# Achieving Coordination with Multiple Heterogeneous Agents

Martina Lippi, martina.lippi@uniroma3.it
Roma Tre University

# About me



PhD in Information Engineering
@ University of Salerno
«Human multi-robot interaction: from workspace sharing to physical collaboration»

Visiting PhD student
@ KTH Royal Institute of Technology

Visiting PhD student
@ University of Cassino

Post-doc & Assistant Professor
@ Roma Tre University
Newline Group

H2020 Project Pantheon
«Precision Farming Of Hazelnut Orchards»

H2020 Project Canopies
«A Collaborative Paradigm For Human Workers And Multi-robot Teams In Precision Agriculture Systems»

# Multi-Human-Multi-Robot (MHMR) teams

**Highly heterogeneous systems:** Multiple humans and robots collaborate in shared environments to accomplish tasks

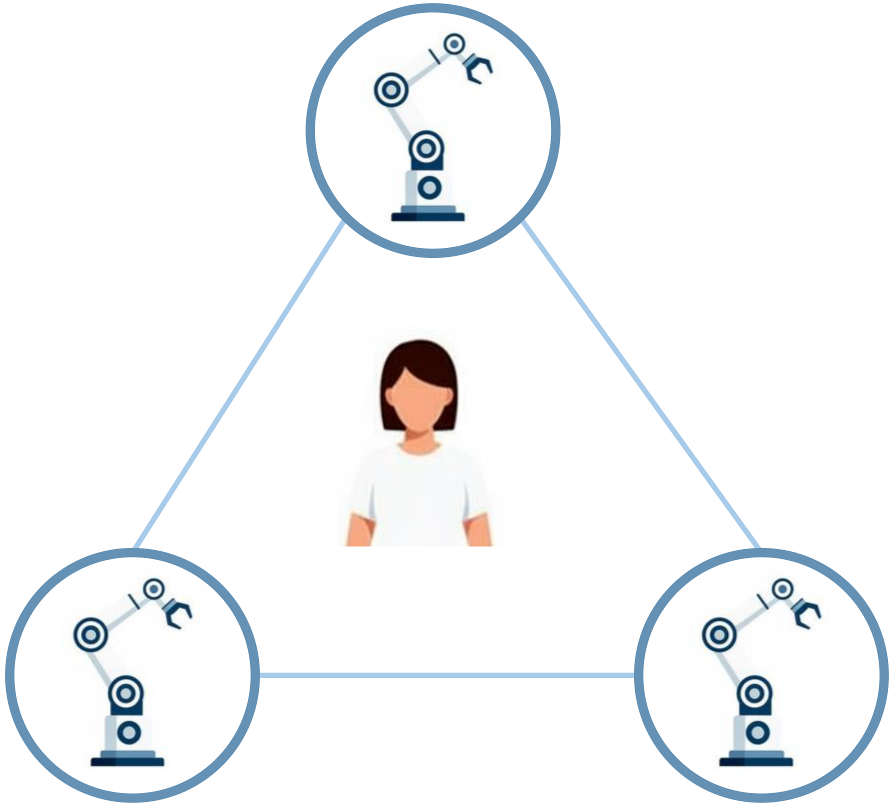
- Pro: Combination of human reasoning/dexterity skills with robots' physical skills can lead to realize **complex** tasks
- Need to design **human-centered multi-robot coordination** strategies

# Task planning in MHMR teams



- Several aspects must be addressed in MHMR teams
  - E.g., safety, human perception, physical co-manipulation, **task planning (i.e., allocation and scheduling)**

- Focus on human-centered task planning accounting for:
  - Human **preferences** and **comfort**
  - Human **higher cognitive/dexterity skills**
  - **Time-varying** human(-dependent) parameters

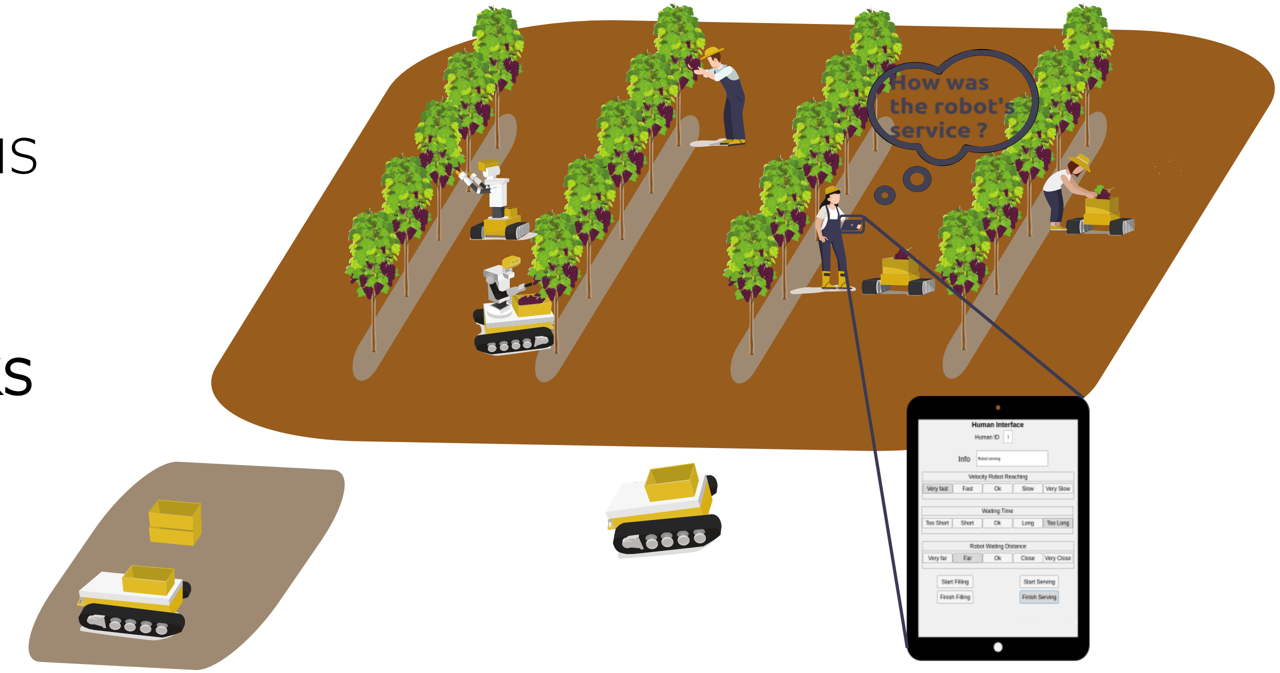


# Setting



Human operators and working robots perform sequences of operations:

- "Complex" operations performed by humans
- **Service robots** assist the previous agents (phases: going, waiting, proximity, service, depositing)
- Humans provide **online feedbacks**



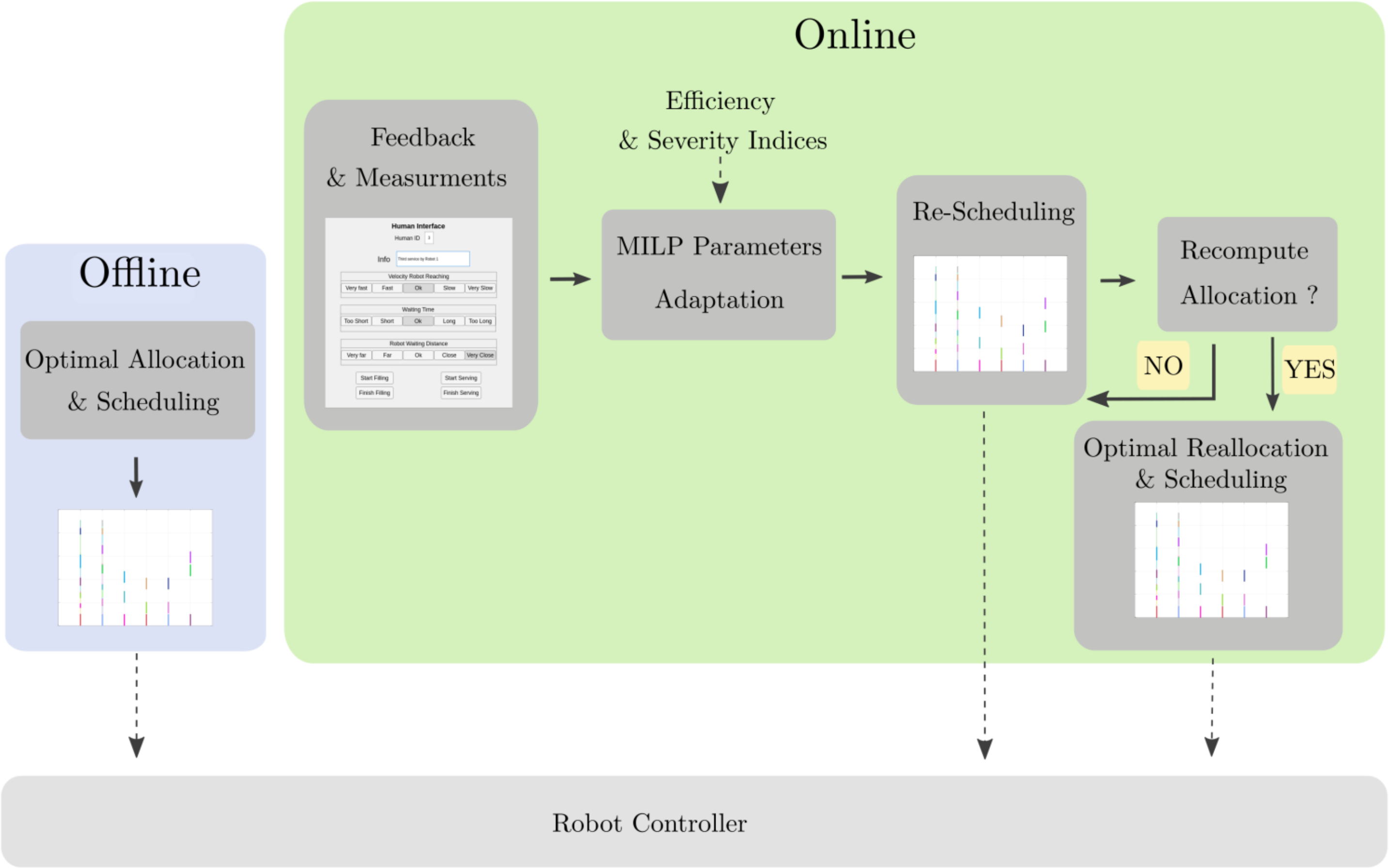

Human feedback

# State of the art and contribution

- Most existing works on human-centered task allocation and scheduling:
  - Do not tackle **human-specific challenges**
  - Handle **limited number of agents**
  - **Lack guarantees** for optimal solutions
  - Optimize for **limited factors** (e.g., makespan only)

- Contribution
  - Mixed-integer-linear programming (MILP)-based framework for **optimal** task allocation and scheduling
  - Scales to **arbitrary numbers** of humans and robots
  - Models **human stochasticity**
  - Adapts to **evolving human preferences** during execution

# Architecture overview




References:


- J. Gallou*, M. Lippi*, J. Palmieri*, A. Gasparri, A. Marino, “A human-centered task allocation and scheduling framework for multi-human-multi-robot collaboration in precision agriculture settings”, IEEE Transactions on Automation Science and Engineering, 2025
- M. Lippi, J. Gallou, J. Palmieri, A. Gasparri, A. Marino, “Human-Multi-Robot Task Allocation in Agricultural Settings: a Mixed Integer Linear Programming Approach” IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), 2023
- M. Lippi, P. Di Lillo, A. Marino, “A Task Allocation Framework for Human Multi-Robot Collaborative Settings”, IEEE International Conference on Robotics and Automation (ICRA), 2023

# Mixed-Integer Linear Programming Problem

Humans' waiting times — Working robots' waiting times — Service robots' energy terms — Makespan

$$\min_{\substack{\text{Allocation variables}\\ \text{Scheduling variables}\\ \text{Velocities}}} \sum_{\substack{(a,i)\in\mathcal{O},\\ a\in\mathcal{H}}} \boxed{\alpha_{a,i}}\, w^{o}_{a,i} + \beta \sum_{\substack{(a,i)\in\mathcal{O},\\ a\in\mathcal{W}}} w^{o}_{a,i} + \frac{\gamma}{3}\sum_{(a,i)\in\mathcal{O}} \left(e^{g}_{a,i} + \boxed{\zeta_{a,i}}\, e^{p}_{a,i} + e^{d}_{a,i}\right) + \kappa\Delta$$

Weights adapted based on human feedback

**Assignment of assist. tasks**

$$\sum_{m\in\mathcal{M}} S_{a,i,m} = 1, \forall (a,i)\in\mathcal{O}.$$

**Assist. tasks duration**

$$\begin{aligned}
\overline{g}_{a,i} - \underline{g}_{a,i} &\geq \sum_{m\in\mathcal{M}} S_{a,i,m} l^{g}_{a,m}/v^{c}_{\max,m},\\
\overline{g}_{a,i} - \underline{g}_{a,i} &\leq \sum_{m\in\mathcal{M}} S_{a,i,m} l^{g}_{a,m}/v^{c}_{\min,m},\\
\overline{p}_{a,i} - \underline{p}_{a,i} &\geq \sum_{m\in\mathcal{M}} S_{a,i,m} l^{p}_{a,m}/v^{p}_{\max,a,m},\\
\overline{p}_{a,i} - \underline{p}_{a,i} &\leq \sum_{m\in\mathcal{M}} S_{a,i,m} l^{p}_{a,m}/v^{p}_{\min,a,m},\\
\overline{d}_{a,i} - \underline{d}_{a,i} &\geq \sum_{m\in\mathcal{M}} S_{a,i,m} \left(l^{d}_{a,m}/v^{c}_{\max,m} + \delta^{d}_{m}\right),\\
\overline{d}_{a,i} - \underline{d}_{a,i} &\leq \sum_{m\in\mathcal{M}} S_{a,i,m} \left(l^{d}_{a,m}/v^{c}_{\min,m} + \delta^{d}_{m}\right),
\end{aligned}$$

**Assist. tasks sequence**

$$\begin{aligned}
\underline{w}^{s}_{a,i} &= \overline{g}_{a,i}, & \underline{p}_{a,i} &= \overline{w}^{s}_{a,i}, \\
\underline{s}_{a,i} &= \overline{p}_{a,i}, & \underline{d}_{a,i} &= \overline{s}_{a,i},
\end{aligned} \quad \forall (a,i)\in\mathcal{O}$$

**Timing service tasks**

$$\begin{aligned}
\overline{s}_{a,i} &= \underline{s}_{a,i} + \sum_{m\in\mathcal{M}} S_{a,i,m}\delta^{s}_{m},\\
\underline{s}_{a,i} &\geq \overline{o}_{a,i},
\end{aligned} \quad \forall (a,i)\in\mathcal{O}.$$

**Operations sequence with chance constraints**

$$\begin{aligned}
\underline{o}_{a,1} &= t_0, && \forall a\in\mathcal{A}\\
\underline{o}_{a,i} &\geq \overline{s}_{a,i-1}, && \forall (a,i)\in\mathcal{O},\\
\overline{o}_{a,i} - \underline{o}_{a,i} &\geq \sqrt{2}\sigma_a \operatorname{erf}^{-1}(2\,pr_{\min} - 1) + \varphi_a, && \forall (a,i)\in\mathcal{O}
\end{aligned}$$

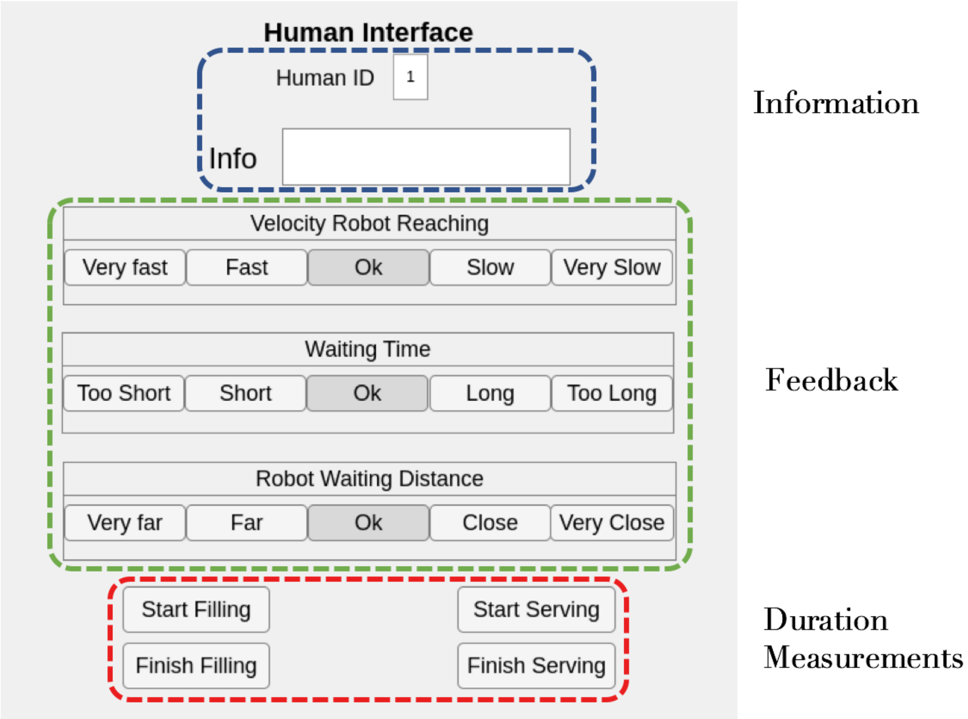
**No simultaneous tasks**

$$\begin{aligned}
\underline{z}_{b,k} - \overline{u}_{a,i} &\geq -c_M(2 - S_{a,i,m} - S_{b,k,m}) - c_M(1 - Q^{uz}_{a,i,b,k,m}),\\
\overline{z}_{b,k} - \underline{u}_{a,i} &\geq -c_M(2 - S_{a,i,m} - S_{b,k,m}) - c_M\, Q^{uz}_{a,i,b,k,m},\\
&\forall (a,i),(b,k)\in\mathcal{O},\ m\in\mathcal{M},\ (a,i)\neq(b,k)
\end{aligned}$$

# Online monitoring and adaptation

- **Human feedback** on: Approaching velocity, Waiting time, Desired waiting distance

- Adaptation based on:
  - **Overall human satisfaction index**
  - **Efficiency and working severity** conditions of the human operator
  - Physical properties of the robots



# Online re-scheduling and re-allocation

- **Online re-scheduling**: An updating algorithm **adjusts** the times of the tasks and operations not to violate any constraint
- **Online re-allocation:** A new MILP solution is computed if optimality performance decreases below a certain threshold

Nominal cost on remaining tasks

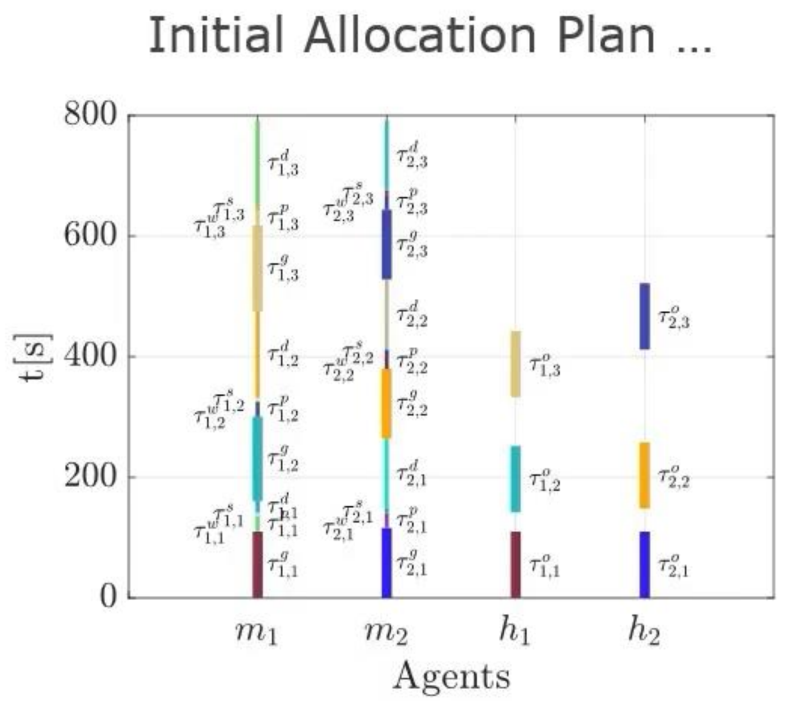
Updated cost on remaining tasks

$$\iota \triangleq \frac{|C^+(t_{opt}) - C^+(t_{upd})|}{C^+(t_{opt})} > \iota_t$$

# Laboratory validation

Harvesting scenario with:

- Two humans filling 3 boxes each
- Two service robots replacing full boxes with empty ones when needed




Generated based on Mixed Integer Linear Programming for our task allocation and scheduling problem for 2 serving robots and 2 humans

This project is funded by the European Union G.A No 101016906

# Laboratory validation with human supervision

Box filling scenario with:

- Two manipulators
- One human performing tasks and supervising

## A Task Allocation Framework for Human Multi-Robot Collaborative Settings

Martina Lippi[1], Paolo Di Lillo[2], Alessandro Marino[2]

[1]Roma Tre University, Italy, martina.lippi@uniroma3.it

[2]University of Cassino and Southern Lazio, Italy, {pa.dilillo,al.marino}@unicas.it

# Assumption so far:

all tasks can be identified and fully characterized (e.g., precedence conditions)

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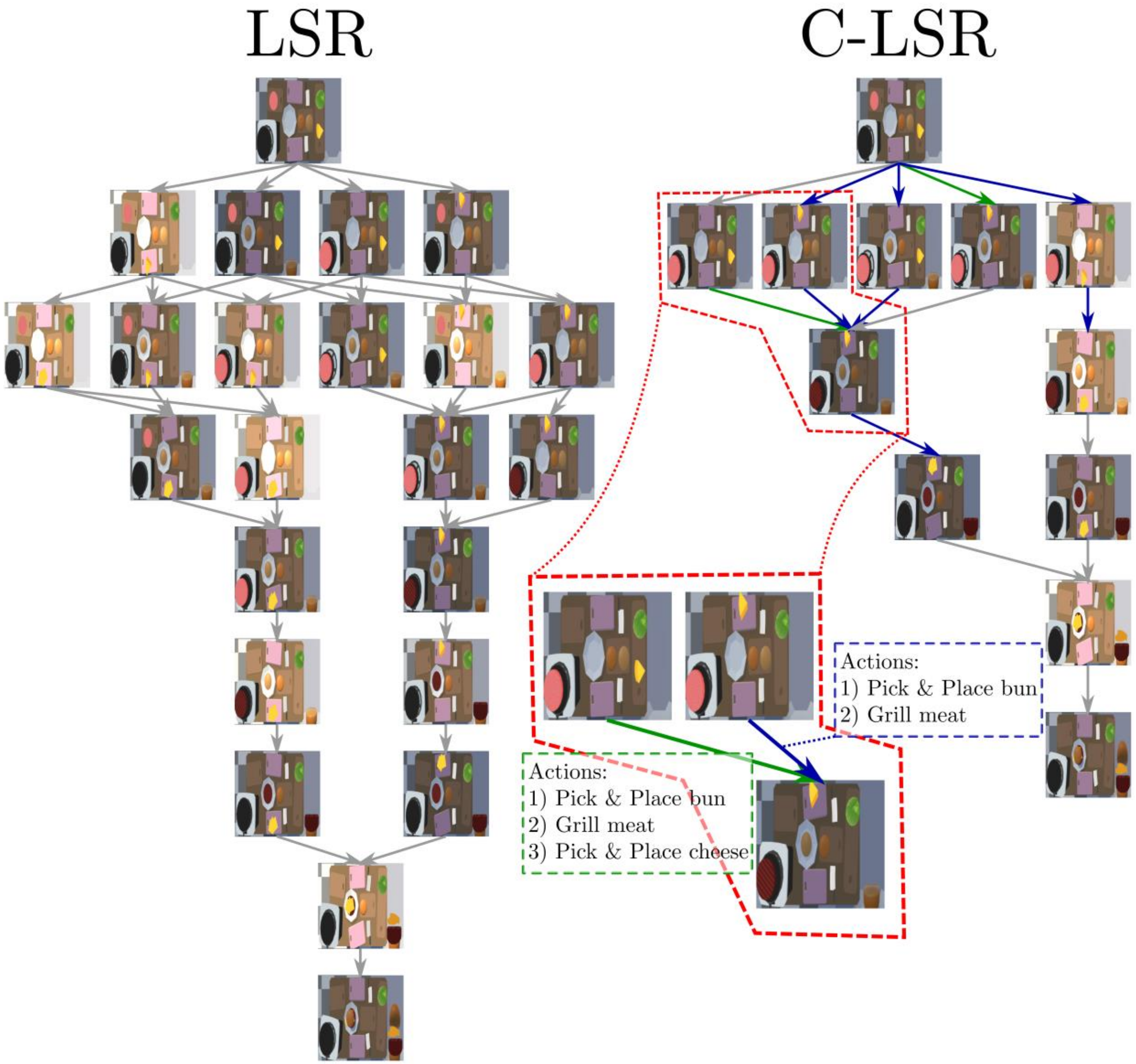
all tasks can be identified and fully characterized (e.g., precedence conditions)

What if we cannot do that (as in highly complex tasks…) ?

# Planning from observations



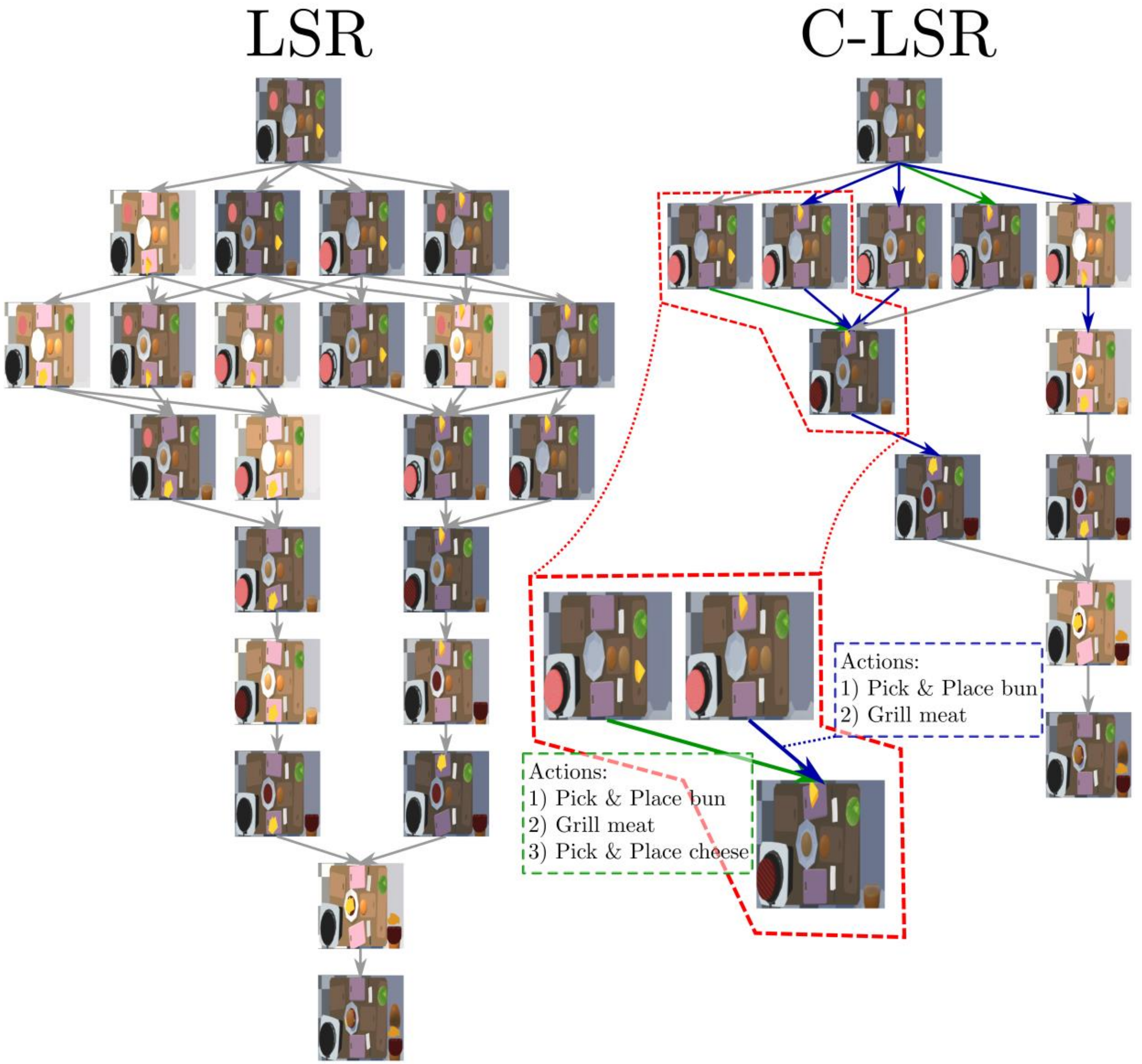
- We can realize planning from **raw observations**!
- In [1] we proposed a Latent Space Roadmap (LSR) framework to realize sequential **visual action planning** for single robots




[1] Lippi, M.*, Poklukar, P.*, Welle, M. C.*, Varava, A., Yin, H., Marino, A., & Kragic, D. (2022). Enabling visual action planning for object manipulation through latent space roadmap. *IEEE Transactions on Robotics*, *39*(1)

# Planning from observations

- We can realize planning from **raw observations**!
- In [1] we proposed a Latent Space Roadmap (LSR) framework to realize sequential **visual action planning** for single robots
- We can extend it to realize visual action planning with **multiple heterogeneous** agents operating **in parallel**

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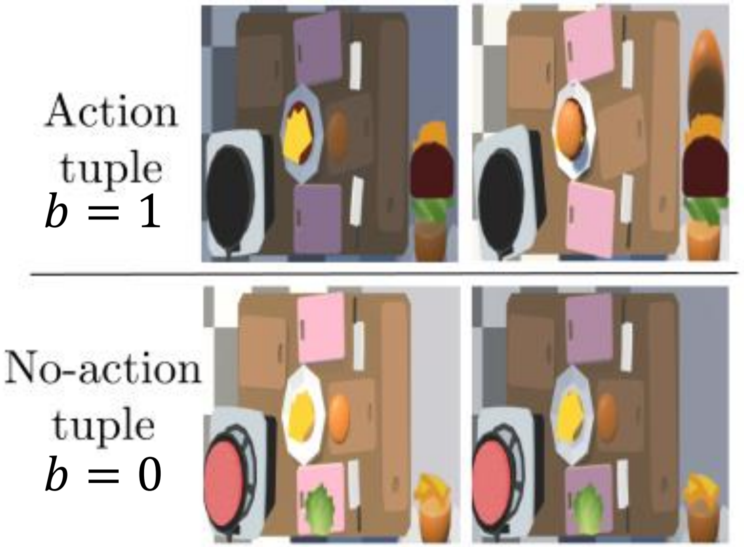
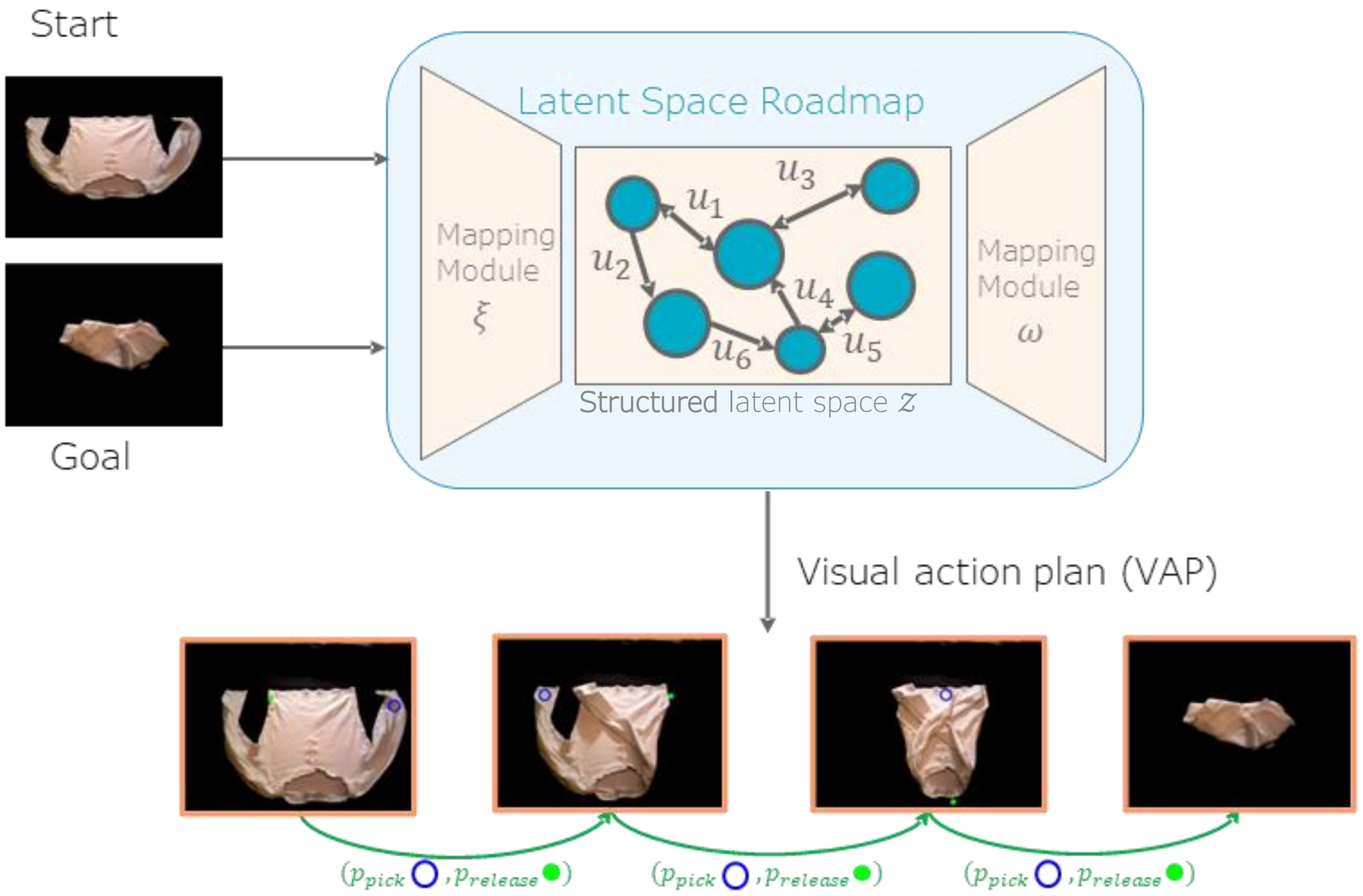
# Dataset structure

- Dataset $\mathcal{T}_o$ containing tuples with the form [1] $(O_1,\ O_2\ ,\ \rho = (b,u))$

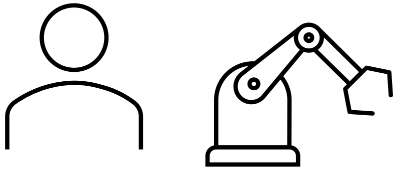



[1] Lippi, M.*, Poklukar, P.*, Welle, M. C.*, Varava, A., Yin, H., Marino, A., & Kragic, D. (2022). Enabling visual action planning for object manipulation through latent space roadmap. *IEEE Transactions on Robotics*, *39*(1)

# Latent Space Roadmap (LSR) framework

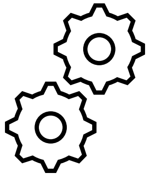


# Multi-Agent Setting



- For each agent $a_i$ we identify

1. The set $\mathcal{S}^{a_i}$ of available **skills**, e.g., tools or sensors
2. The average normalized workload $w_{i,j} \in [0,1]$ for performing each action $u_j$
3. A reachability function $r_i(x) \in [0,1]$



For each action $u_j \in \mathcal{U}$ we identify

1. The set $\mathcal{S}^{u_j}$ of skills, e.g., tools or sensors, required to perform the action
2. The set $\mathcal{P}_j$ of relevant poses for the action which must be traversed to execute it

# Planning from observations

## Problem formulation

Given a dataset $\mathcal{T}_o$ we aim to generate **parallel** VAPs $P^{par} = (P_o^{par}, P_u^{par})$ such that:

1. The goal state is reached by executing multiple actions **in parallel** by different agents (if possible)
2. The assignment couples are **valid** (the assigned agent possesses the required capabilities and can reach the locations)
3. The overall workload and reachability indices are optimized

- **Condition 1**: Multiple actions $\{u_1, \dots, u_p\}$ can be executed in parallel if executing them in arbitrary order from a certain state results in the same final state

Reference:


- M. Lippi*, M.C. Welle*, M. Moletta, A. Marino, A. Gasparri, D. Kragic, "Visual Action Planning with Multiple Heterogeneous Agents", *IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, 2024

# Parallel LSR (P-LSR)

A directed graph $\mathcal{G}^{par} = (\mathcal{V}^{par}, \mathcal{E}^{par})$, called **Parallel-LSR**, is built where

- Nodes encode underlying system states
- Edges encode potential parallel actions executable by a multi-agent system, **regardless** of the number of agents and their individual capabilities

**Algorithm 1** P-LSR building

**Require:** LSR $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, threshold $\tau$

$\mathcal{V}^{par} = \mathcal{V}$<br>
$\mathcal{E}^{par} = \mathcal{E}$<br>
**for each** $n \in \mathcal{V}$, $t \in \mathcal{V}, n \neq t$ **do**<br>
    **if** has-path-longer-one$(\mathcal{G}, n, t)$ **then**<br>
        $\mathcal{U}_n$ =get-all-actions-from-node$(n)$<br>
        $SP_{nt}$ =all-shortest-paths$(\mathcal{G}, n, t)$<br>
        **for each** $P_{nt} \in SP_{nt}$ **do**<br>
            $\mathcal{U}_{nt}$ =get-path-actions$(P_{nt})$<br>
            $\mathcal{U}_p$ =compute-intersection$(\mathcal{U}_n, \mathcal{U}_{nt}, \tau)$<br>
            **if** $|\mathcal{U}_{nt}| = |\mathcal{U}_p|$ **then**<br>
                $\mathcal{E}^{par} \leftarrow$ add-edge$(\mathcal{U}_p)$<br>
            **end if**<br>
        **end for**<br>
    **end if**<br>
**end for**<br>
**return** $\mathcal{G}^{par} = (\mathcal{V}^{par}, \mathcal{E}^{par})$

# Capability LSR (C-LSR)

A directed graph $\mathcal{G}^c = (\mathcal{V}^c, \mathcal{E}^c)$, called **Capability LSR**, is built where

- Nodes encode underlying system states
- Edges encode **valid assignment couples** and respective costs
  - Cost $c_{ij}$ for agent $i$ to perform action $j$ defined as

$$c_{i,j} = \begin{cases} \alpha \frac{1}{|\mathcal{P}_j|} \sum_{k \in \mathcal{P}_j} (1 - r_i(x_k)) + \beta w_{i,j}, & \text{if } \mathcal{S}_j^u \subseteq \mathcal{S}_i^a \text{, and} \\ & r_i(x_j) > 0,\ \forall x_j, \\ \infty & \text{otherwise} \end{cases}$$

  - An **Integer Linear Programming** problem finds the optimal (valid) assignment

**Algorithm 2** Capability LSR building

**Require:** P-LSR $\mathcal{G}^{par} = (\mathcal{V}^{par}, \mathcal{E}^{par})$, Agents $\mathcal{A}$

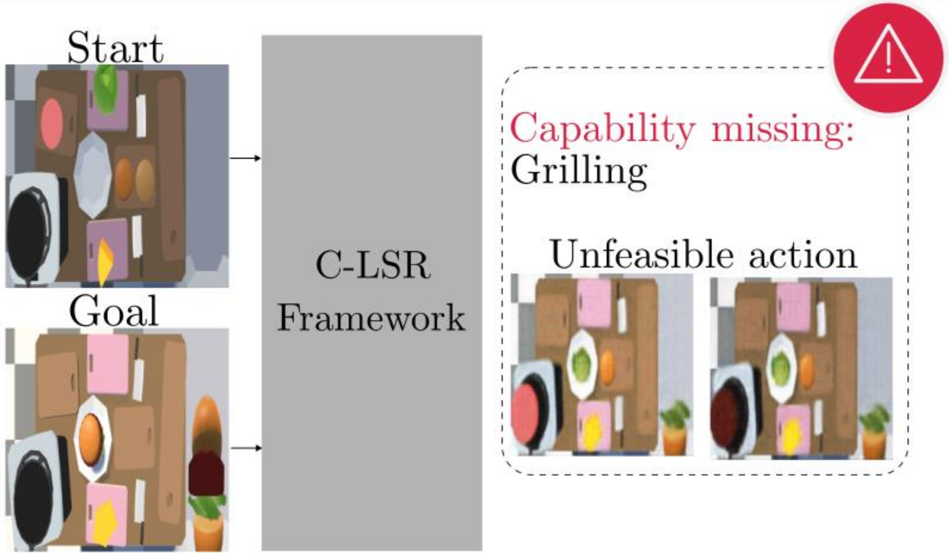
$\mathcal{V}^c = \mathcal{V}^{par}$<br>
$\mathcal{E}^c = \{\}$<br>
**for each** $e \in \mathcal{E}^{par}$ **do**<br>
    $\mathcal{U}_e$ =get-edge-actions$(n)$<br>
    **for each** $a_i \in \mathcal{A}$, $u_j \in \mathcal{U}_e$ **do**<br>
        $c_{i,j} \leftarrow$ compute-cost$(a_i, u_j)$ [Eq. (1)]<br>
    **end for**<br>
    $X \leftarrow$ solve-ILP-assignment$(\mathcal{U}_e, \mathcal{A}, c)$<br>
    **if** $X$ feasible and finite objective **then**<br>
        $\overline{\mathcal{U}}_e \leftarrow$ get-assignment-couples$(X)$<br>
        $c_e$ compute-edge-cost$(\mathcal{U}_e, \mathcal{A}, c, X)$ [Eq. (3)]<br>
        $\mathcal{E}^c \leftarrow$ add-edge$(\overline{\mathcal{U}}_e, c_e)$<br>
    **end if**<br>
**end for**<br>
**return** $\mathcal{G}^{par} = (\mathcal{V}^{par}, \mathcal{E}^{par})$

# Planning with C-LSR



- Given start and goal observations, the following steps are executed:
  - The closest nodes in C-LSR are found
  - The path in C-LSR with minimum cost is found
  - The respective parallel VAP $P^{par} = (P_o^{par}, P_u^{par})$ is extracted
  - Re-planning is executed after each operation

- If no-path is found, the system can suggest **missing capabilities**

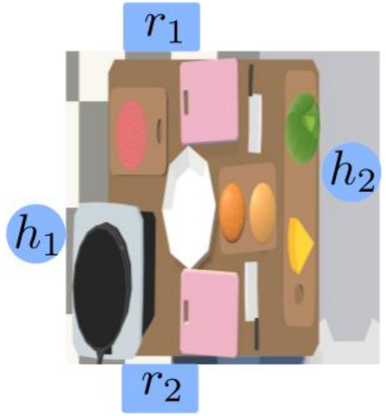


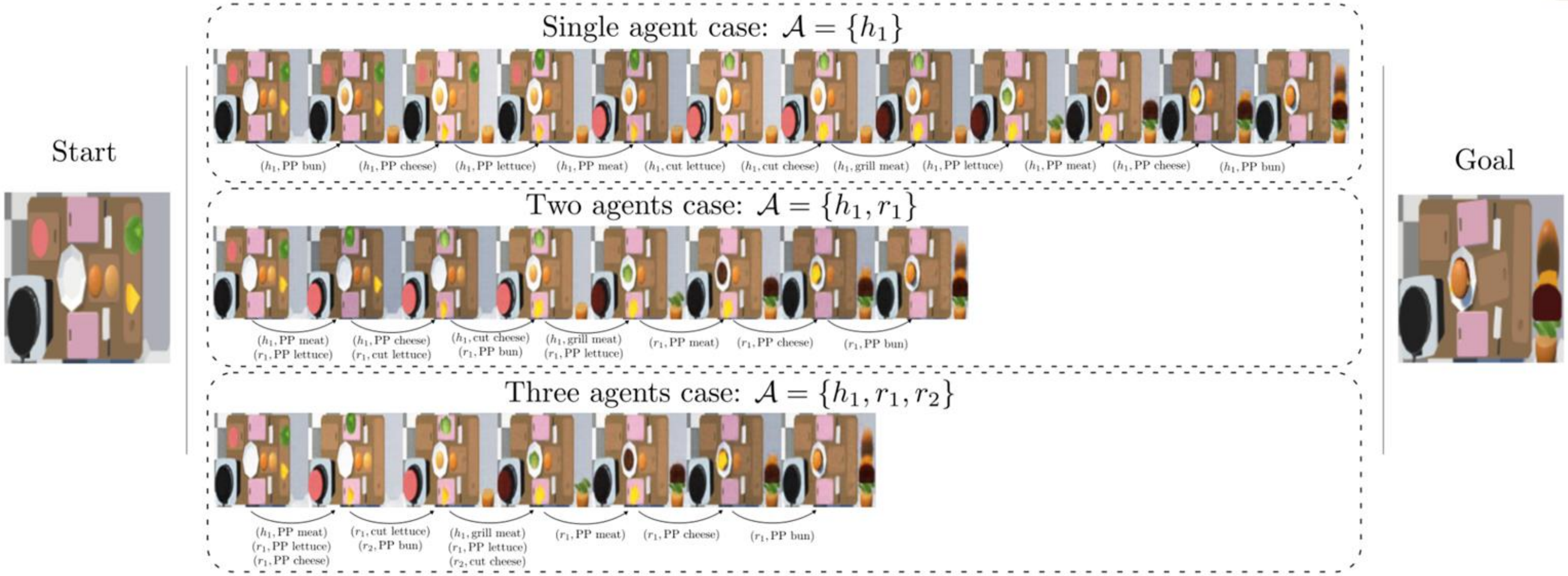

Agents = $\{r_1, r_2\}$ (no grilling skill)

# Simulation Setup

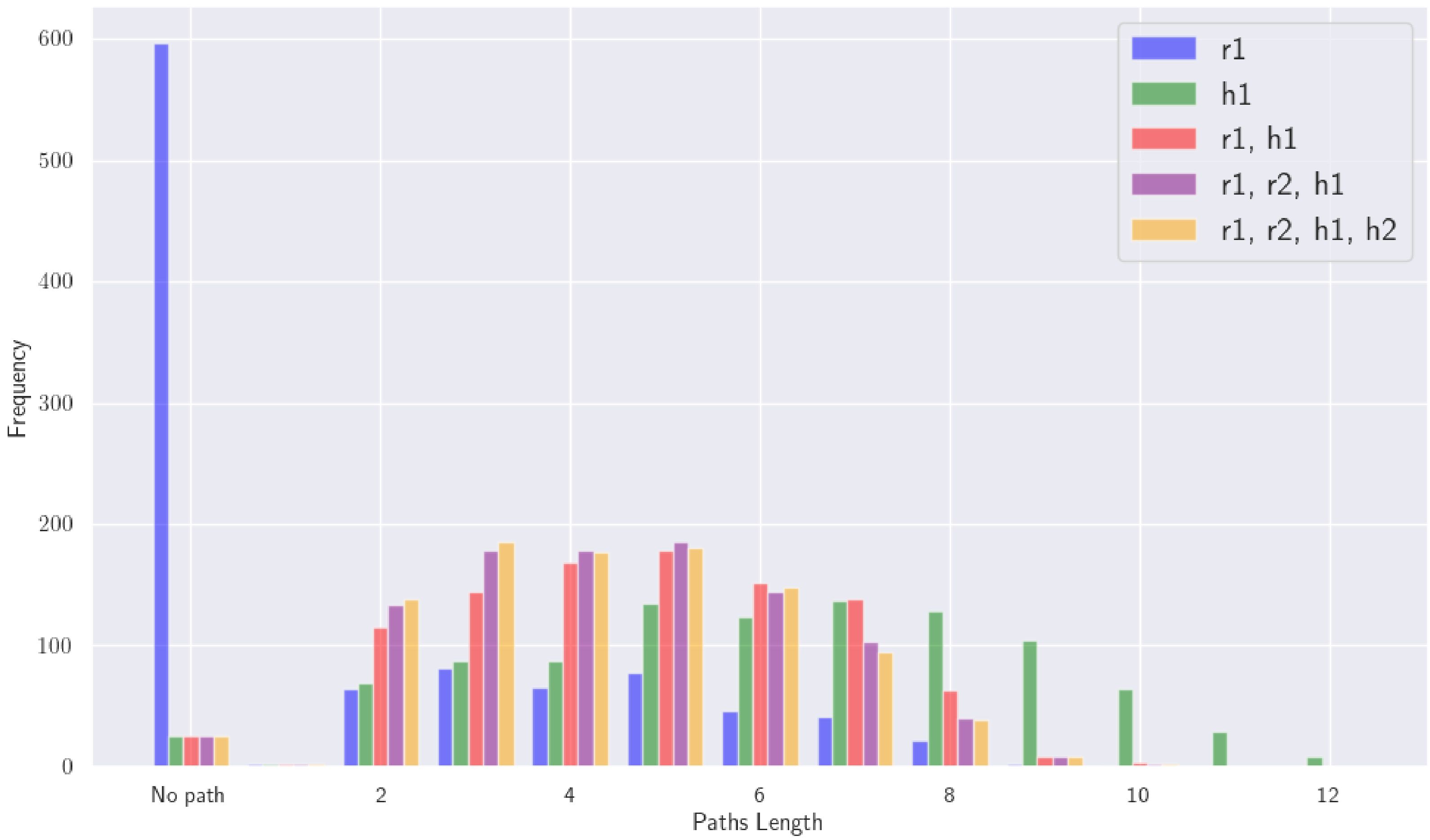
Burger cooking task involving

- Objects: Meat patty, cheese, lettuce, top and bottom bun parts
- Manipulation skills: gripping, cutting, and grilling
- Maximum two robots (with no grilling skills) $r_1$ and $r_2$, and two humans (with all skills) $h_1$ and $h_2$



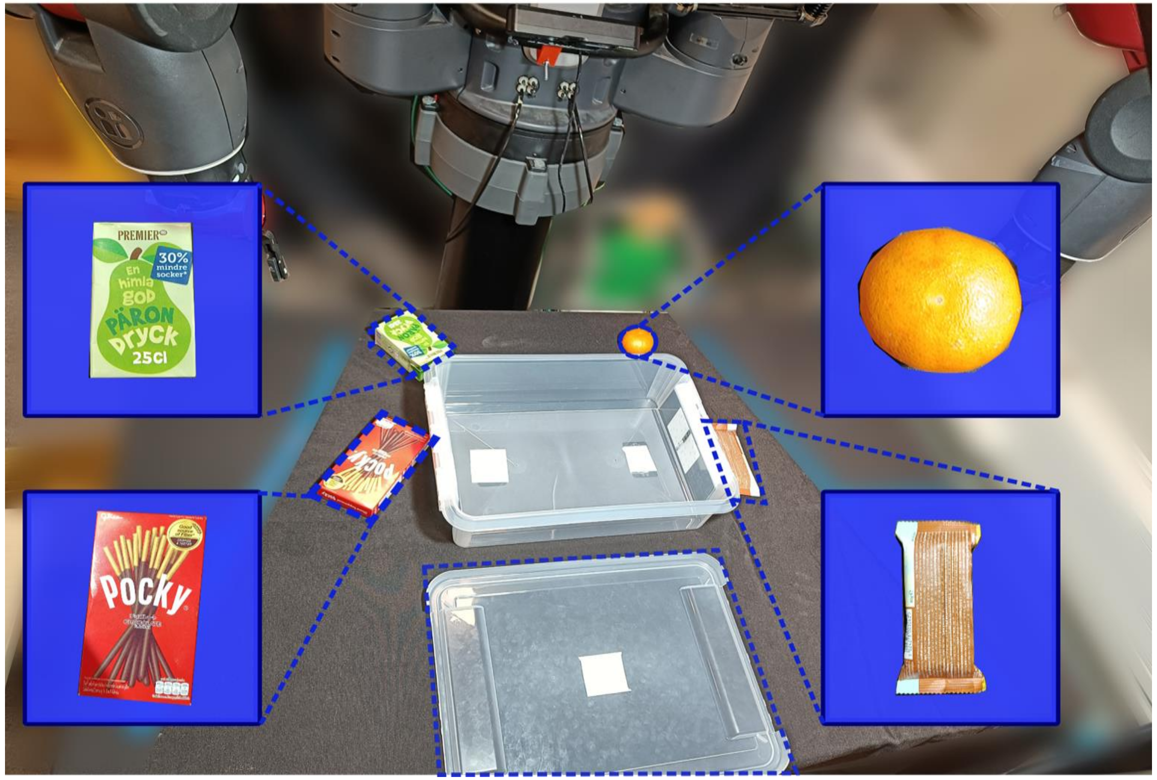



# Quantitative results



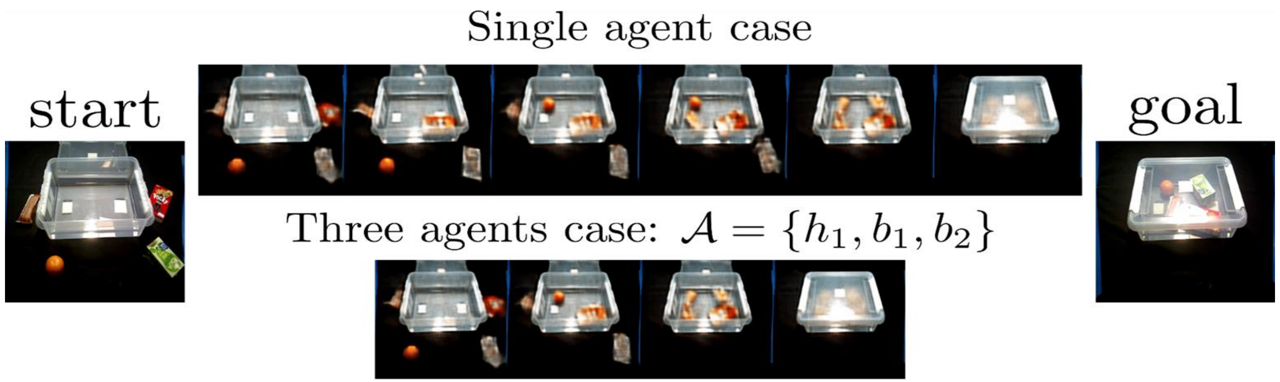
# Real world validation






Box packing task:

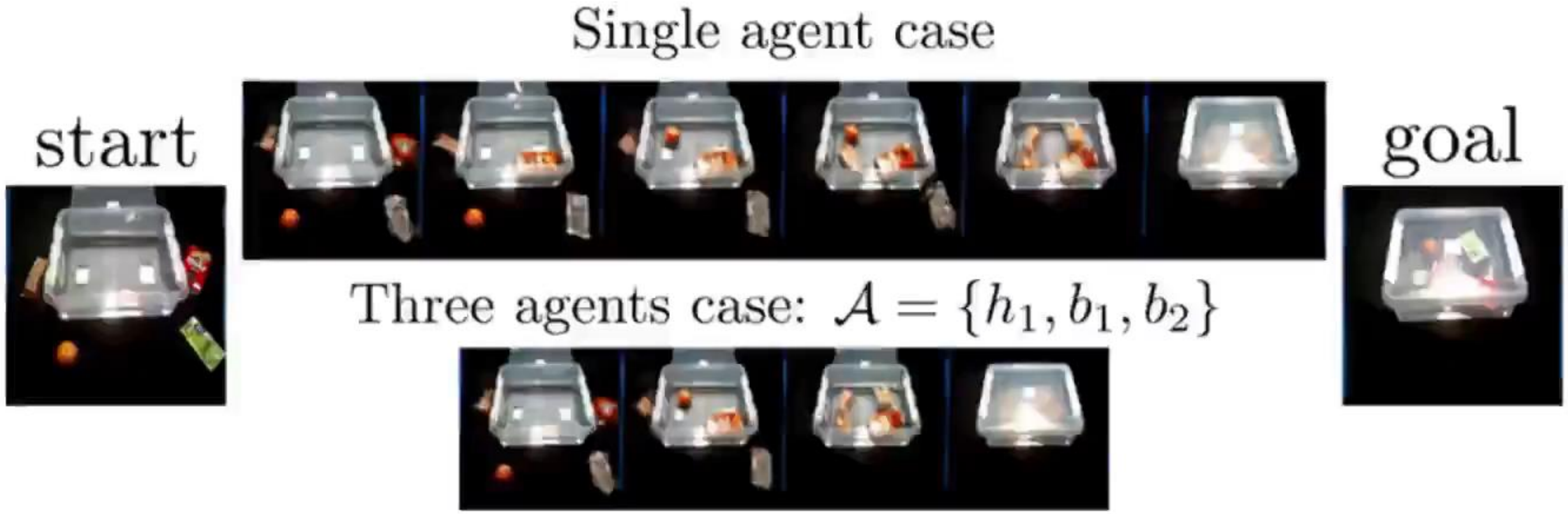
- Baxter left (pick&place)
- Baxter right (pick&place)
- Human (close lid)



# Agents description

- Two robotic arms (belonging to a Baxter robot) and a human operator are present in the scene
- The two arms have gripping skills only, while the human has dexterous manipulation skills

VAPs



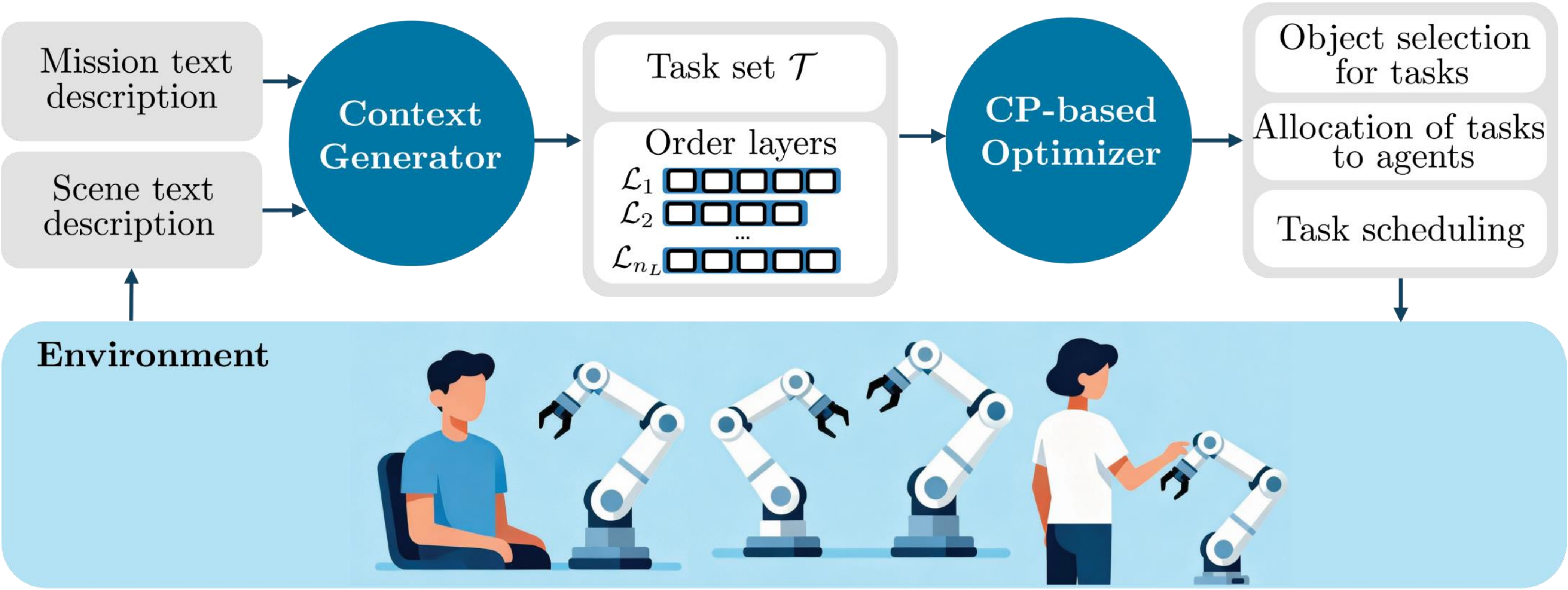
# Alternatively… the desired mission can be provided in natural language

Alternatively… the desired mission can be provided in natural language

↓

Tasks and constraints can be inferred exploiting Large Language Models (LLMs) !

# Hybrid solution overview




Reference:


- J. Palmieri, M. Lippi, A. Marino, "Hybrid Task Planning and Scheduling in Heterogeneous Multi-Agent Systems based on LLMs and Constraint Programming", Submitted to Robotics and Autonomous Systems, 2025

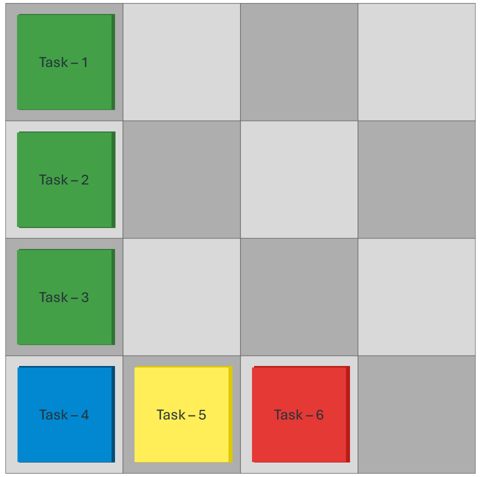
# Laboratory validation

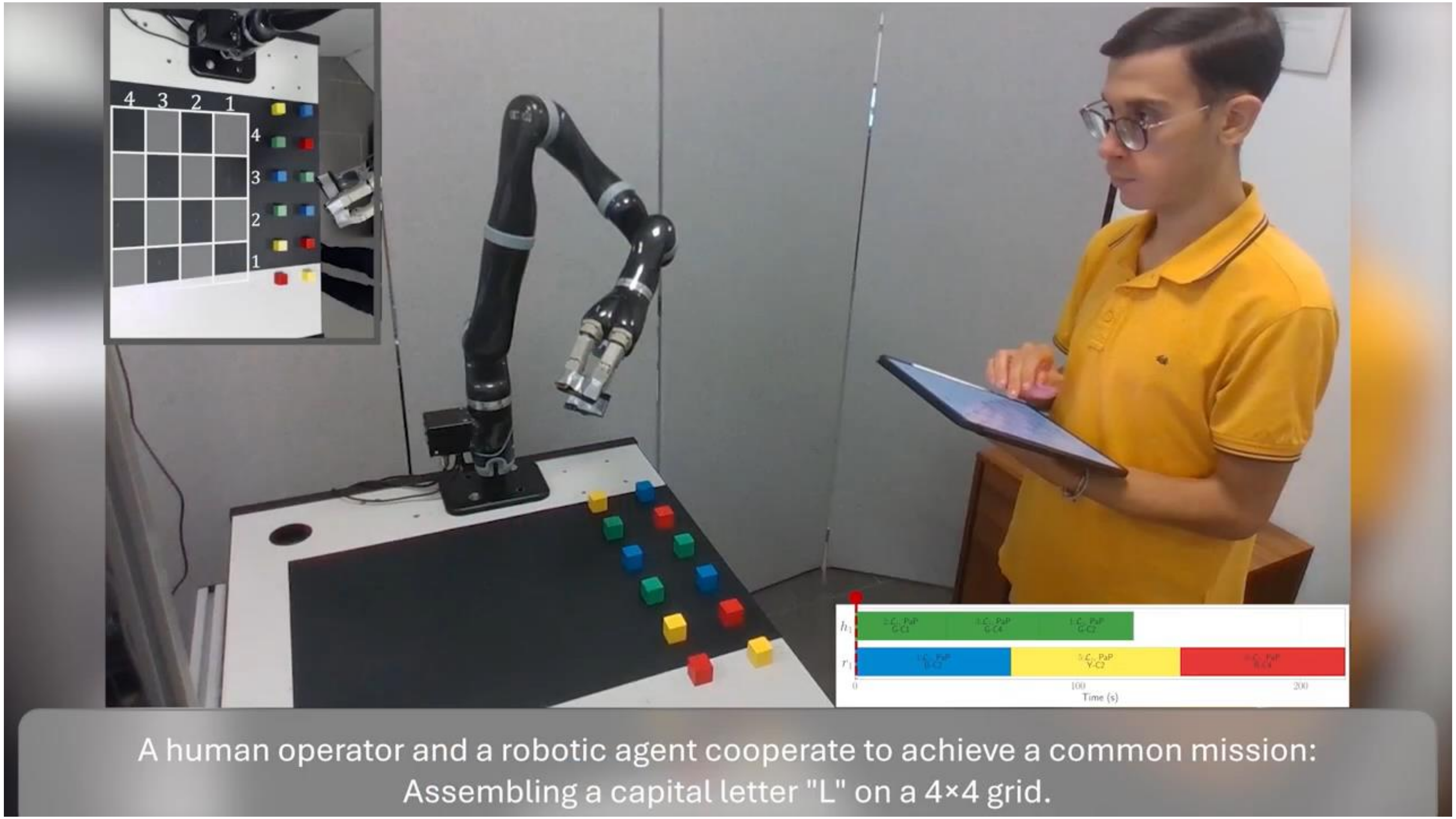
Letter assembly:

- 1 human
- 1 manipulator
- 12 blocks

User prompt:
*Build the letter "L" within the grid*

## LLM output



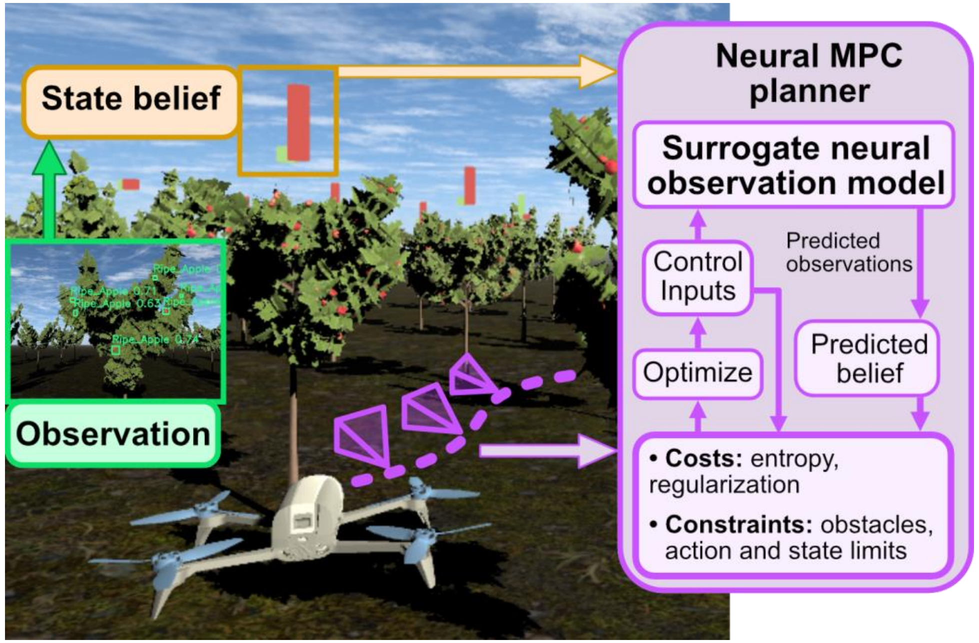
# Summary

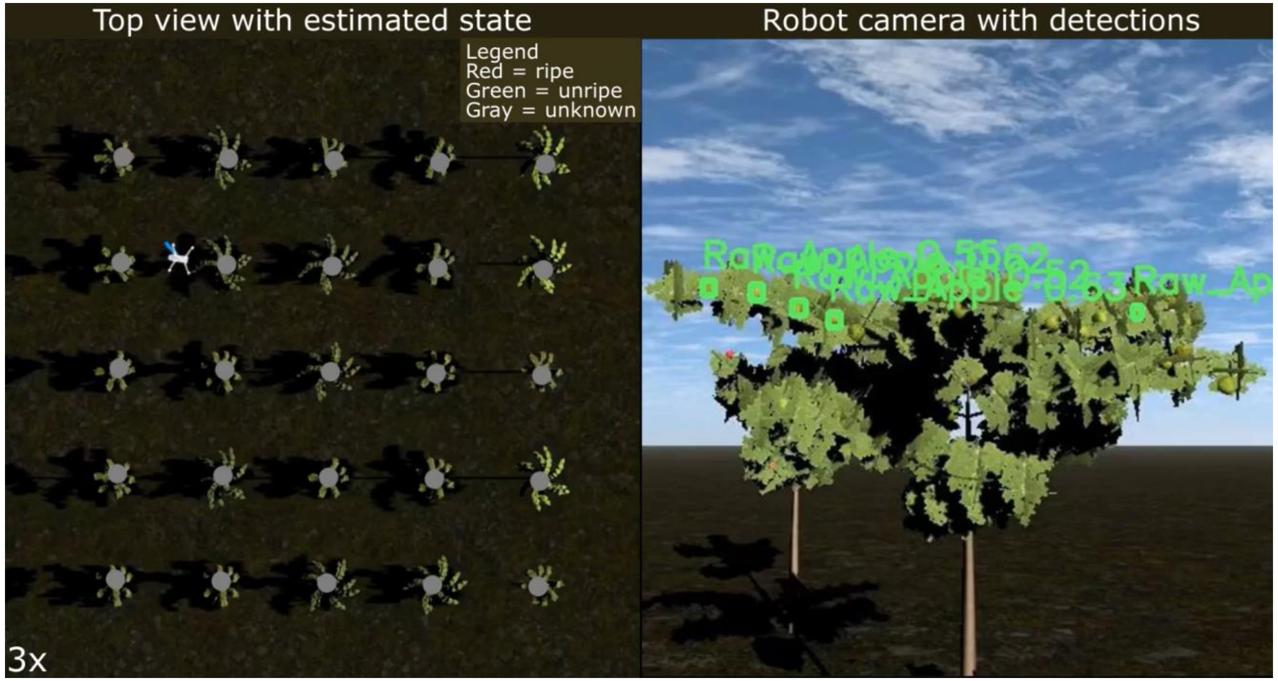
- Task planning methods for highly heterogenous multi-agent systems
- Learning methods combined with optimization-based ones to achieve higher flexibility and generality

# Along this direction… - I

Works on **Neural** Model Predictive Control for:

- Active perception to select the most informative viewpoints to properly perform the semantic tasks

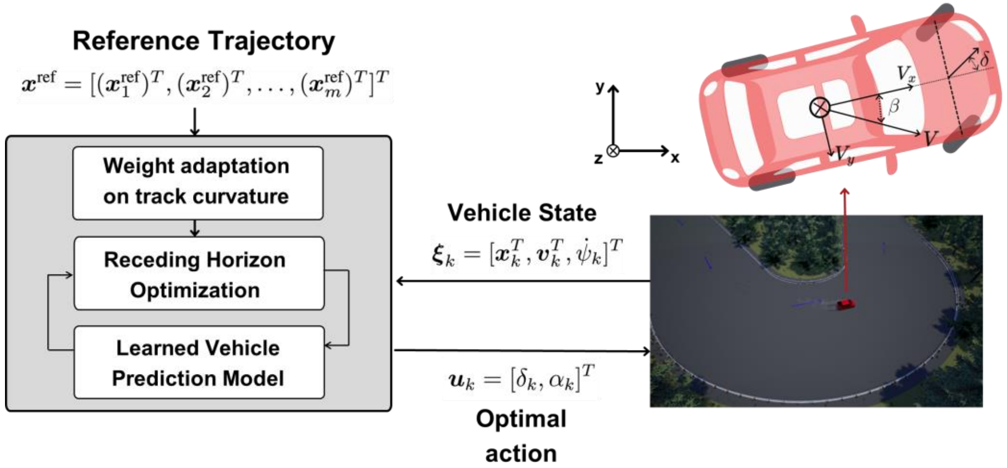



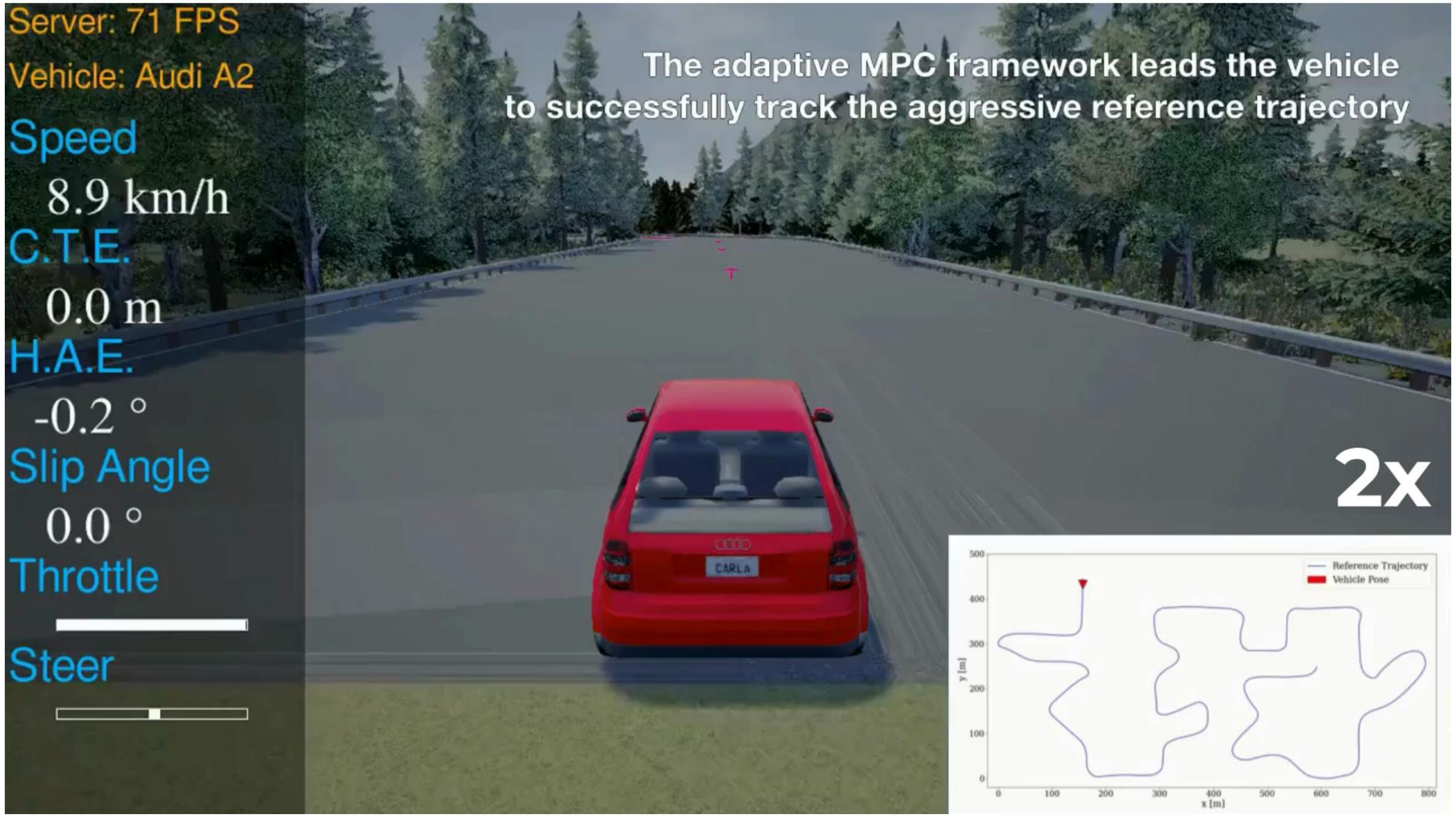




"A Neural-based Model Predictive Control Framework for Active Monitoring", Submitted

# Along this direction… - II

- Aggressive driving with learned dynamics




N. Bonucci, M. Lippi, E. Montijano, A. Gasparri "An Adaptive Neural-based Model Predictive Control Framework for Autonomous Aggressive Driving", European Conference on Mobile Robots, 2025

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## Questions?

Martina Lippi, martina.lippi@uniroma3.it
Roma Tre University