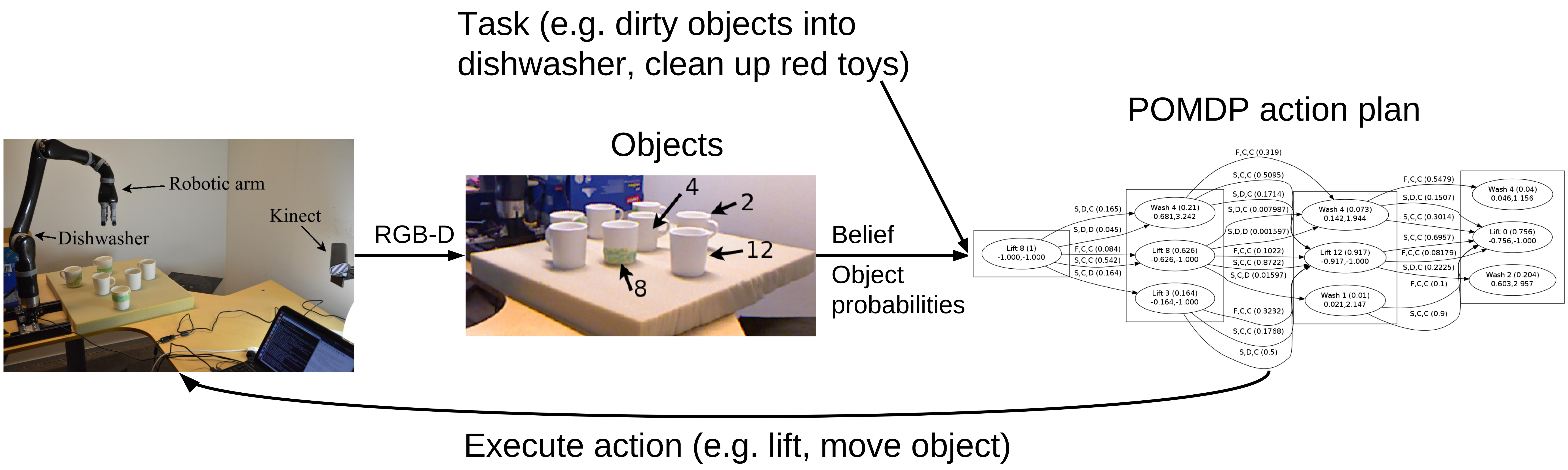
Intelligent Robotics group
Department of Electrical Engineering and Automation
Aalto University, Finland

Aalto University
School of Electrical Engineering

Joni Pajarinen, Ville Kyrki

Robotic manipulation of multiple objects as a POMDP



1. Summary

- Setting: Unknown objects in a crowded environment
- Challenges: Occlusion, imperfect observations, and uncertain action success
- Approach: Task planning as a partially observable Markov decision process (POMDP)
  - Occlusion dependent probabilities
  - Model adapts automatically object grasp probabilities

2. Probability and belief estimation

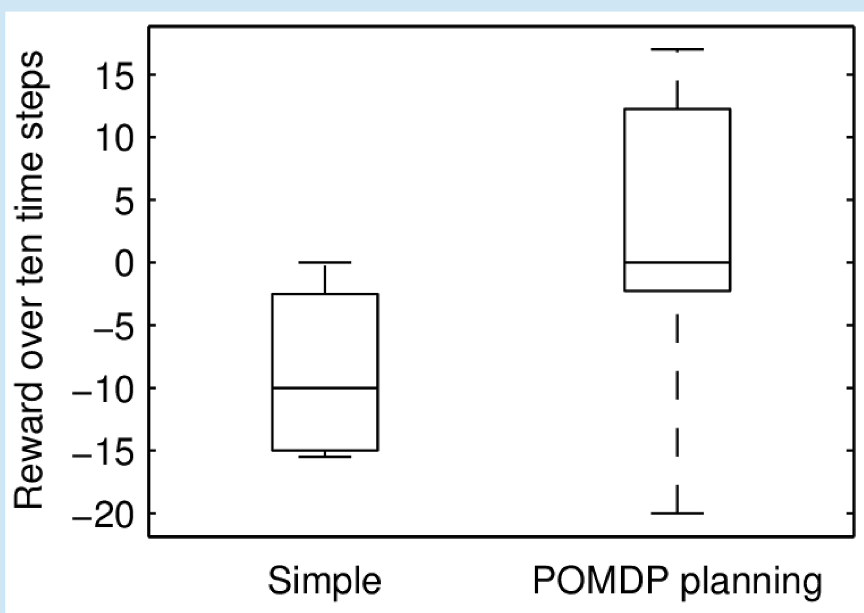
- At each time step estimate probability model and belief
- *Probability model*:
  - Find occluding objects from segmented RGB-D
  - Compute model-free occlusion ratios using 2D object edges
  - Occlusion decreases grasp and observation probabilities
  - Object grasp probability depends on previous grasp successes
- The *belief* consists of sampled particles
- Particle consists of N objects, each having
  - Semantic location (e.g. on table)
  - Attributes (e.g. color)
  - # succeeded/failed grasps

3. Planning

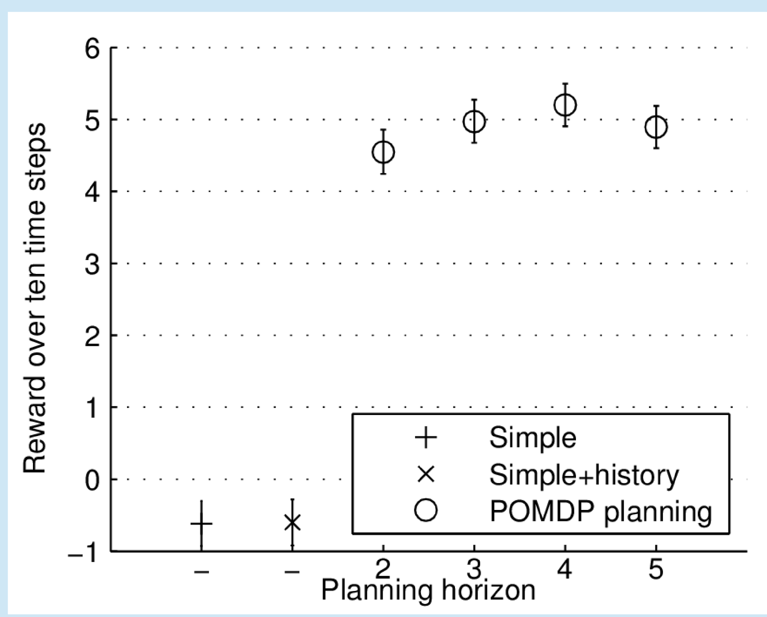
- A POMDP defines optimal behavior under uncertain action effects and observations
- POMDP: probabilities define world dynamics, rewards encode task specific goal/utilities
- We propose an online POMDP approach that generates an efficient understandable policy graph

4. Experiments

- Example application: dirty objects into dishwasher
- Actions: move object into dishwasher; lift an object to see behind it
- Comparison of POMDP approach to heuristic approach “Simple”



Robot arm experiments



Simulated dynamics

REFERENCES
[1] J. Pajarinen and V. Kyrki. Robotic manipulation of multiple objects as a POMDP. ArXiv e-prints, 2014.
[2] J. Pajarinen and J. Peltonen. Periodic Finite State Controllers for Efficient POMDP and DEC-POMDP Planning. In Proc. of NIPS, 2011