Exploration strategies for autonomous mobile robots

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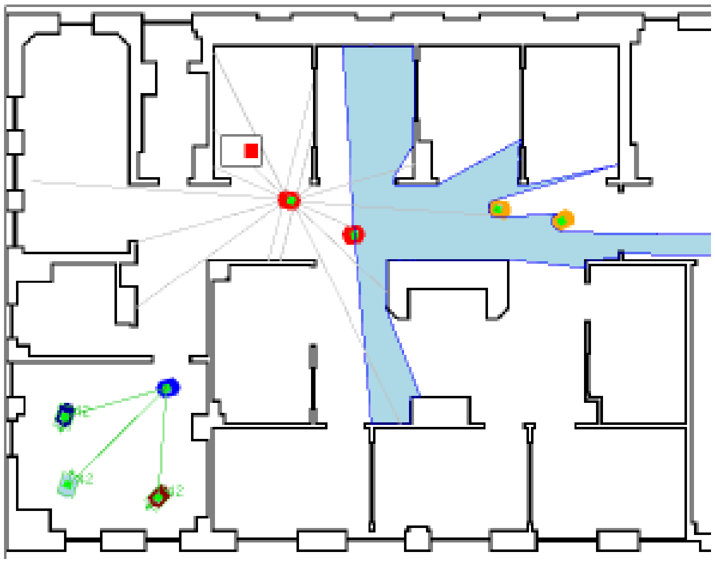
Autonomous Exploration

- **Problem**: a robot is deployed in an initially unknown environment

- **Sensors** (e.g., laser range scanners) allow it to acquire spatial data in its surroundings



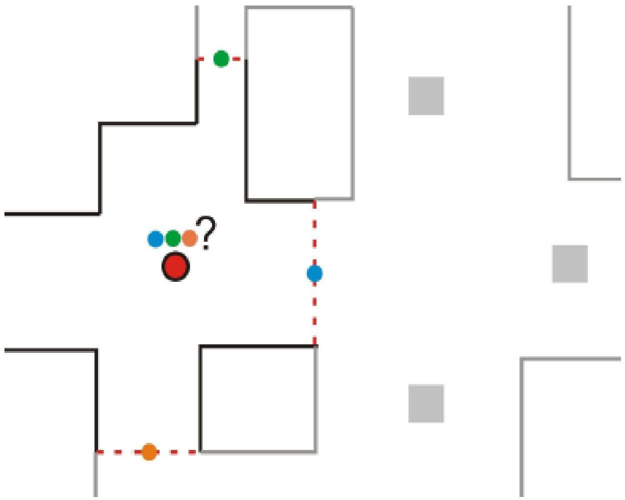
- **Goal**: we want to build a map of the whole environment

- **Performance**: we want an accurate map and we want to do it quickly

Autonomous Exploration

- Next Best View approach ([Yamauchi 1997], [Latombe et al. 2002], [Tovar et al. 2006], [Basilico et al. 2011]):
  - acquire a partial map
  - integrate the partial map in the global map
  - select the next best observation location among a set of candidate locations
  - reach the selected location

- Determine decisions in step 3: where to perform the next sensing action? Exploration strategy



Combining Criteria

- Evaluate candidate locations with an **utility function** that combines different evaluation criteria: travelling cost, information gain estimate, overlap

- Optimize decisions locally in order to optimize performance globally

Map Building
minimize the travelled distance
minimize the power consumption
maximize the map quality

Search and Rescue
minimize the needed time
maximize the mapped area
keep in contact with the base station
maximize found victims

- Different works proposed *ad hoc* methods to combine criteria, e.g.,

$$A(p)e^{-\lambda d(p)}$$

Latombe et al. 2002

$$U_{t'} - \beta \cdot V_{t'}^{i'}$$

Burgard et al. 2005

$$\sum_{i=1}^{m}\left(e^{(lv_i - sv_i)}\prod_{j=1}^{q_i}\left(\frac{e^{-|\theta_j|}}{\sqrt{s_j}+1}\right)\times\left(\frac{1}{n_i}\sum_{k=1}^{n_i}p_k + Ne_i\right)fmin_i(d_l)\right)$$

Tovar et al. 2006

$$\frac{A(p)P(p)}{d(p)}$$

Visser et al. 2008

Multi-Criteria Decision Making

- A decision theoretic approach: Multi-Criteria Decision Making (MCDM)
  - Assign a weight $\mu(A)$ every subset of criteria *A*
  - If $\mu(\{c_1, c_2\}) < \mu(c_1) + \mu(c_2)$ criteria are redundant
  - If $\mu(\{c_1, c_2\}) > \mu(c_1) + \mu(c_2)$ criteria are synergic
  - Compute utility for a candidate location *p* by combining utilities of each single criterion with the Choquet fuzzy Integral:

$$u(p) = \sum_{j=1}^{n} (u_{(j)}(p) - u_{(j-1)}(p))\mu(A_{(j)})$$

where $u_{(1)}(p) \leq \ldots \leq u_{(n)}(p) \leq 1$ and $A_{(j)} = \{i \in N | u_{(j)}(p) \leq u_i(p) \leq u_{(n)}(p)\}$

- “Distorted average” that accounts for relationships between criteria

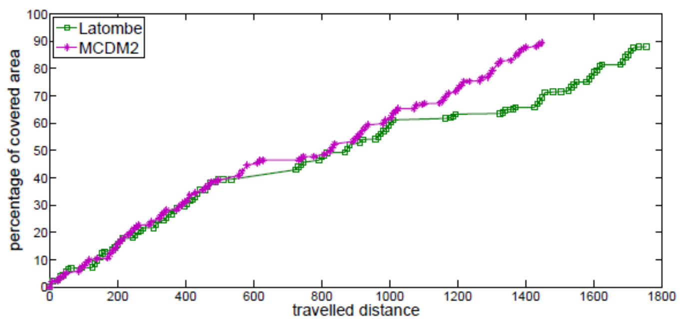
- Theoretical properties, e.g., Pareto optimality, stability, continuity, idempotence
- Generalizes some of the techniques proposed in literature
- Criteria contributions are explicitly quantified only by weights

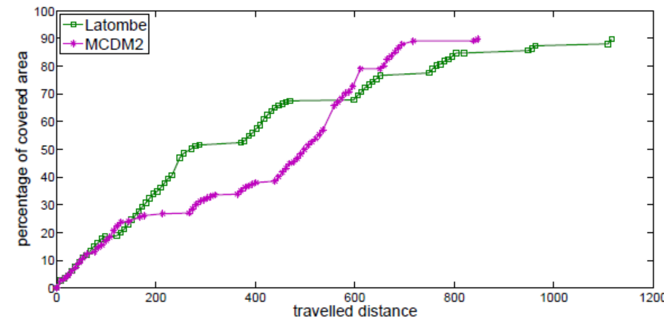
- The number of weights to set is exponential in the number of criteria $2^n - 2$

Example results

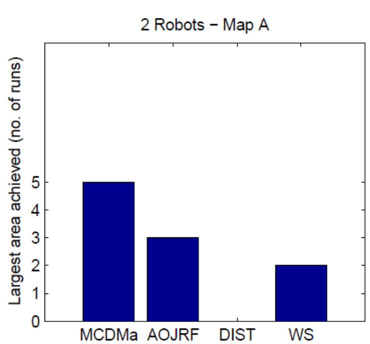
- Objective: assess better informed exploration strategies (MCDM) can achieve better global performance

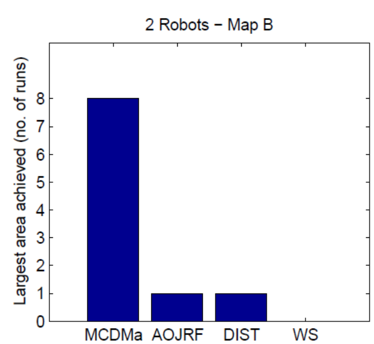
- Map-building: simulated exploration in Player/Stage, grid-based and geometrical map

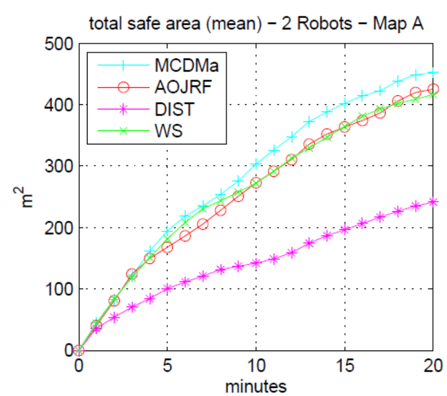


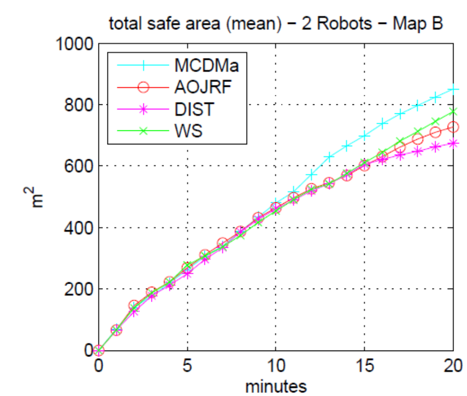


- Search and Rescue: simulations in USARSim, exploiting a controller from Robocup Virtual Rescue Competition

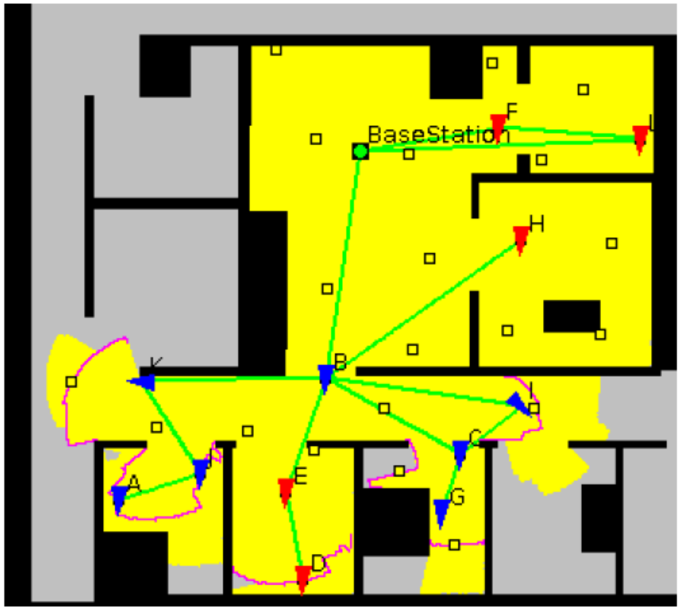








Multi-robot exploration

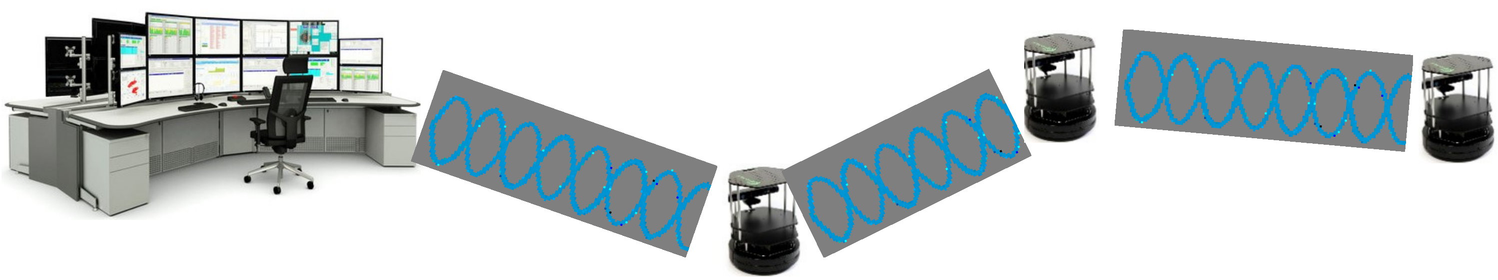


- Let’s consider a more complex scenario where:
  - Multiple robots are present
  - Robots deliver perception data to a base station (BS) which collects them and maintains a global map
  - Communication introduces constraints!

Communication

- Communication between robots is limited by communication range (it is unrealistic to assume that robots are always all-to-all connected)

- Exploration strategies must abide to some communication requirements (besides pursuing the performance objectives)



Communication requirements

- **Continuous connection** ([Birk et al., 2007]): each can exchange data with the BS at any time
- **Periodic reconnection**: communication opportunities with the BS must occur each T time units (e.g., [Hollinger et al., 2010])
- **Recurrent reconnection** ([Stump et al., 2011]): communication opportunities with the BS must occur each time they acquire new information (hard or soft)

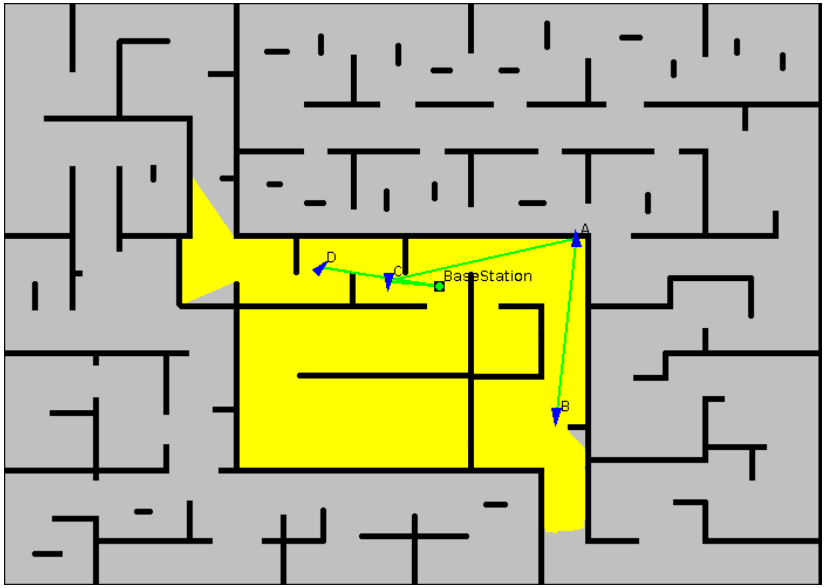
Hard vs soft recurrent reconnection

- **hard** constraint: (i) when a robot acquires some information at some location, it must be able to forward it to the BS from that same location, and (ii) before any new plan is computed, the whole team (robots and BS) must be globally connected

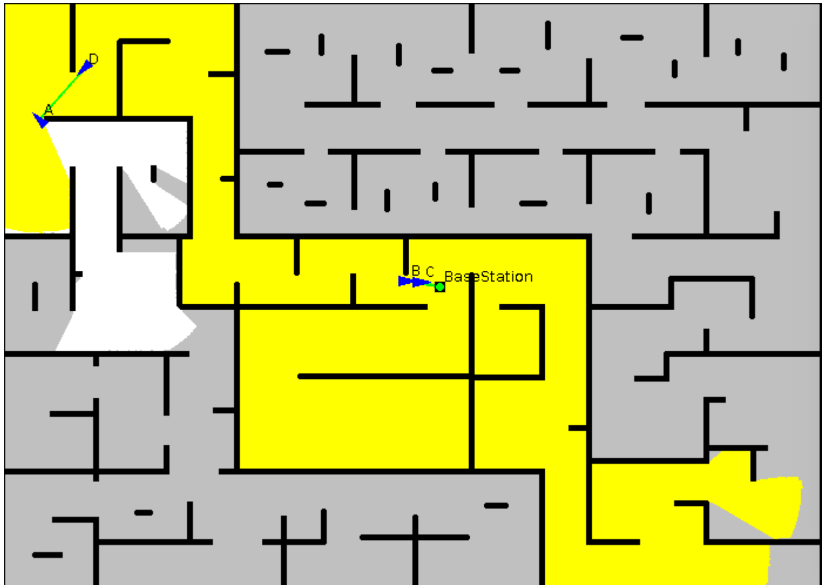
- **soft** constraint: the communication between the BS and the robots, despite being a desired condition, needs not to be maintained on a regular basis

Hard vs soft recurrent reconnection

Hard



Soft



Model Assumptions

- Two-dimensional environments to explore represented with occupancy grids derived from real maps
- One fixed base station (BS)
- differential drive mobile robots equipped with a 180° laser range scanner
- Limited line-of-sight communication model (conservative approach, as the environment is unknown)

Exact formulation (hard recurrent communication)

$$\text{maximize} \sum_{a \in A} \sum_{v \in V^{t+1}} (g(v) - \alpha d(q_a^t, v)) z_{av} \quad (1)$$

subject to

$$\sum_{a \in A \setminus \{BS\}} z_{av} = y_v \qquad \forall v \in V^{t+1} \setminus \{b\} \quad (2)$$

$$\sum_{v \in V^{t+1} \setminus \{b\}} z_{av} = 1 \qquad \forall a \in A \setminus \{BS\} \quad (3)$$

$$\sum_{(i,j) \in \mathcal{C}^-(v)} x_{ij} = y_v \qquad \forall v \in V^{t+1} \setminus \{b\} \quad (4)$$

$$\sum_{(i,j) \in \delta^-(S)} x_{ij} \geq y_v \qquad v \in S, b \notin S, \ \forall S \subseteq V^{t+1} \quad (5)$$

Given:

- Graph G=(V,E) representing the environment
- Robot locations

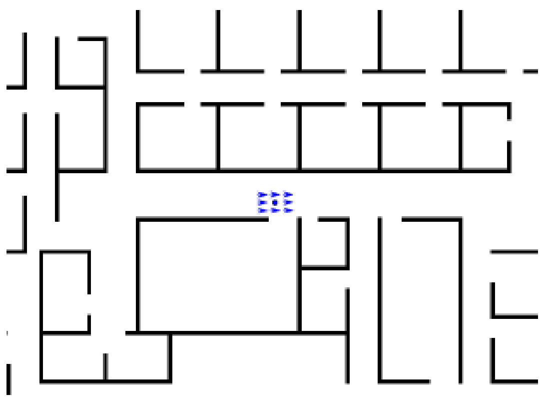
Assign each robot s.t.:

- communication is guaranteed
- objective function is maximized

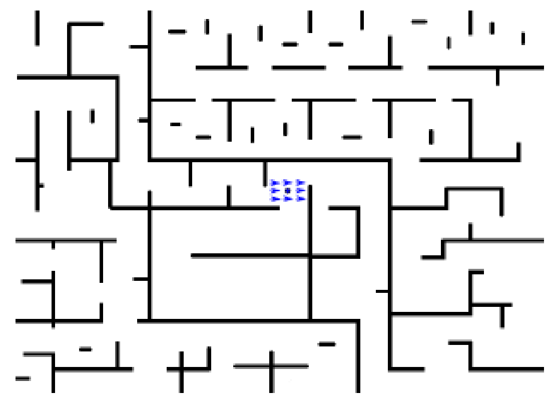
Experimental setting

- Environments

Office



Maze



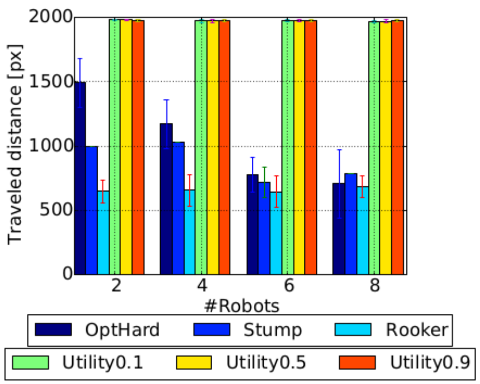
- Teams of 2, 4, 6, and 8 robots

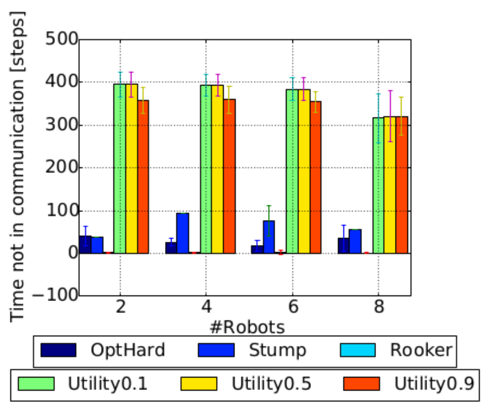
- For each environment, team, exploration strategy, we execute 5 runs of 500 time steps

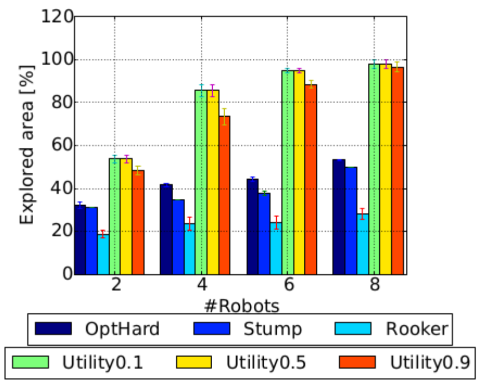
- Performance metrics:
  - Traveled distance by the robots
  - Time robots are not in communication with the BS
  - Amount of explored area known by the BS

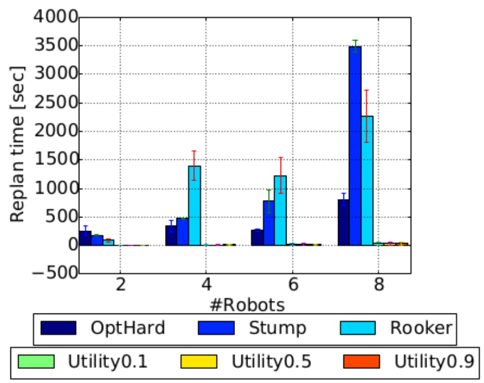
Experimental results

Office environment









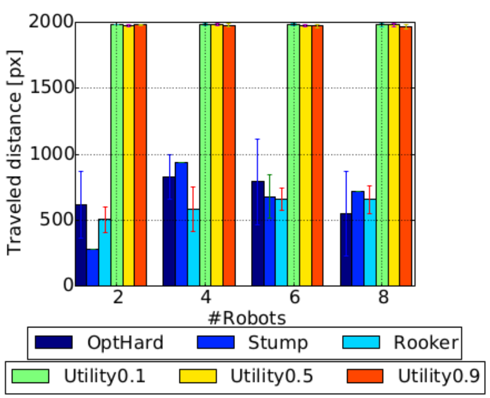
→ The stricter the communication constraint, the less traveled distance and explored area

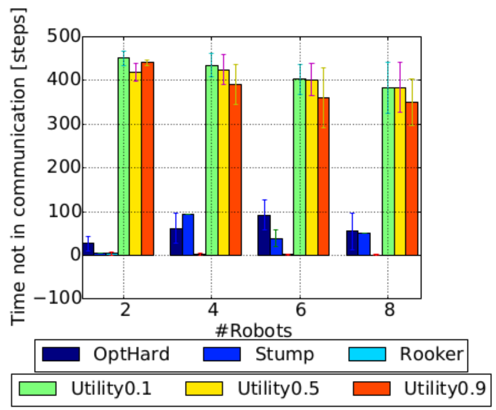
→ The looser the communication constraint, the higher the time robots are not in communication with the BS

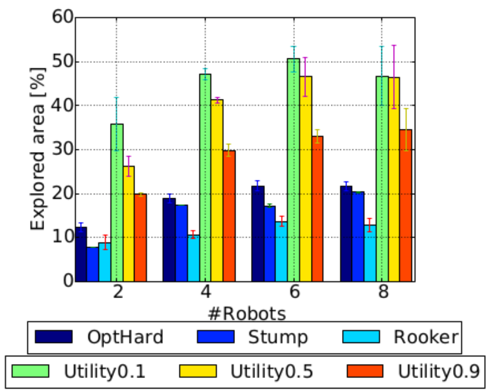
→ Replan time is higher for centralized methods with hard communication constraints

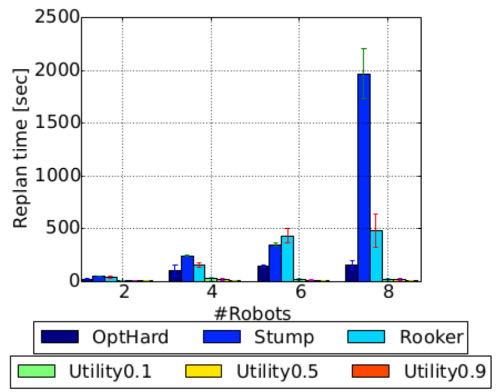
Experimental results

Maze Environment





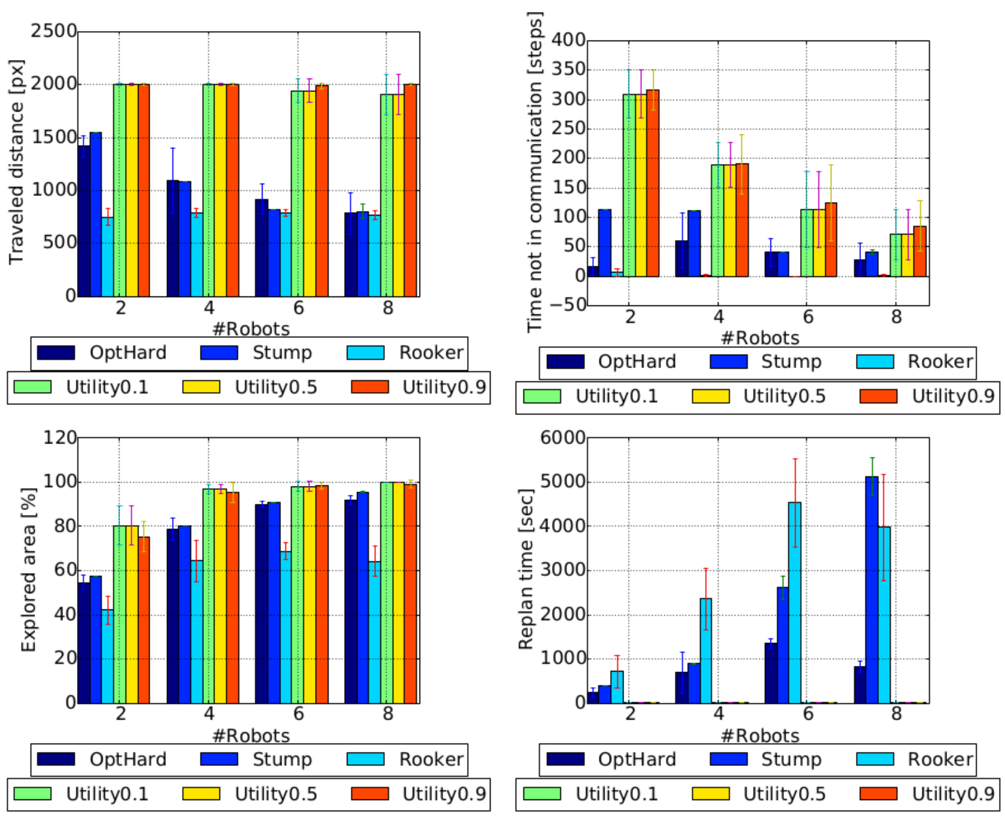




- → Similar trends to those in the office environment
- → The more complex structure of the environment leads methods enforcing soft communication constraints to make robots travel over already explored area

Experimental results

Open Environment



→ In more unstructured environments, it is easier:

- → to explore the environment also for exploration strategies with hard constraints
- → to maintain communication also for strategies that consider soft communication constraints

Recurrent communication

- Hard recurrent connectivity requires to solve an ILP at each planning epoch
- Can we make it resolution more efficient in practice by incurring in some quality loss? Let’s separate the problem:

Optimal configuration problem:
find the subset of vertices to be occupied by a robot, maximize expected information gain

?

Optimal deployment:
compute who goes where in a given configuration, minimize cumulative travelled distance

P

Recurrent communication

- The optimal configuration problem it's basically a R-BPCST: Rooted Budget Prize Collecting Steiner Tree Problem
  - *Steiner Tree Problem*: given a graph find a subgraph which connects a set of terminals and that is a tree
  - *Prize collecting*: each connected terminal gives a prize, maximize the total prize
  - *Budget*: the tree has a cost given by the sum of individual edge costs, it must not exceed a budget
  - *Rooted*: one terminal to be connected is fixed

$$U(f) = \frac{g(f)}{\min_{j \in R^t} d^2_{p_j^t f}}.$$ *prize of a frontier node*

Recurrent communication

- R-BPCST is NP-Hard on graphs (even on those with unitary edges and on arbitrary trees)
- On unitary trees? (P? …)

- It belongs also to APX (*4+eps* approximation algorithm available in literature)
- We designed a **ceil(k/delta)** approximation algorithm where delta is an arbitrary positive integer and k is the number of robots. If we operate with a reasonably small number of robots, it gives a better quality guarantee than the constant factor algorithm.