



Esplorazione Corridoio

Torna indietro per rilocalizzarsi



Riassunto

- A decision-theoretic approach to exploration in the context of RBPF-SLAM
- The approach utilizes the factorization of the Rao-Blackwellization to efficiently calculate the expected information gain
- Reasons about measurements obtained along the path of the robot
- Considers a reduced action set consisting of exploration, loop-closing, and place-revisiting actions
- Experimental results demonstrate the usefulness of the overall approach