Performing Tasks while doing Simultaneous Localization And Mapping

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Abstract

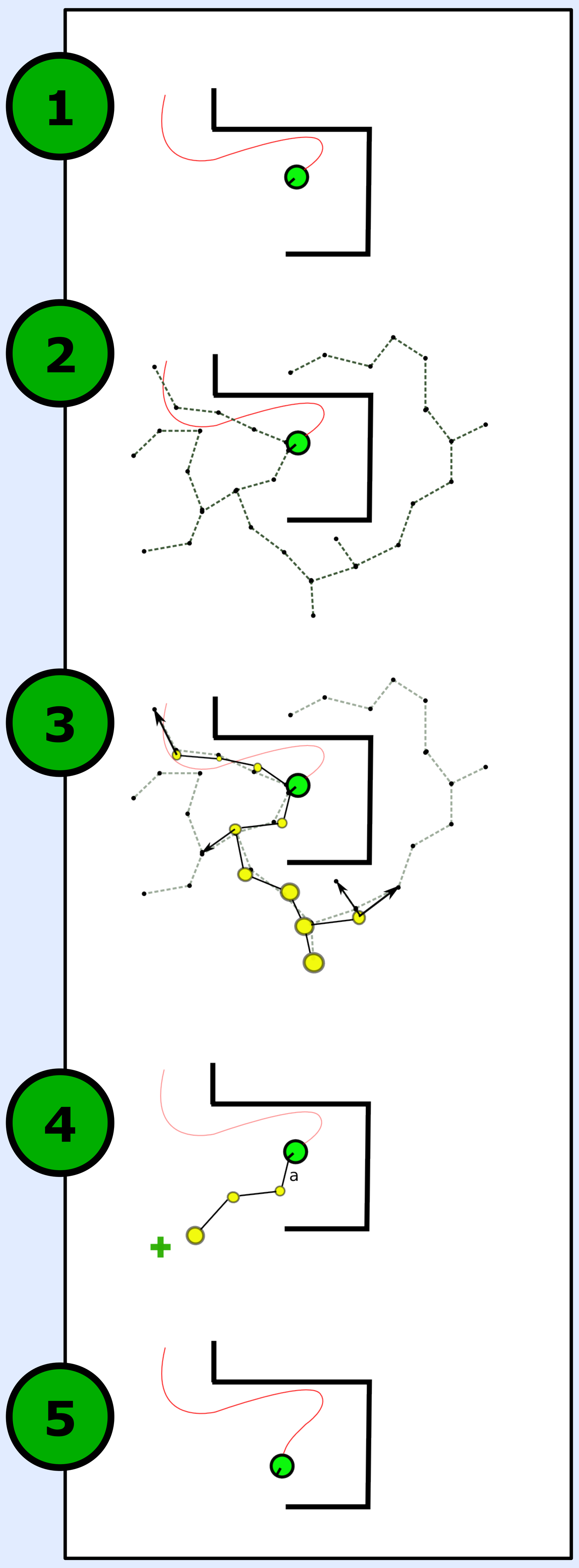
The problem of simultaneous localization and mapping (SLAM) is one of the most studied in the robotics literature. Most existing approaches, however, focus on scenarios where localization and mapping are the only tasks on the robot's agenda. In many real-world scenarios, a robot may be called on to perform other tasks simultaneously, in addition to localization and mapping. These can include target-following (or avoidance), search-and-rescue, point-to-point navigation, re-fueling, and so on. **We propose a framework that balances localization, mapping, and other planning objectives, thus allowing robots to solve sequential decision tasks under map and pose uncertainty.** Our approach combines a SLAM algorithm with an online POMDP approach to solve diverse navigation tasks, without prior training, in an unknown environment.

Methods

- Planning state space: $S = \mathbf{M} \times \mathbf{X} \times \mathbf{P}$
  - $\mathbf{M}$ the set of possible maps
  - $\mathbf{X}$ the set of possible trajectories
  - $\mathbf{P}$ the set of additional planning states
- Reward function: task dependent
- Observation function: laser + odometry + task-related measurements
- State estimation: modified **Rao-Blackwellized Particle Filter** (RBPF) [1]
- Planning: **online POMDP** [2] approach
  At each step:
  - Use current posterior distribution
  - Sample sequences of actions and observations
  - Recursively expand search tree in belief space
  - Estimate value of the leaf nodes using a heuristic
  - Select action that maximizes the sum of discounted rewards

Action selection

- Need to sample long trajectories to get good value estimate
- Make it tractable by approximating the search tree:



1 Posterior updated, time to plan

2 The robot builds *M* **Rapidly-Exploring Random Trees** (RRTs) [3] using the expected map and pose.

3 **Use RRTs to direct search in belief space**:
Step i: Simulate action in direction of next RRT node
Step ii: Sample observation
Step iii: Do a posterior update

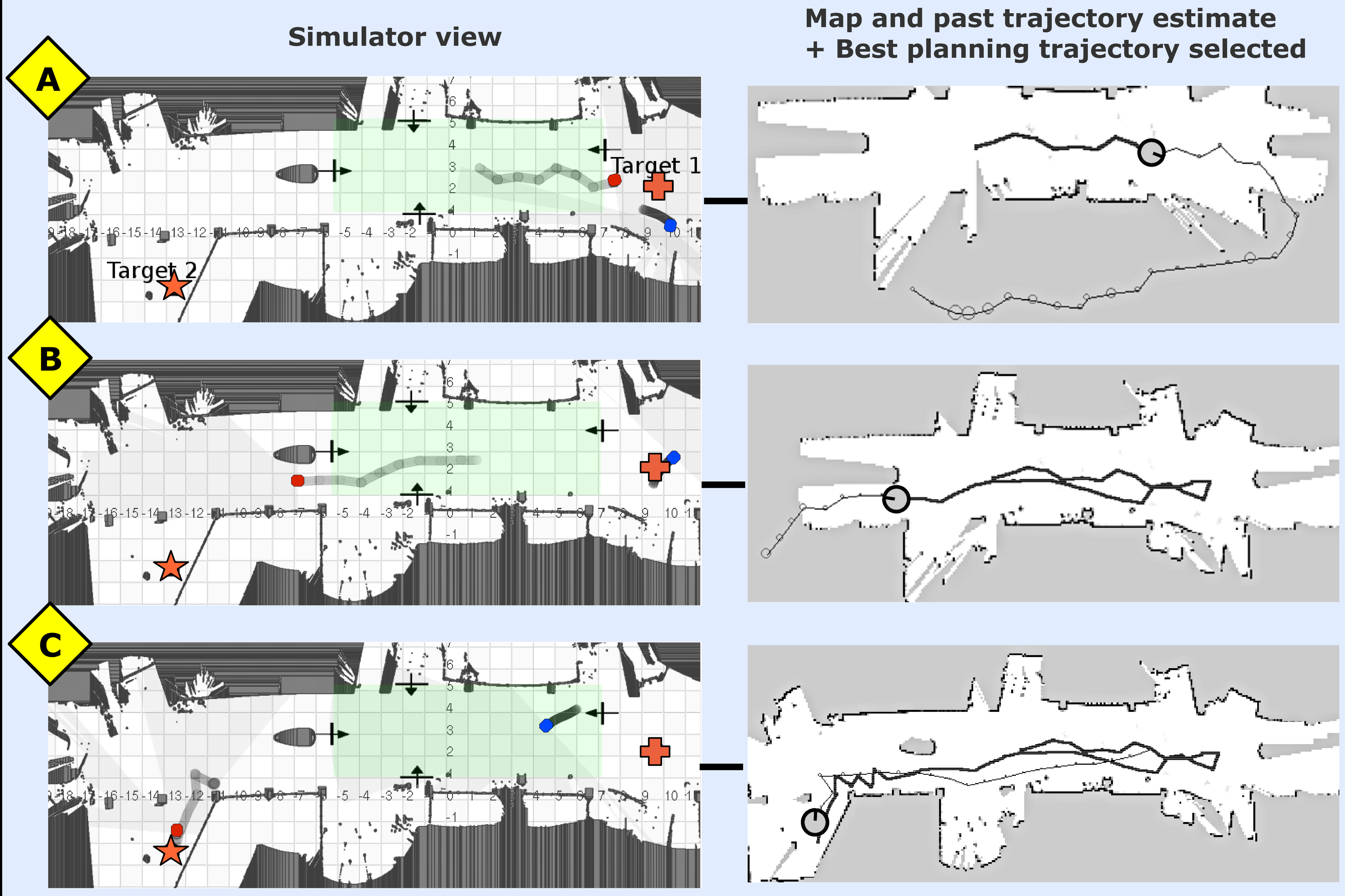
Repeat this for all nodes.

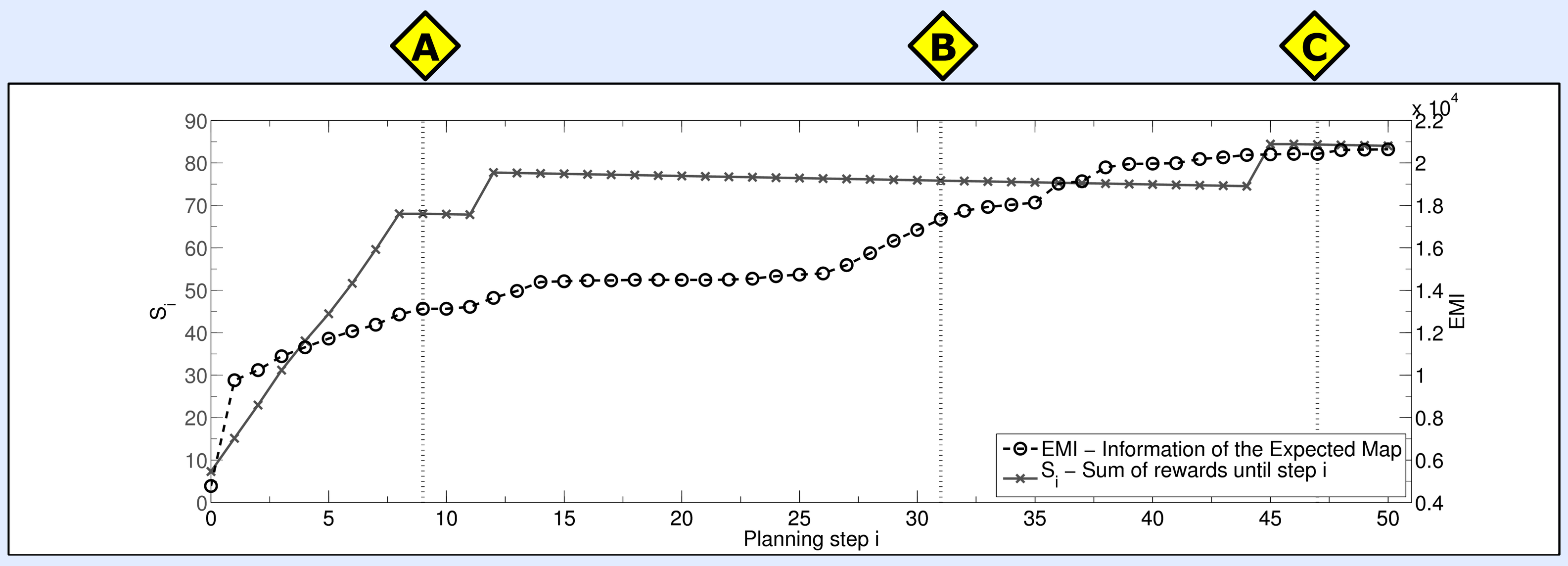
4 Back up the discounted rewards for each step of all trajectories, use heuristic state value at the end of trajectories. **Select action that leads to best expected sum of discounted reward.**

5 Execute action using low-level controller and plan again to choose next action.

Experiment

- Simulated environment (Player/Stage), California Science Center floor map. Pioneer robot ( ) equiped with laser range finder.
- **Task:** In region, follow other robot (, moves randomly) Else go to and then to and stay at





- **Step A:** outside the region
  goes to
- **Step B:** explores to reach
- **Step C:** inside the region
  comes back to follow
- Balance between map exploration, task execution and localization.

Conclusion

Framework for performing SLAM when the mapping and localization are not the primary focus of the robot.

- Decision-theoric framework: handles map and pose uncertainty + online planning algorithm capable of solving diverse planning tasks in that setting.
- Simulated experiments suggest easy transfer to real-world setting.
- Main limitation: approximation in the decision making process to keep it tractable.

References

[1] G. Grisetti, C. Stachniss, and W. Burgard, "Improving grid-based SLAM with Rao-Blackwellized particle filters by adaptive proposals and selective resampling," in ICRA 2005. pp. 2432–2437.

[2] S. Ross, J. Pineau, S. Paquet, and B. Chaib-draa, "Online planning algorithms for POMDPs," Journal of Artificial Intelligence Research, vol. 32, pp. 663–704, 2008.

[3] J. Kuffner Jr and S. LaValle, "RRT-connect: An efficient approach to single-query path planning," in ICRA 2000.