Task and Motion Planning
for Multi-robot System and Robotic Manipulation

Meng Guo

[Bosch Center for Artificial Intelligence (BCAI)](https://mengguo.github.io/personal_site/)

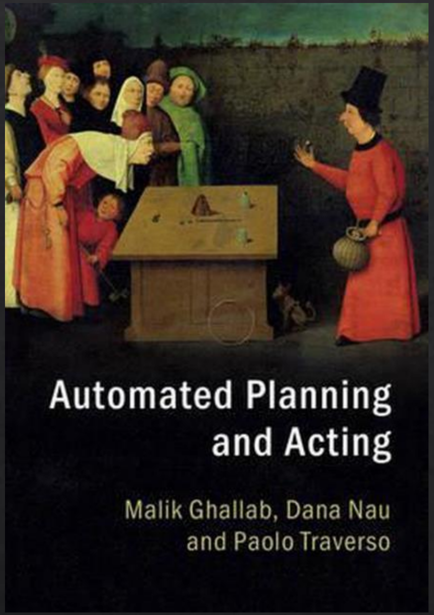
Meng.Guo2@de.bosch.com

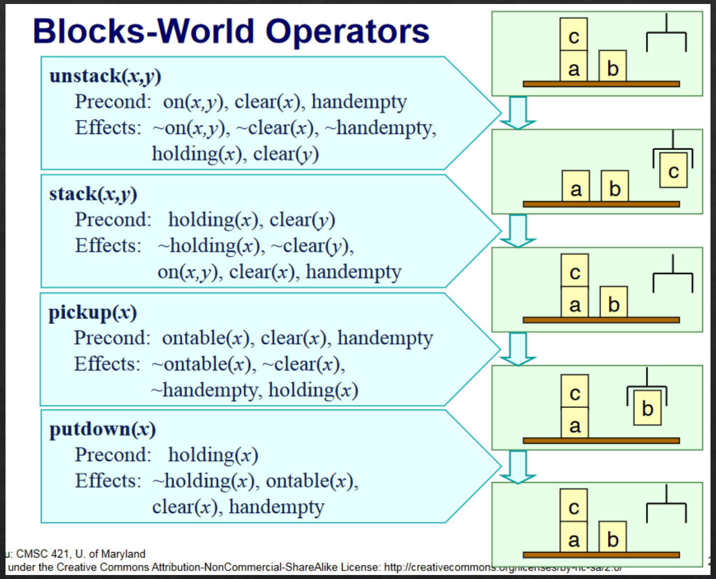
https://mengguo.github.io/personal_site/

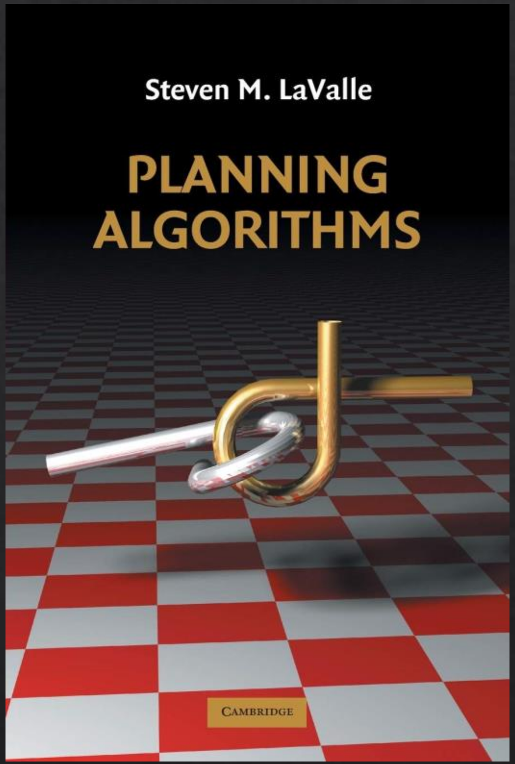
Outline

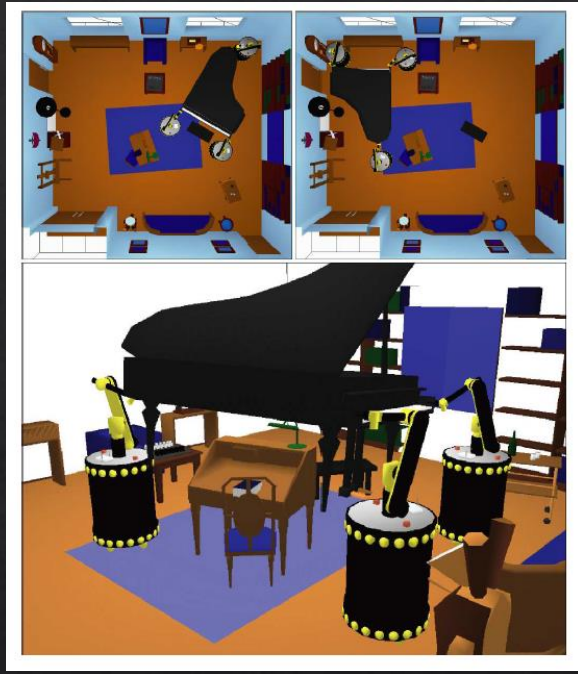
- Intro.
  - Task and Motion Planning (TAMP).
  - Applications.
- Multi-robot system
  - Bottom-up Vs. Top-down.
  - Dynamic constraints.
- Robotic Manipulation
  - Learning from Demonstration (LfD).
  - TAMP over LfD skills.

- Task Planning (PDDL, STRIPS…)
- Motion Planning (RRT, PRM, MPC)



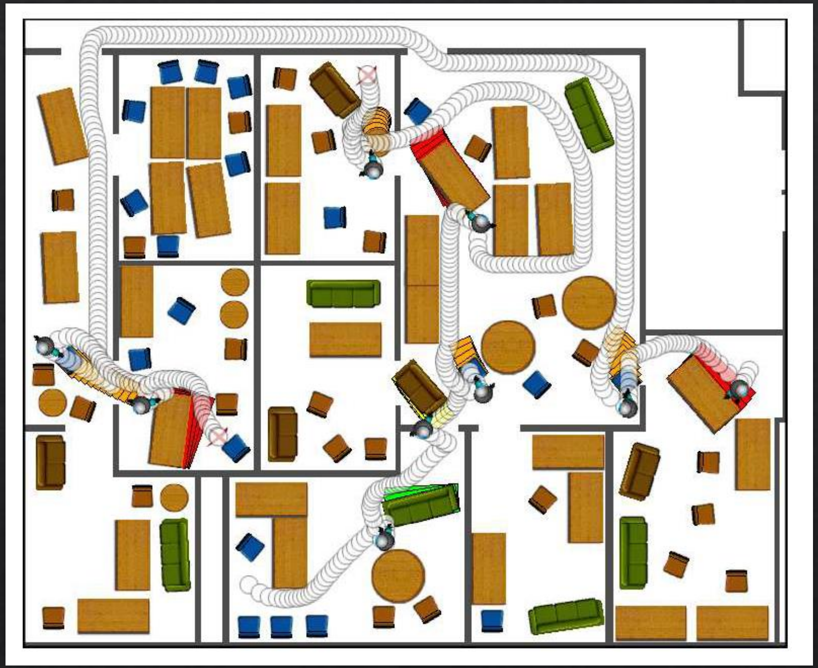






TAMP

- Task planning: decide what actions to do.
- Motion planning: how to do them.



Navigation among movable obstacles: Real-time reasoning in complex environments. Stilman and Kuffner. Humanoids 04.

- Each aspect difficult.
  - Computation complexity. Completeness
- Even more, if coupled.

https://www.moley.com/

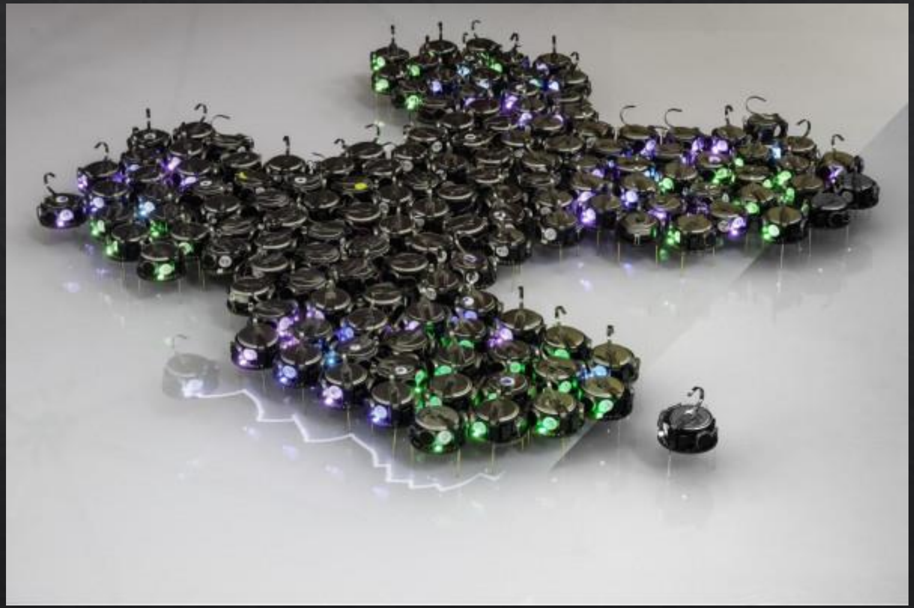
Amazon Picking Challenge

Multi-robot Systems

Collaborative Motion

- Consensus, formation, schooling…

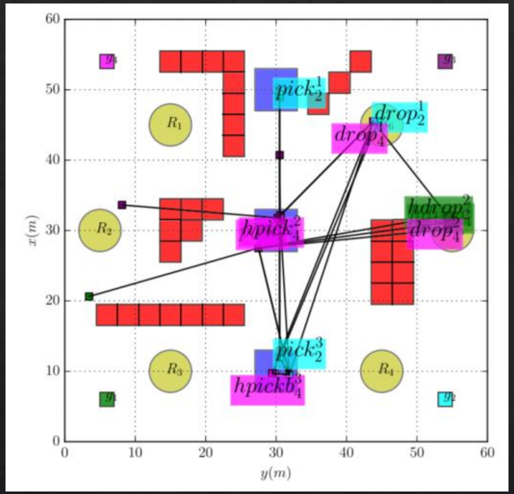
Robotarium @ Georgia Tech

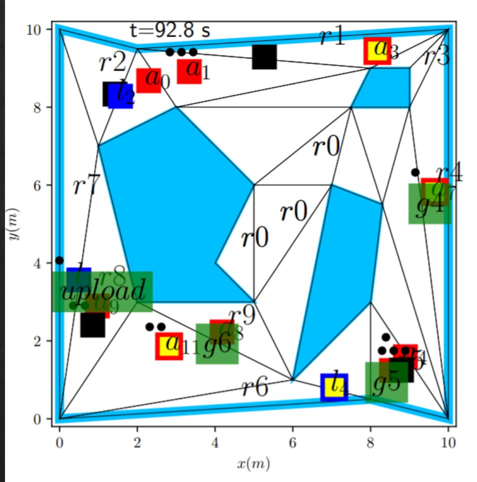


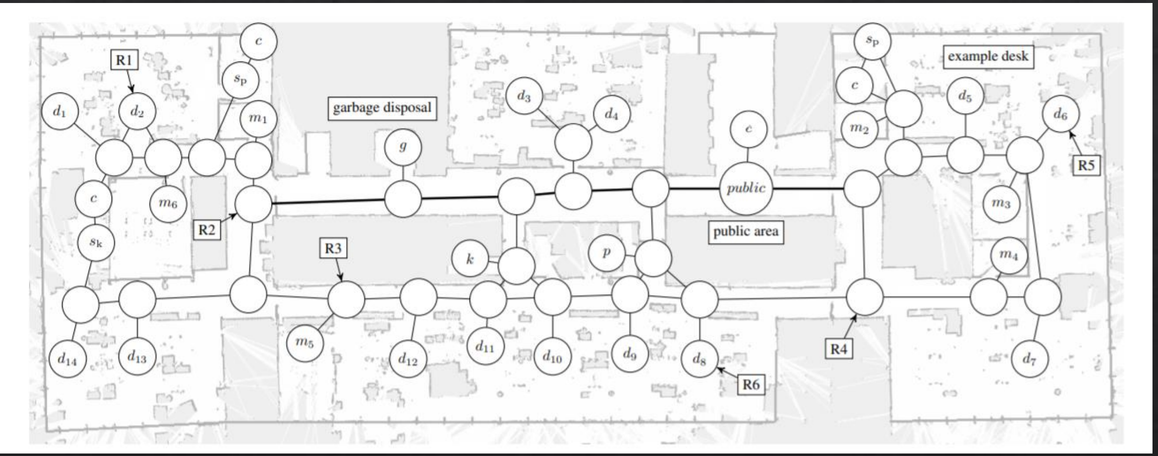
Kilobots @ Harvard

Collaborative Motion and Task

- Perspective one:
  - Each robot has its own task (even dependent).
  - Decentralized and bottom-up view.
- Perspective two:
  - The team has a global task.
  - Centralized and top-down view.







Multi-Robot Data Gathering Under Buffer Constraints and Intermittent Communication. Guo & Zavlanos. TRO 18

Multi-agent plan reconfiguration under local LTL specifications. Guo, Dimarogonas. IJRR 15.

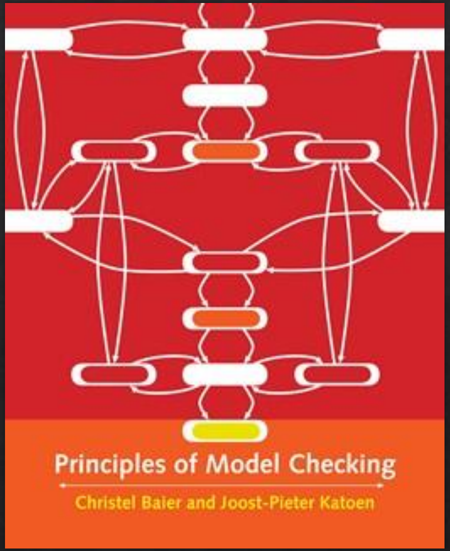
Hierarchical LTL-Task MDPs for Multi-Agent Coordination through Auctioning and Learning. Schillinger, Bürger, & Dimarogonas, IJRR 19.

STyLuS*: A Temporal Logic Optimal Control Synthesis Algorithm for Large-Scale Multi-Robot Systems. Kantaros, Zavlanos. IJRR 20.

Linear Temporal Logic

- Combination of 1st-order logic and temporal operators.

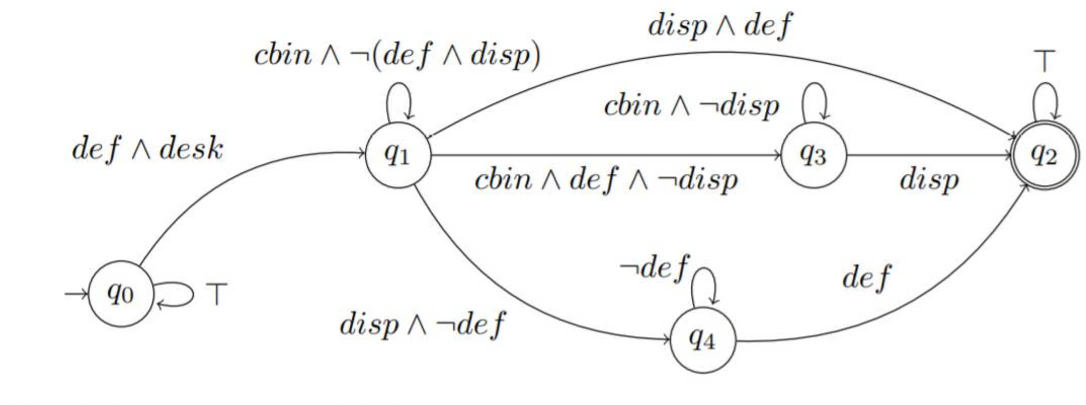
$$\varphi ::= \mathtt{True} \mid a \mid \varphi_1 \vee \varphi_2 \mid \neg\varphi \mid \bigcirc\varphi \mid \varphi_1 \,\mathsf{U}\, \varphi_2$$



$$\begin{aligned} \varphi^{\text{hard}}_{\mathtt{Gw\_i}} &= (\Box\Diamond\neg\mathtt{obs}) \wedge \varphi_{\text{order}} \\ \varphi^{\text{soft}}_{\mathtt{Gw\_i}} &= (\Box(\Diamond\mathtt{b1} \wedge \Diamond\mathtt{b2} \wedge \ldots \wedge \Diamond\mathtt{b7})) \end{aligned} \quad (23)$$

where $\varphi_{\text{order}} \triangleq (\quad \Box\Diamond\mathtt{water}) \wedge (\quad \Box(\mathtt{water} \Rightarrow \bigcirc(\neg\,\mathtt{water}\ \mathsf{U}(\varphi_{\text{one}}))) \wedge (\quad \Box((\varphi_{\text{one}}) \Rightarrow \bigcirc(\neg(\varphi_{\text{one}})\ \mathsf{U}\ \mathtt{water})),$

Multi-agent plan reconfiguration under local LTL specifications. Guo, Dimarogonas. IJRR 15.

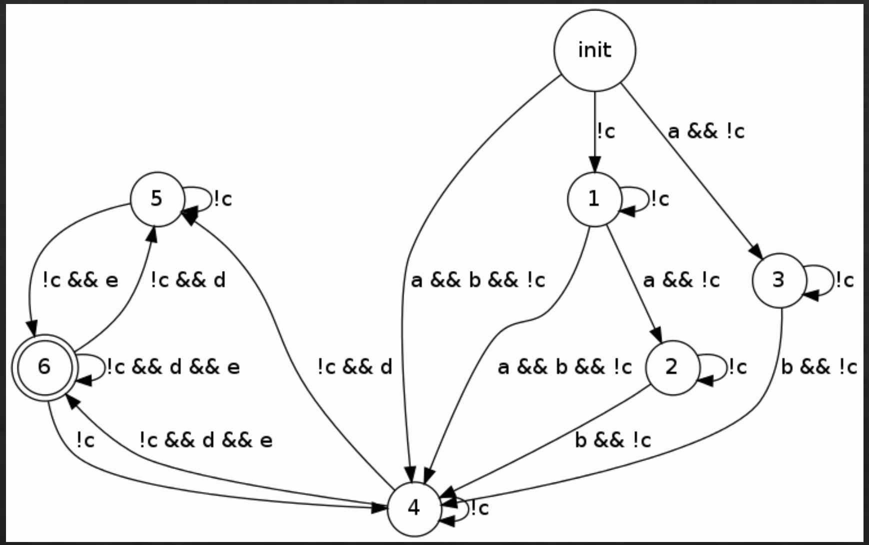


NFA for the formula $\phi_1 = \Diamond(desk \wedge default \wedge \bigcirc((carrybin\ \mathcal{U}\ dispose) \wedge \Diamond default))$.

Simultaneous task allocation and planning for temporal logic goals in heterogeneous multi-robot systems
Schillinger, Bürger, & Dimarogonas. IJRR 18.

LTL → NBA, NFA

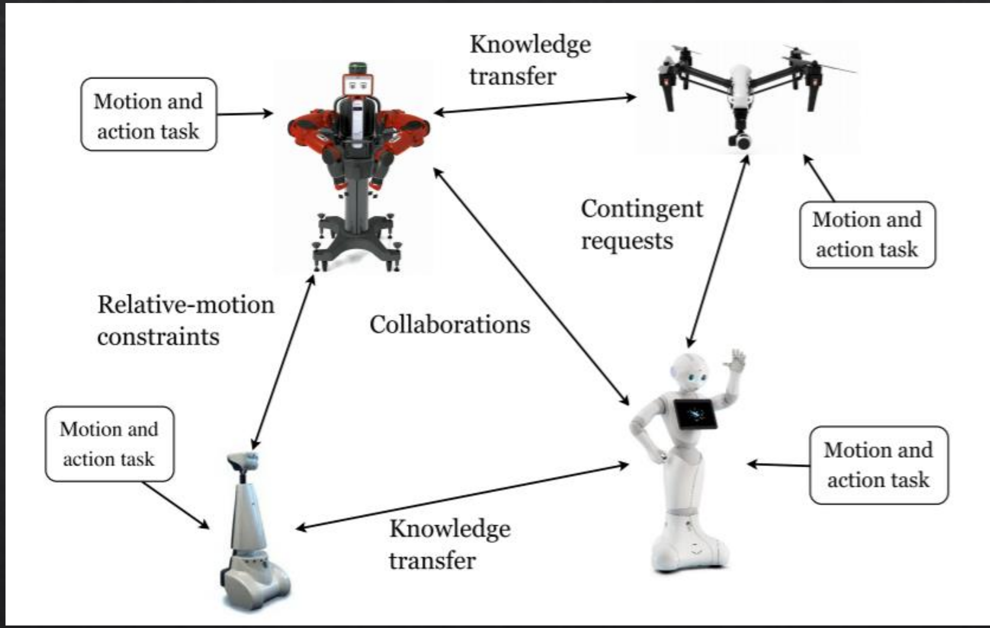
- Automatic translation to Non-deterministic Buchi Automaton (NBA).
  - For task with infinite recurrence, such as surveillance.
- Automatic translation to Non-deterministic Finite Automaton (NFA)
- Tools:
  - http://www.lsv.fr/~gastin/ltl2ba/
  - https://github.com/MengGuo/P_MAS_TG
  - https://spot.lrde.epita.fr



F (a && F b) && G ! c && GF d && GF e

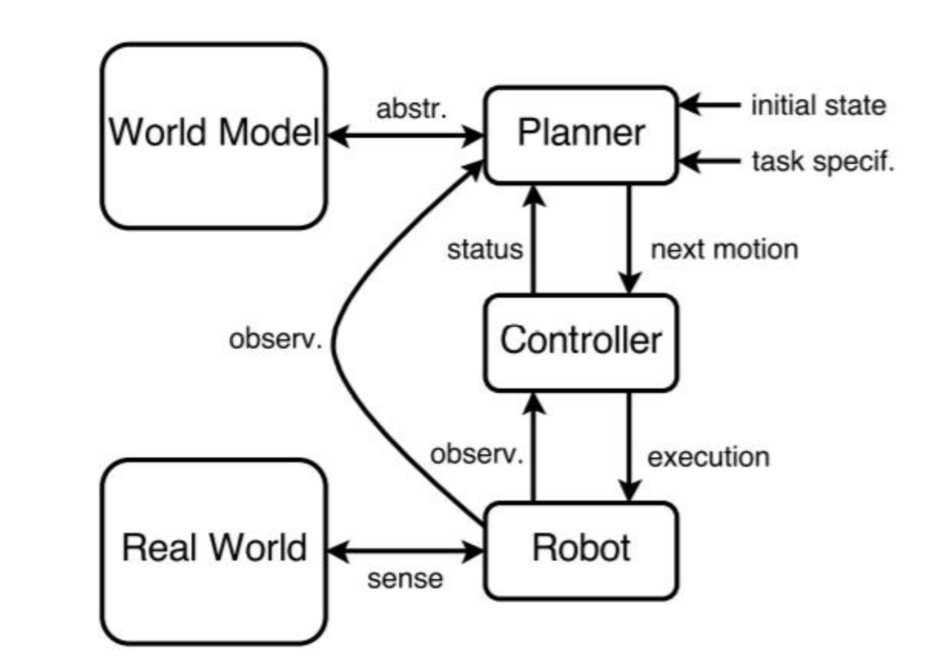
Perspective One: Bottom-up

- Each robot has its own local tasks.
  - Independent.
    - Collaboration via sharing real-time information about the workspace model.
  - Dependent.
    - Collaboration via collaborative actions.
- Each robot motion.
  - Homogenous. Collision avoidance.
  - Heterogenous, e.g., UAV, UGV.
- Advantages:
  - Inherently decentralized and distributed.



Paper 1

- Multi-agent plan reconfiguration under local LTL specifications. Guo, Dimarogonas. IJRR 15.
- Partially infeasible tasks.
  - Relaxed product automaton
  - Allow violation of certain rules with a *cost*.
- Partially known workspace.
  - Improve/learn workspace model *while* execution plans.
  - Transfer/share such knowledge to other agents.
  - Online plan revision.



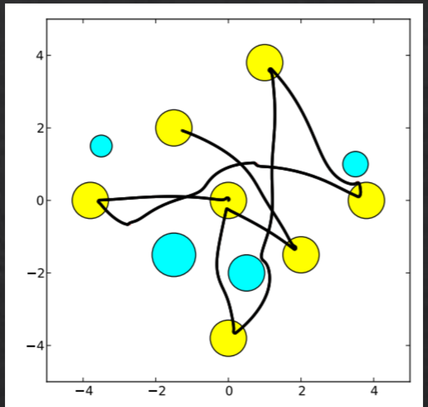
Paper 1 con't

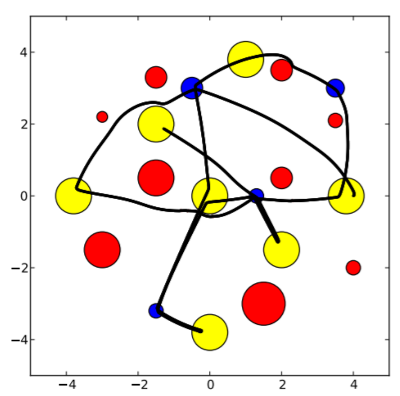
- Communication protocol.
  - Task-driven and feature driven.

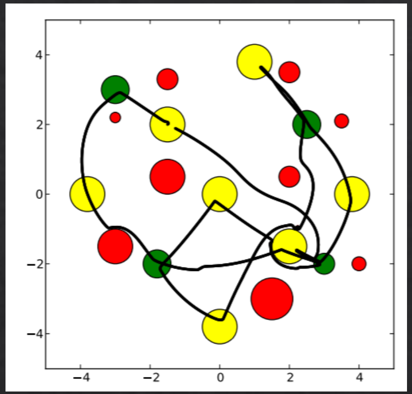
$$\mathbf{Request}^{t}_{j,i} = (j,\ \varphi_j|_{AP_j},\ i)$$

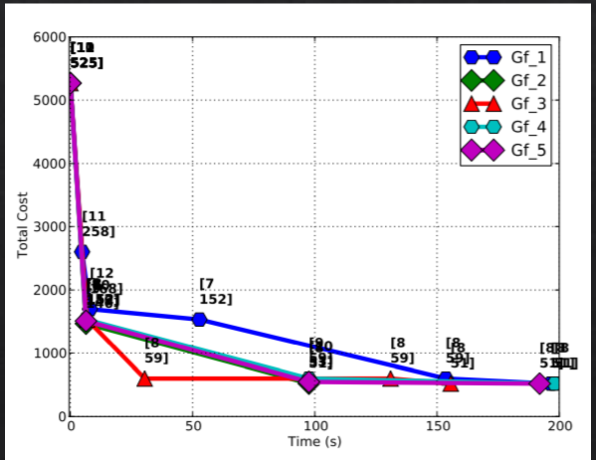
$$\mathbf{Reply}^{t}_{i,j} = \{(\pi,\ S',\ S'_{\neg})\}$$

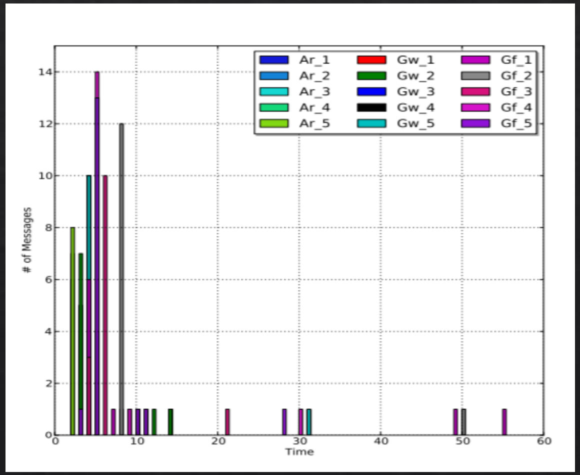
- Online plan verification and modification.





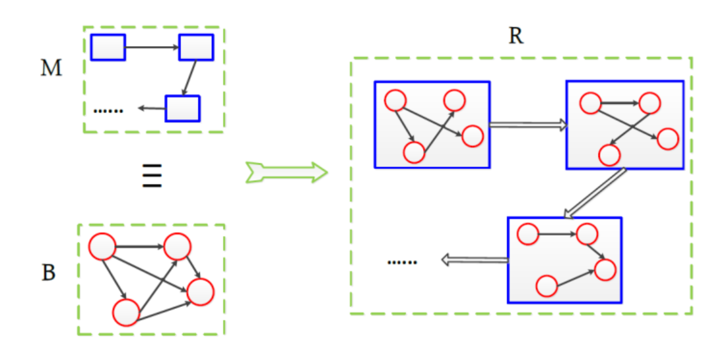






Paper 2

- Task and Motion Coordination for Heterogeneous Multi-agent Systems with Loosely-coupled Local Tasks. Guo and Dimarogonas. TASE17
- Dependent local tasks:
  - Motion *and* actions.
  - Collaborative actions.



- Contingent adaptation, with:
  - Unknown number of agents;
  - Unknown tasks.
- Local, collaborative, and assisting actions.
  - Task/capability dependence.
  - *NOT* agent ID dependent.

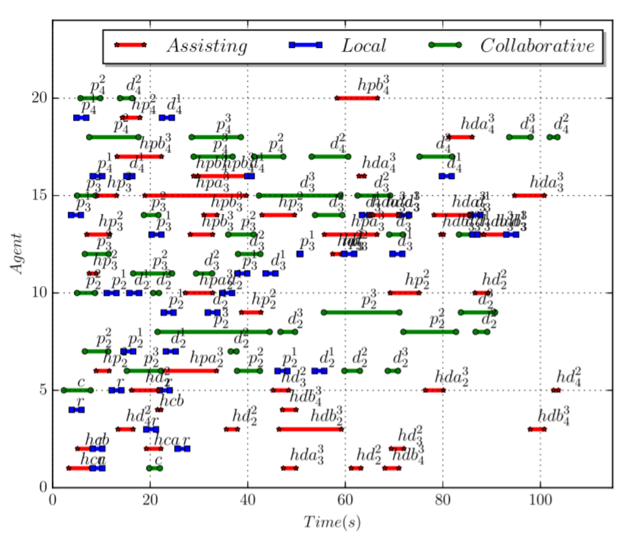
Paper 2 con't

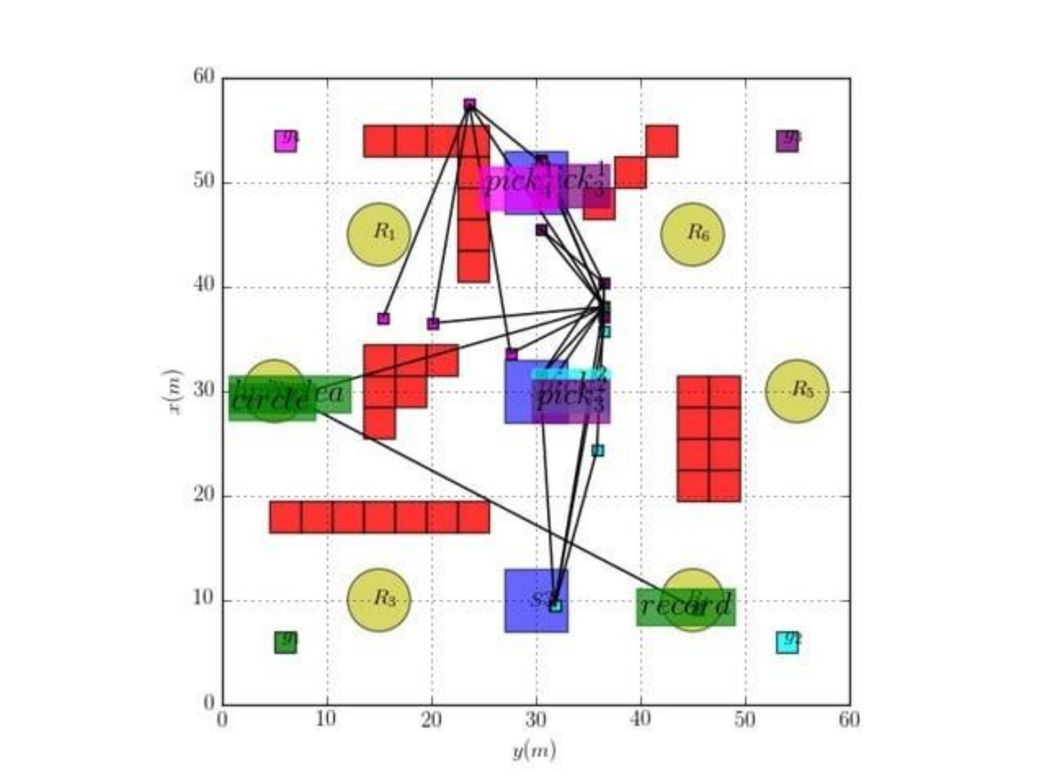
- Online task coordination.

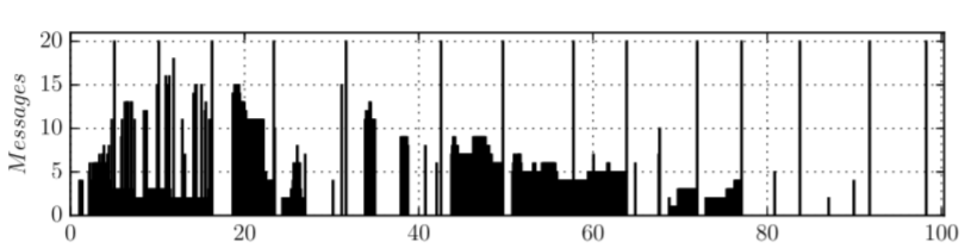
$$\textbf{Request}^i = \{(\sigma_d, \pi_v, T_m), \forall \sigma_d \in \mathtt{Depd}_i(\sigma_m)\}$$

$$\textbf{Reply}_i^j = \{(\sigma_d, b_d^j, t_d^j), \forall (\sigma_d, \pi_v, T_m) \in \textbf{Request}_j^i\}$$

- Local task planning
  - Solving MILP.
  - Distributed auction.



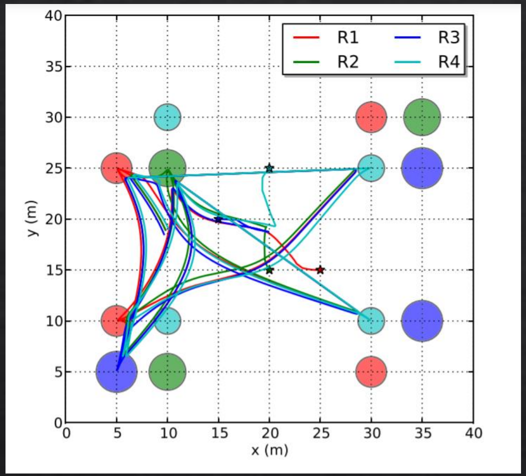


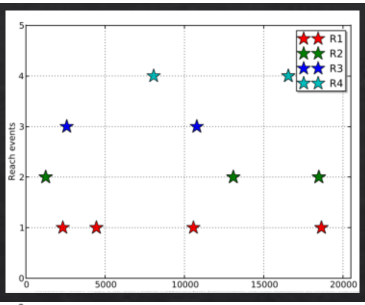


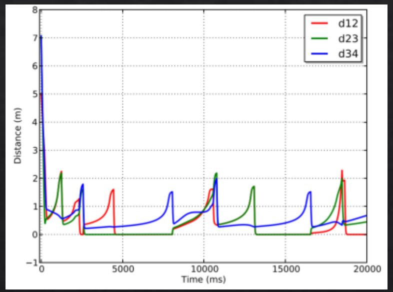
Dynamic Constraints

- Relative distance constraints.

$$\|x_i(t) - x_j(t)\| < r, \forall\,(i,j) \in E_0(0), \forall\, t \in [0,T]$$







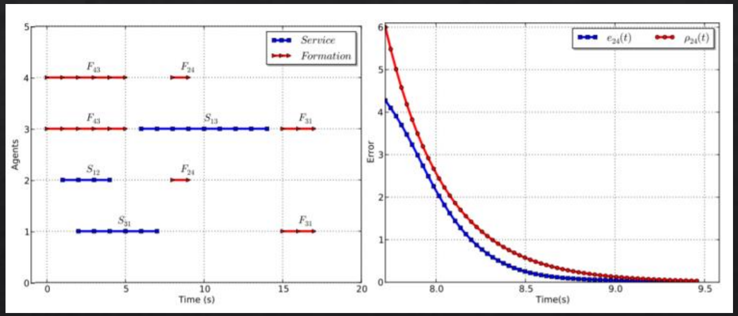
[Communication-Free Multi-Agent Control under Local Temporal Tasks and Relative-Distance Constraints](). Guo, Tumova and Dimarogonas. TAC 2016.

- Prescribed formation constraints.

$$e_{ij}(t) \triangleq p_i(t) - p_j(t) - c_{ij}. \tag{3}$$

Let us also define $\mu_{ij} \triangleq e_{ij}^T e_{ij}$ as a scalar measure of the formation error and

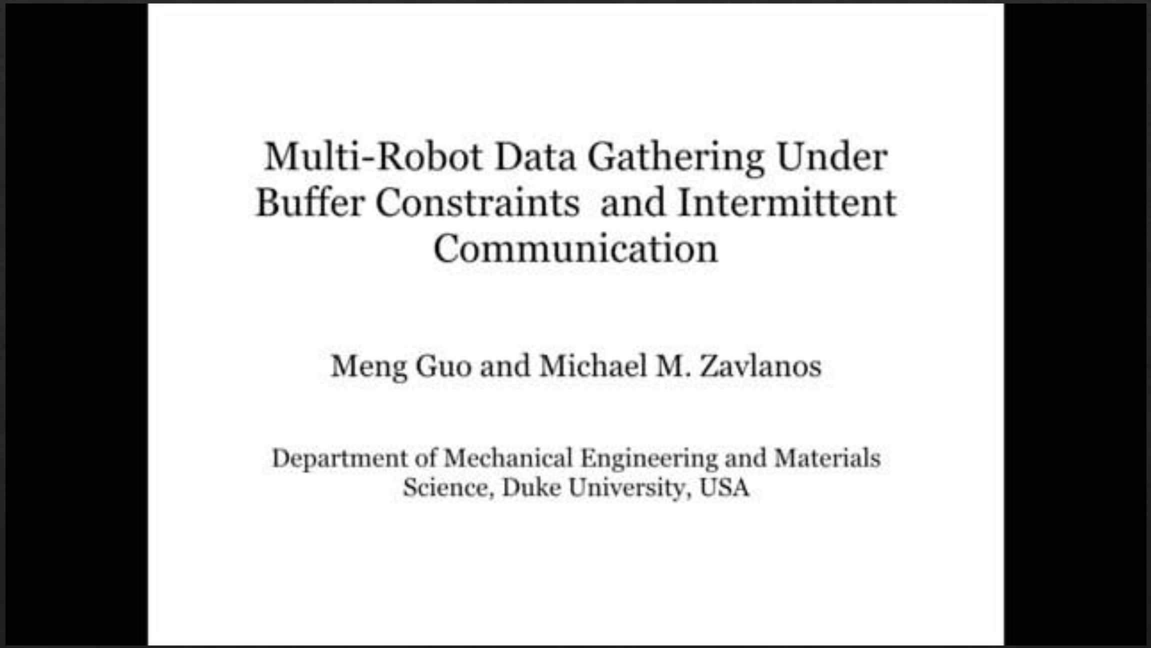
$$\widehat{\mu}_{ij}(t) \triangleq \frac{\mu_{ij}(t)}{\rho_{ij}(t)} \tag{4}$$

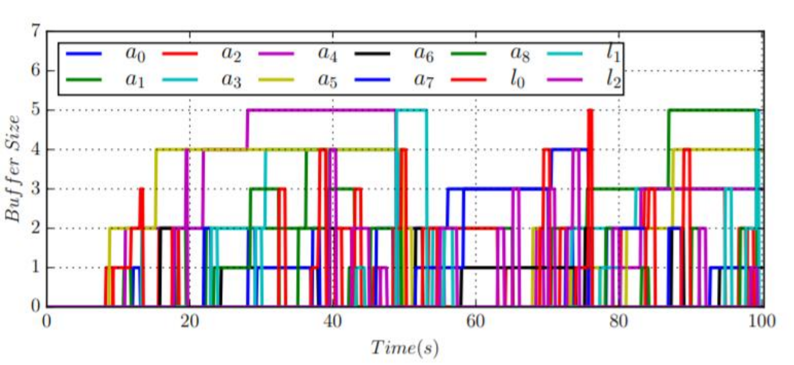


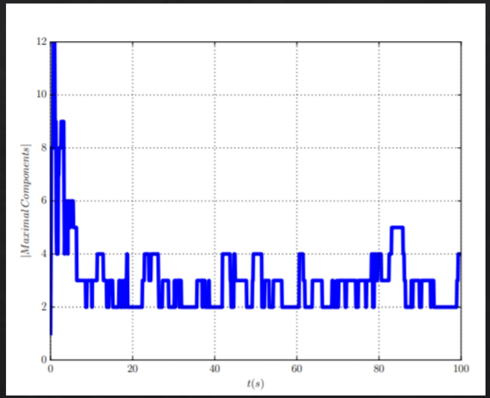
[Hybrid Control of Multi-agent Systems with Contingent Temporal Tasks and Prescribed Formation Constraints](). Guo et al., TCNS 16.

Resource Constraints

- Buffer constraints and Intermittent communication.







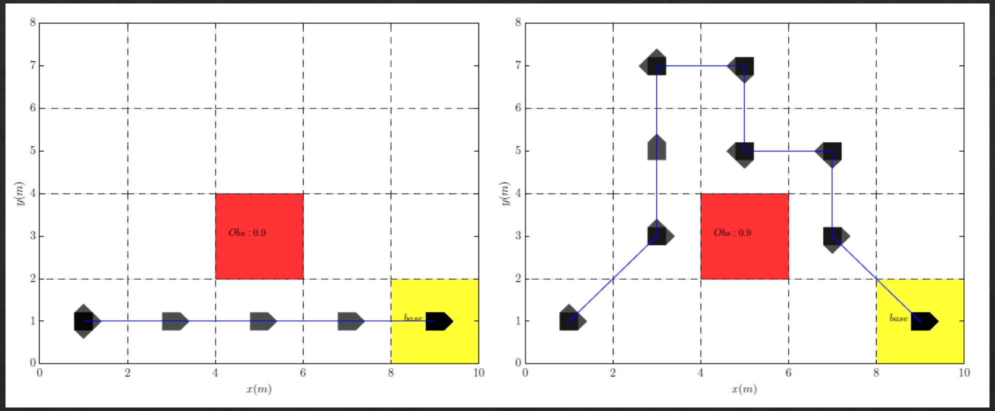
Multi-Robot Data Gathering Under Buffer Constraints and Intermittent Communication.
Guo & Zavlanos. TRO 18

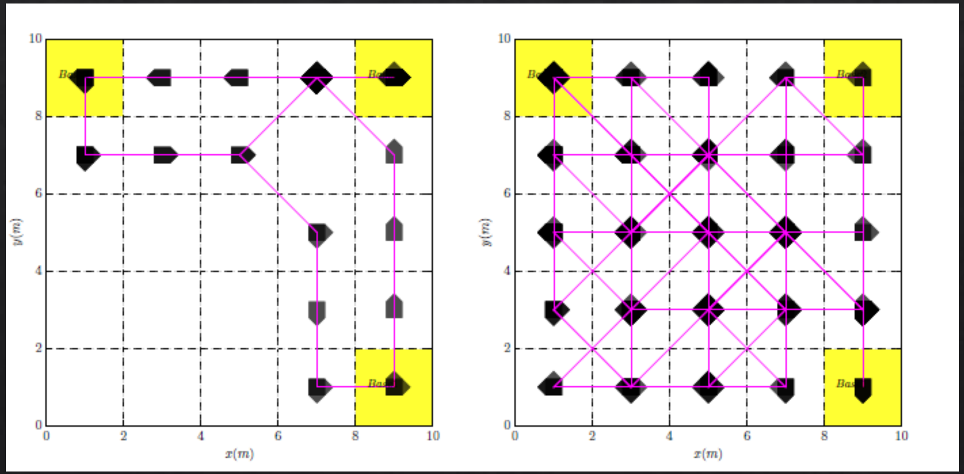
Temporal Logic Task Planning and Intermittent Connectivity Control of Mobile Robot Networks.
Kantaros, Guo, & Zavlanos. TAC 18.

Paper 3

- [Probabilistic Motion Planning under Temporal Tasks and Soft Constraints](). Guo & Zavlanos. TAC 18
  - Standard MDP.
  - LTL as soft constraints.

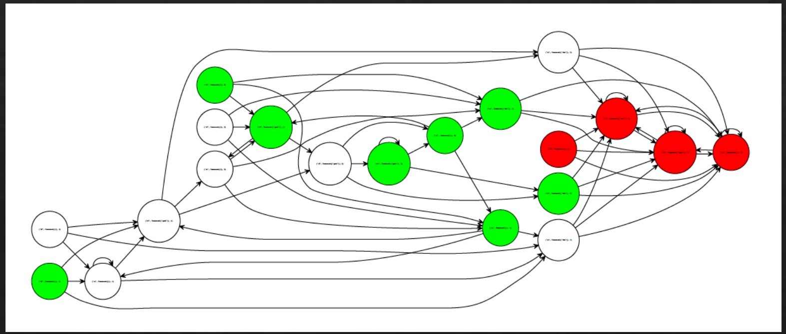
$$
\begin{aligned}
\min_{\boldsymbol{\mu}\in\overline{\boldsymbol{\mu}}} \quad & \mathbb{E}^{\boldsymbol{\mu}}_{\mathcal{M}}\{\textbf{Cost}(R_\infty)\} \\
s.t. \quad & \textbf{Risk}^{\boldsymbol{\mu}}_{\mathcal{M}}(\varphi) \leq \gamma,
\end{aligned}
$$

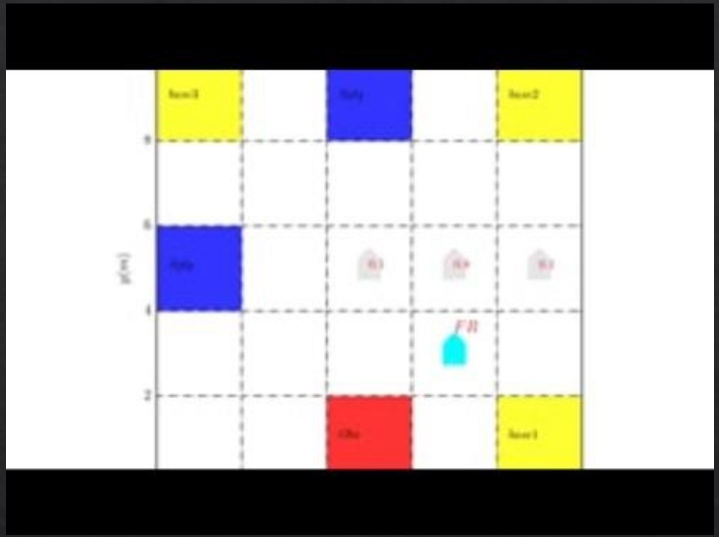


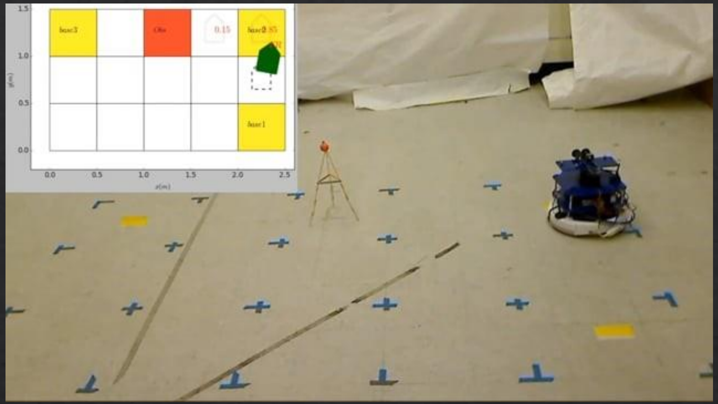


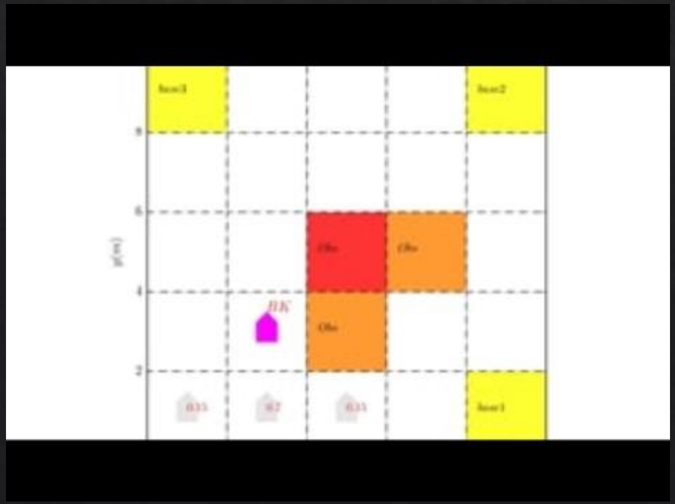
Paper 3 con’t

- Solution outline
  - Prefix policy to reach SCC.
  - Suffix policy to stay in SCC.
  - Two dependent LP.
- Infeasible tasks.









γ_{prex}	d	γ_{sufx}	Failure	Pre. Success	Suf. Success
0.1	300	0.05	106	894	852
0.2	300	0.05	169	831	785
0.3	300	0.05	318	682	650
0.4	300	0.05	409	591	549
0.1	280	0.85	888	901	117
0.1	270	0.98	997	903	4

https://github.com/MengGuo/P_MDP_TG

Further topics

- Other constraints.
  - Information gathering.
  - Real-time event. STL, MITL.

Asymptotically Optimal Planning for Non-myopic Multi-Robot Information Gathering. Kantaros et al. RSS 19

Distributed state estimation using intermittently connected robot networks. Khodayi-mehr et. al, TRO19.

Multi-robot routing and scheduling with temporal logic and synchronization constraints Mosca, C Belta et al. ICCRT 19.

- Temporal model learning.
  - Motion trajectory.
  - Causality

Temporal logic inference for classification and prediction from data. Kong et. Al, HSCC14.

Reactive sampling-based path planning with temporal logic specifications. Vasile & Belta. IJRR20

- Deep learning.
  - MDP + LTL + DNN
  - extension to Multi-agents.

Reinforcement Learning for Temporal Logic Control Synthesis with Probabilistic Satisfaction. Hasanbeig et al. CDC19.

Q-learning for robust satisfaction of signal temporal logic specifications. Aksaray et. al., CDC16.

Temporal logics for learning and detection of anomalous behavior. Kong et. al., TAC16.

Automata Guided Semi-Decentralized Multi-Agent Reinforcement Learning. Belta et al., ACC 20.

A formal methods approach to interpretable reinforcement learning for robotic planning. Li & Belta. Science Robotics 20.

Predictive Safety Network for Resource-constrained Multi-agent Systems. Guo & Bürger. CoRL19.

Bounded Suboptimal Search with Learned Heuristics for Multi-Agent Systems. Spies et al, AAAI19.

Further topics, con't

- Hierarchical TAMP
  - LTL as high-level guidance for efficient exploration to sub-goals.
  - RL as motion planner.

A formal methods approach to interpretable reinforcement learning for robotic planning. Li & Belta. Science Robotics 20.

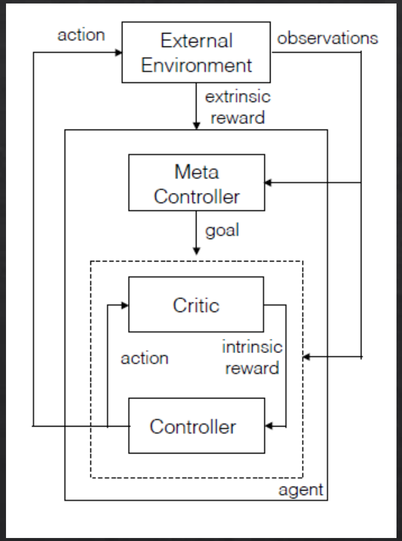
Integrating Temporal Abstraction and Intrinsic Motivation. Kulkarni et. al, NIPS 2016.

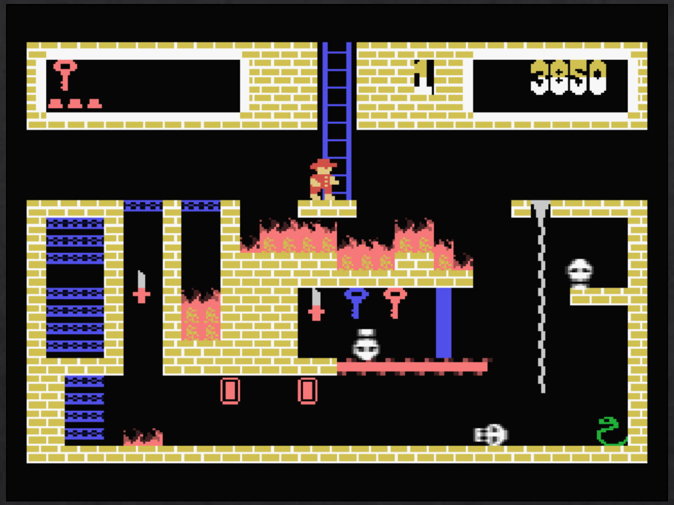
Hybrid Reward Architecture for Reinforcement Learning. Seijen et. al., NIPS 2017.

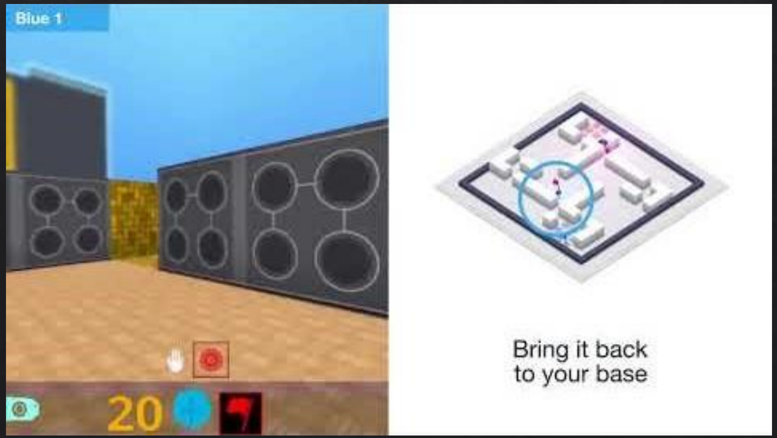
Human-level performance in 3D multiplayer games with population-based reinforcement learning, Jaderberg et al., Science 19.

Deeploco: Dynamic locomotion skills using hierarchical deep reinforcement learning. Peng et al., ACM-TG 17.

Bounded Suboptimal Search with Learned Heuristics for Multi-Agent Systems. Spies et al., *AAAI* 2019.







Robotic Manipulation

Why?

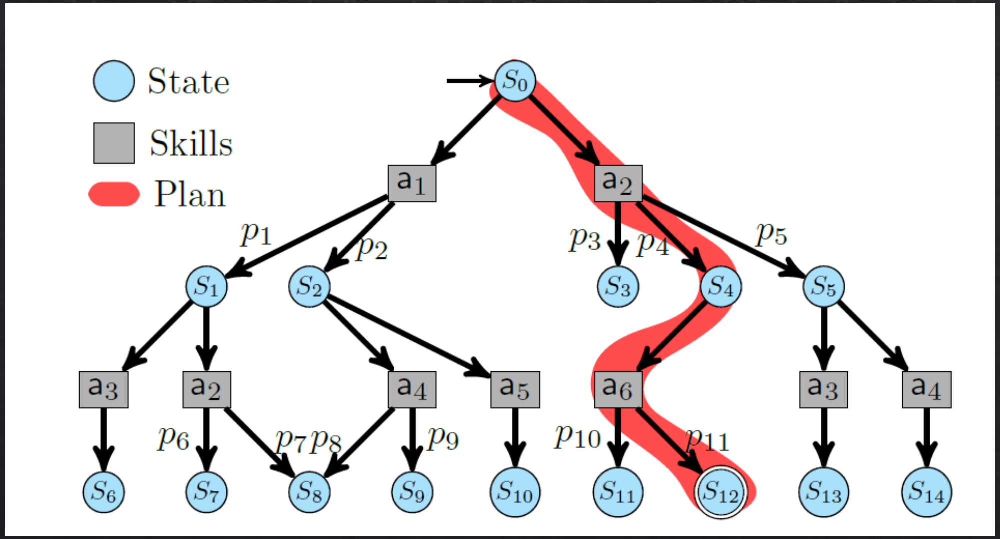
- Motion → Action = Manipulation.
- Isn't it already *solved*?
- Missing:
  - Un-structure environment.
    - Perception.
    - Motion and vision uncertainty.
  - Human co-worker.
    - Easy and friendly usage.
    - Safety.

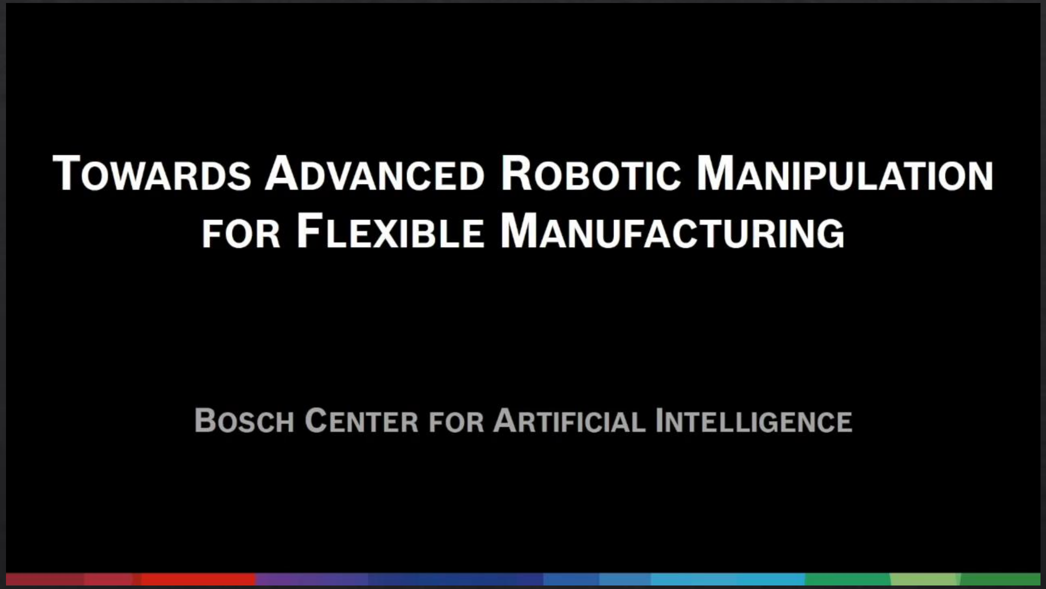
BMW

XYZ robotics.

KUKA robotics

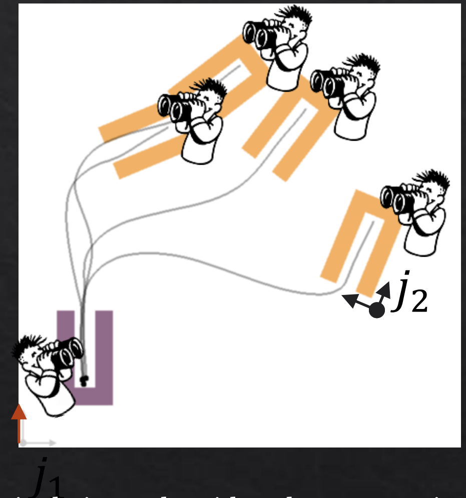
TAMP for manipulation

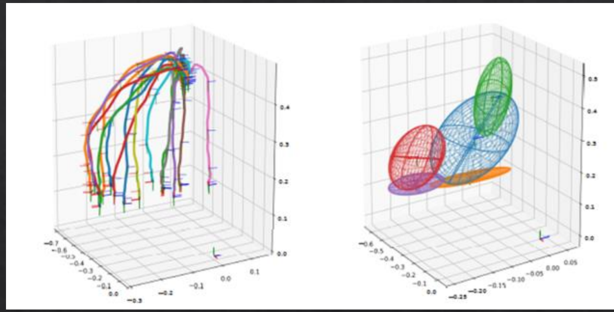


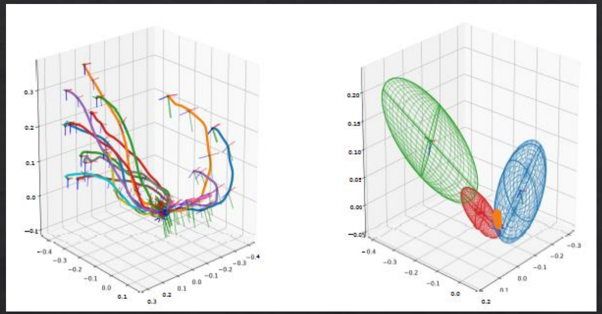


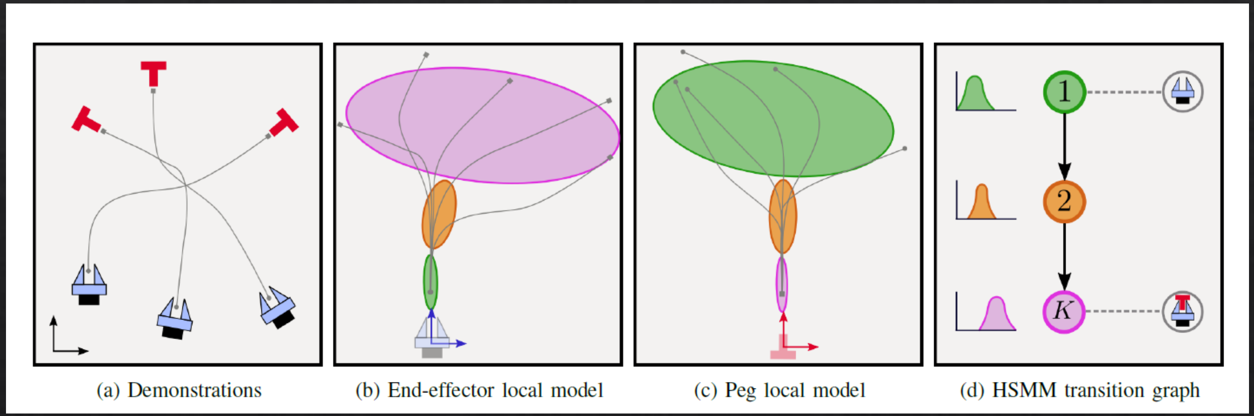
Robot Skill Representation

- Learning from Demonstration (LfD).
- Task-parameterized Gaussian Mixture Models (TP-HSMM).





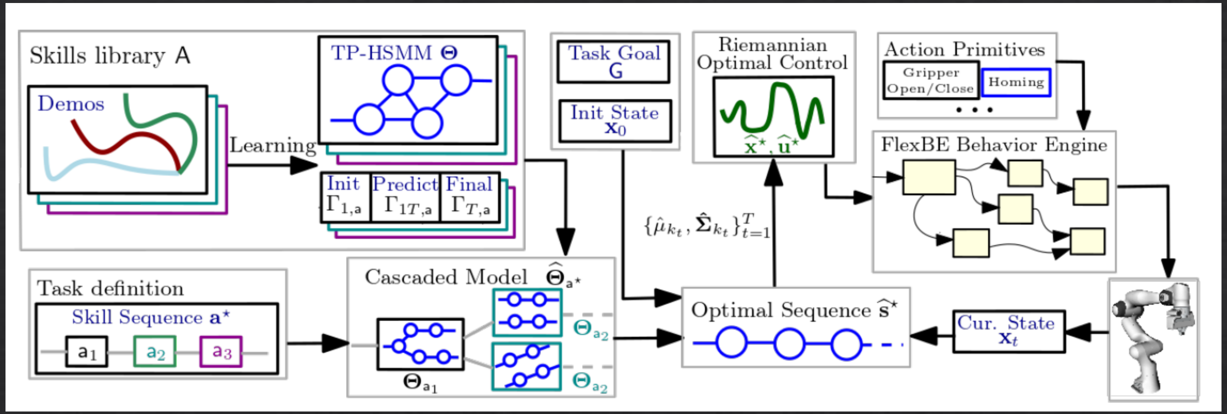


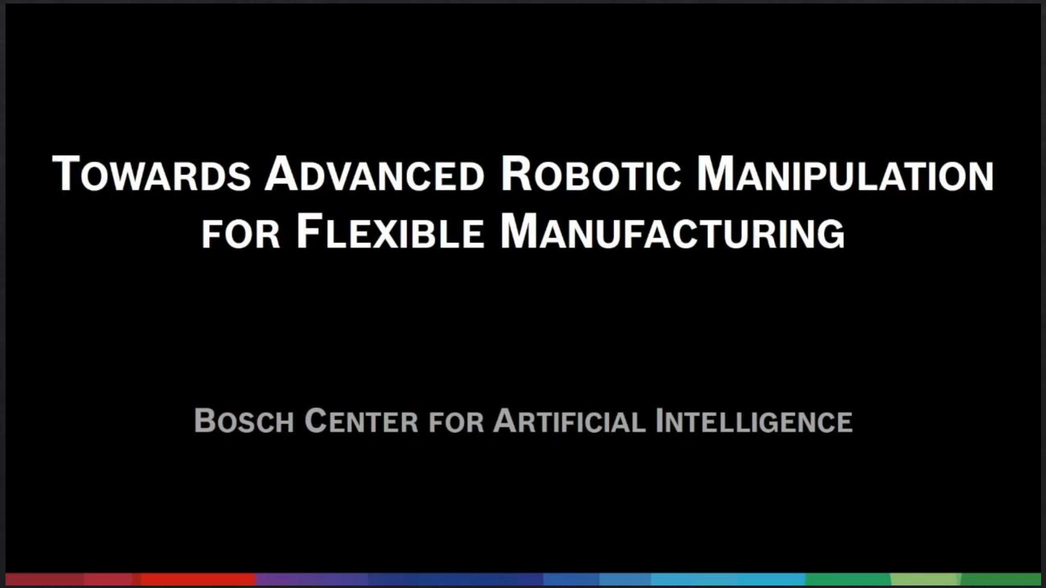


Learning robot manipulation tasks with task-parameterized hidden semi-markov model. AK Tanwani, S Calinon, RA-L16.

Modular Composition of LfD Skills

- Skills with multiple branches.
- Automatic choice of task parameters and branches.
- Online adaptation with fault recovery.



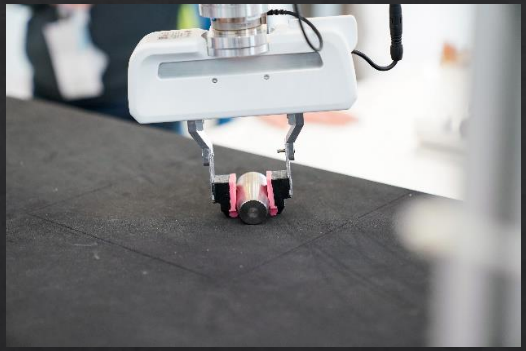


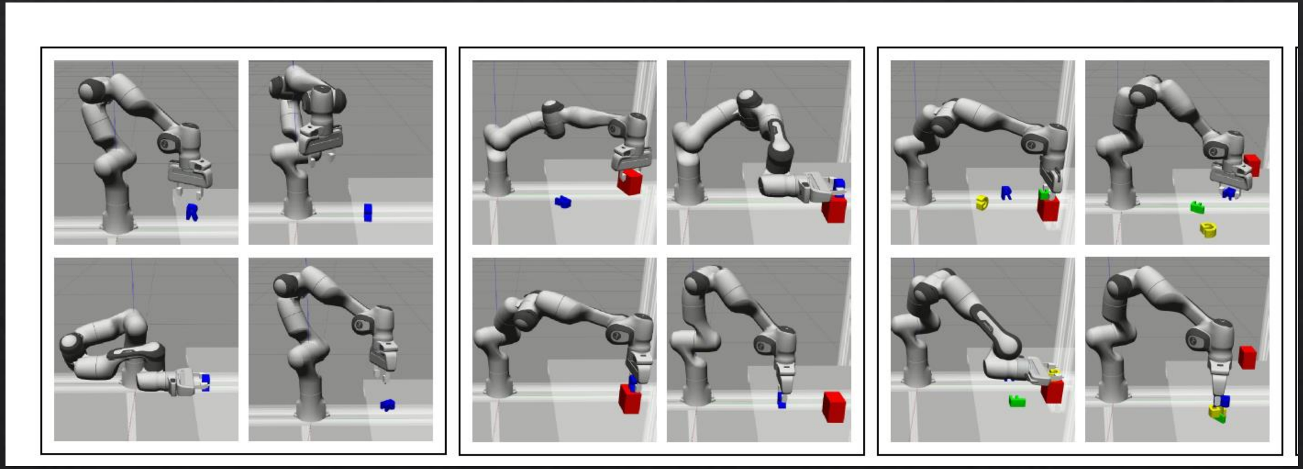
Learning and Sequencing of Object-Centric Manipulation Skills for Industrial Tasks.
Rozo, Guo, Kupcsik. IROS20.

Optimizing Sequences of Probabilistic Manipulation Skills Learned from Demonstration.
Schwenkel, Guo, Bürger. CoRL19.

Further topics

- Learning of skill sequence and parameters.
- Vision-based skill learning.
- Forceful tasks.





Learning Task Priorities from Demonstrations. Silvério et. al., TRO19.

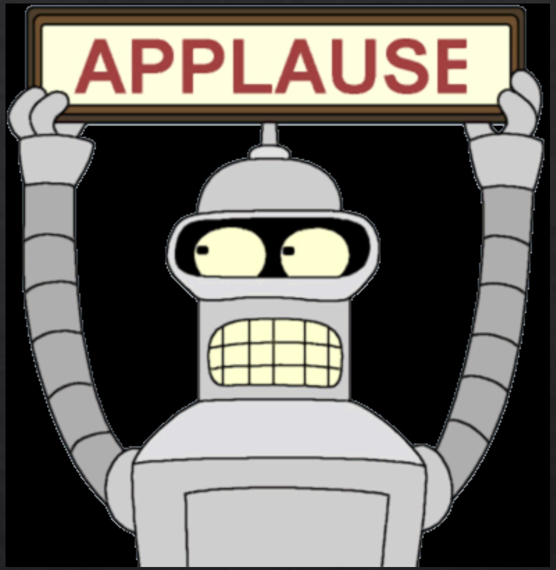
Learning Physical Collaborative Robot Behaviours from Human Demonstrations. Rozo et al. TRO16.

FFRob: Leveraging symbolic planning for efficient task and motion planning. C. R. Garrett et. al., IJRR18.

From skills to symbols: Learning symbolic representations for abstract high-level planning. Konidaris et al., J-AIR 18.

Summary

- Multi-robot system
  - Bottom-up Vs. Top-down.
  - Dynamic constraints.
- Robotic Manipulation
  - Learning from Demonstration (LfD).
  - TAMP over LfD skills.



We are constantly looking for Interns, Industrial PhDs, PhD Sabbaticals to join BCAI, see BCAI openings