

ROMANDIC winter school 2026

Kranjska Gora, Slovenia, Feb. 10th 2026

Attendees' pitch presentations Wednesday



ROMANDIC

Robot Manipulation of Deformables through
Dynamic Actions

3 mins per presenter!

| | | |
|----|--------------------|-------------|
| 1 | Adriano | del Rio |
| 2 | Andrej | Čilag |
| 3 | Artemiy | Oleinikov |
| 4 | Giwan | Lee |
| 5 | Joana | Plewnia |
| 6 | Julia | Lopez Gomez |
| 7 | Mahed | Dadgostar |
| 8 | Michel | El Saliby |
| 9 | Miha | Dežman |
| 10 | Pietro | Dardano |
| 11 | Simone | Rotondi |
| 12 | Julia | Hohensee |
| 13 | Srđan | Apostolović |
| 14 | Veljko | Todić |
| 15 | Vinayvivan Pedrick | Rodrigues |
| 16 | Vishnu | Nair |
| 17 | Yu | Li |

Adriano del Rio



WANDERCRAFT

Exploring Diffusion Policies for Humanoid Manipulation

Adriano del Rio

Wandercraft SAS

Our goal: Calvin for dexterous manipulation tasks

We want to develop **learning-based control** methods and efficient **data-collection pipelines**, that solve the manipulation problem.

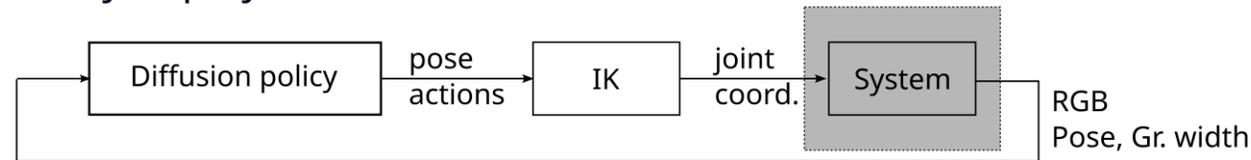
Start with something easy:

Replicate the results of some papers that introduce diffusion policies (1, 2) .

Data collection



Policy deployment



Why diffusion? Ability to handle multimodal data distributions and action sequences.

(1) Chi, C., Xu, Z., Feng, S., Cousineau, E., Du, Y., Burchfield, B., Tedrake, R., & Song, S. (2023). *Diffusion Policy: Visuomotor Policy Learning via Action Diffusion*, 2023, ICRA

(2) Chi, C., Xu, Z., Feng, S., Cousineau, E., Du, Y., Burchfield, B., Tedrake, R., & Song, S. (2024). *Universal Manipulation Interface: In-The-Wild Robot Teaching Without In-The-Wild Robots*, 2024, CVPR

Hardware and software testing platforms

Simulation pipeline:

Data-collection and deployment of policy in Isaac lab.

Isaac lab interfaces the diffusion policy codebase.



Hardware pipeline:

Replicate the hardware of the diffusion papers, and collect data with the hand-held gripper design open sourced in the paper.



Industrie-driven research questions

- **Synthetic data augmentation:** To what extent can synthetic augmentation reduce the number of expert real-world demonstrations required for high task success rates ?
- **Embedding constraints:** How can kinematic collision constraints be learned or enforced during the sampling process without inducing "off-distribution" sampling artifacts ?
- **Sensor-Architecture Synergy:** Which combination of sensor modalities (visual, geometric, tactile, acoustic) and model architectures provide robust performance over long task horizons ?



Andrej Čilag

ROMANDIC project
Winter School 2026
Kranjska Gora, Slovenia

Andrej Čilag

Ph.D. Student in Mechatronics



University of Novi Sad
Faculty of Technical Sciences
Chair of Mechatronics, Robotics and Automation

@andrejchilag 
andrej.chilag@uns.ac.rs 



Who am I ?

Where do I come from?

Republic of Serbia, Novi Sad

EDUCATION:

- B.Sc., Mechatronics, robotics and automation, Faculty of Technical Sciences, University of Novi Sad, 2019.

Thesis title: "Development of a head mobile robot within the Probotech team to participate in EUROBOT 2019"

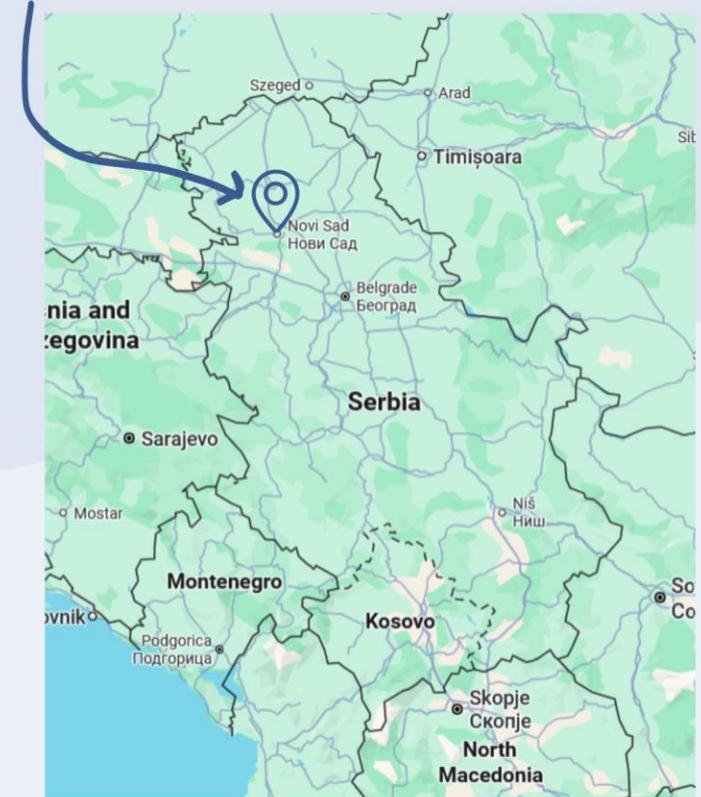
- M.Sc., Mechatronics, robotics and automation, Faculty of Technical Sciences, University of Novi Sad, 2020.

Thesis title: "ROS application for palletizing industrial crates using ABB IRB140 robotic arm"

- Ph.D., Mechatronics, robotics and automation, Faculty of Technical Sciences, University of Novi Sad, Present.

APPOINTMENTS:

- Teaching Assistant, Faculty of Technical Sciences, University of Novi Sad
- Member of the National Organizing Committee, Eurobot Serbia



University of Novi Sad
Faculty of Technical Sciences
Chair of Mechatronics, Robotics and Automation

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@andrejchilag



What am I working on ?

Research interests:

- Industrial robotics
- Bimanual manipulation
- Simulation - NVIDIA IsaacSim

Ph.D. Research:

- The topic of Ph.D. theses is bimanual fabric manipulation
- Research at Department of Automatics, Biocybernetics, and Robotics, of Jožef Stefan Institute, Ljubljana, Slovenia in 2023 for three months



ROMANDIC project
Winter School 2026
Kranjska Gora, Slovenia

Thank you for your attention

I'm open to any questions and comments...



 @andrejchilag

 andrej.chilag@uns.ac.rs



University of Novi Sad
Faculty of Technical Sciences
Chair of Mechatronics, Robotics and Automation

Artemiy Oleinikov

Bridging Visual–Language–Action Models and Model Predictive Control for Robust Robotic Manipulation

PhD student: Artemiy Oleinikov,

Supervisors: Juan Antonio Corrales Ramon¹, Youcef Mezouar²

CiTIUS, University of Santiago de Compostela¹ (Spain) and Institut
Pascal, Clermont Auvergne INP² (France).

Motivation

- Constraint satisfaction
- Distribution shift
- Safety guarantees during execution

System Overview

- Robot: Franka Emika Panda (7-DoF)
- Sensor: Intel RealSense RGB-D (eye-in-hand)
- VLA model for low-rate semantic planning
- MPC for high-rate (≥ 100 Hz) torque or velocity control



Figure 1: Franka Emika Panda manipulator with Intel RealSense RGBD camera setup with objects from Yale-CMU-Berkeley (YCB) Object and Model set simulator in IsaacSim.

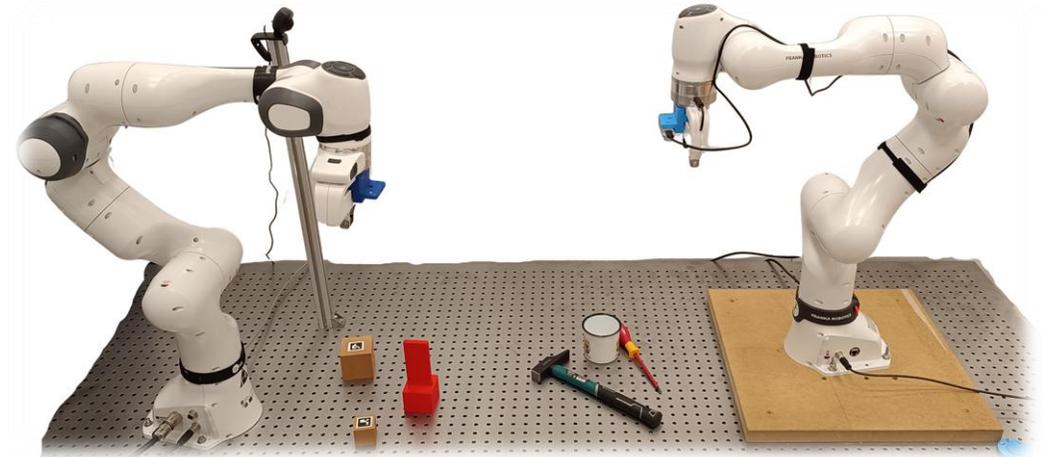


Figure 2: Experimental setup for bimanual manipulation, Franka Emika Panda manipulator (left) and Franka Emika FR3 manipulator (right).

Methodology

High-Level Planning: A Vision–Language–Action model interprets language and visual observations to generate task goals and symbolic constraints.

Low-Level Control: Model Predictive Control optimizes continuous trajectories subject to robot dynamics, joint limits, and collision constraints. Nonlinear model predictive control formulation with joint-space dynamics, Cartesian end-effector tracking, velocity regularization, and unilateral table-avoidance constraint.

$$\begin{aligned} \min_{\{x_k, u_k\}_{k=0}^{N-1}} \quad & \sum_{k=0}^{N-1} \ell(x_k, u_k) + \ell_f(x_N) \\ \text{s.t.} \quad & x_{k+1} = f(x_k, u_k), \quad x_k = \begin{bmatrix} q_k \\ \dot{q}_k \end{bmatrix}, \quad u_k = \ddot{q}_k, \\ & y_k = \begin{bmatrix} p(q_k) \\ \text{vec}(R(q_k)) \end{bmatrix}, \\ & g(x_k) \geq 0, \\ & g_u(u_k) \geq 0, \\ & h(x_k) \geq 0, \\ & h_u(u_k) \geq 0, \end{aligned} \tag{1}$$

| | |
|--------------------------------|--|
| x_k | system state at step k (joint positions q_k and velocities \dot{q}_k) |
| u_k | control input (joint accelerations \ddot{q}_k) |
| $f(\cdot)$ | discrete-time robot dynamics model |
| y_k | end-effector pose (position p and orientation R) |
| Notation: $\ell(\cdot)$ | stage cost (tracking, smoothness) |
| $\ell_f(\cdot)$ | terminal cost |
| $g(\cdot), g_u(\cdot)$ | inequality state and input constraints |
| $h(\cdot), h_u(\cdot)$ | collision and workspace constraints |
| N | prediction horizon |

Acknowledgements

A. Oleinikov was funded by the Spanish Ministry of Science, Innovation and Universities (Ref. MICIU/AEI/10.13039/501100011033) through the research project FedeMINDex (Ref. CNS2024-154907), by the Interreg VI-B SUDOE Programme through the research project ROBOTA-SUDOE (Ref. S1/1.1/P0125), by ANR-25-PERO-0003 PEPR Robotique France 2030 - PC DRMI (Dexterous Robotic Manipulation for Industry) and by the European Union (European Regional Development Fund - ERDF).

**Interreg
Sudoe**



Co-funded by
the European Union

ROBOTA-SUDOE



UNIVERSITAT DE VALÈNCIA



Giwan Lee

From Robot Perception to Topology-Aware Fabric Manipulation

Giwan Lee

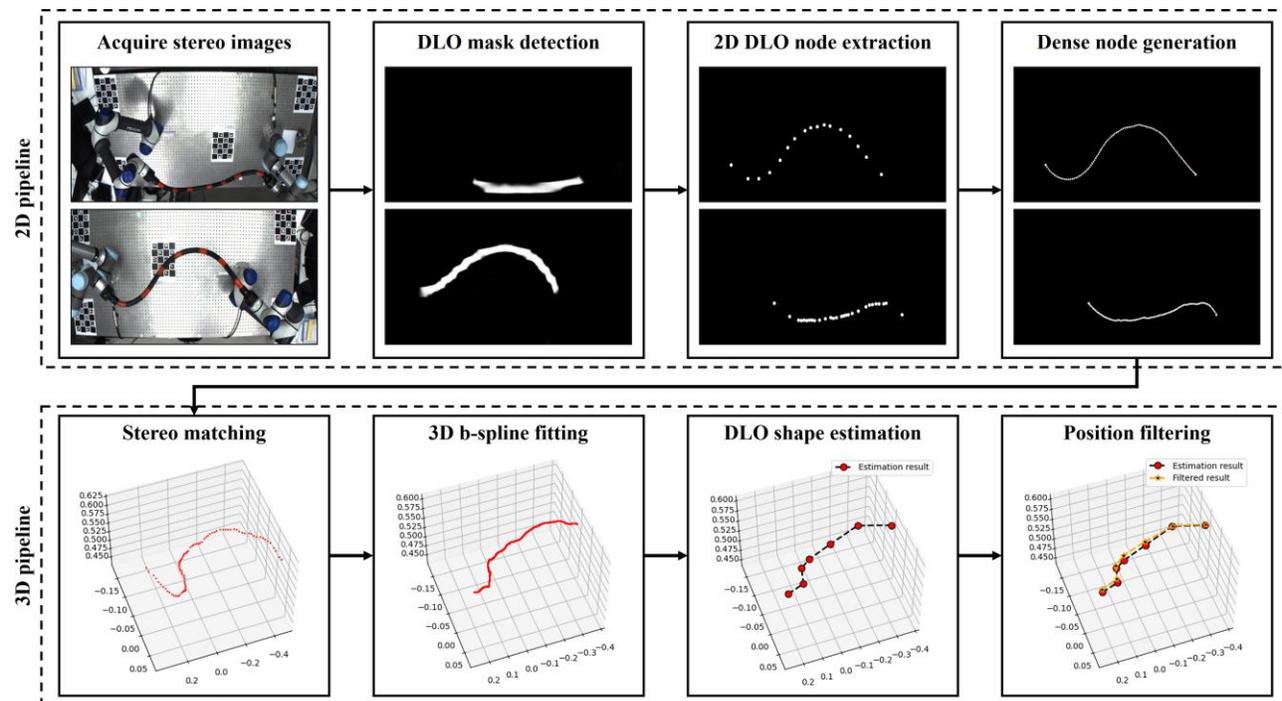
Autonomous and Intelligent Robotics Lab

Department of Mechanical Engineering, Chonnam National University

Introduction

My previous research – DLO perception

- **DLO Position Estimation using B-spline Curve Fitting**
 - Occlusion-robust DLO position estimation method using B-splines and the robot's Tool Center Point(TCP)
 - Deep learning-based 2D DLO extraction -> Stereo matching + B-spline fitting

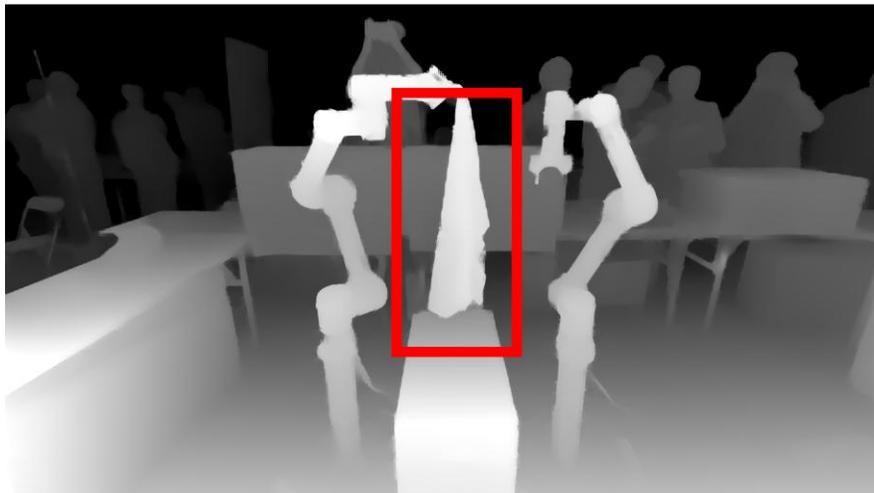


Overall framework of the DLO position estimation method

Introduction

My previous research – Cloth manipulation competition

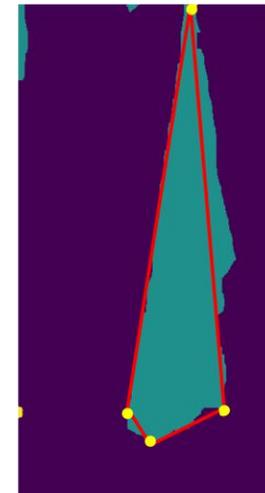
- **Cloth Grasp Point Detection Using Simplified Polygon Approximation for ICRA 2024 Cloth Competition**
 - Depth images from the fixed ROI -> We approximated the garment's contour as a polygon.
 - The optimal grasping point -> The vertex with the second-greatest distance from the robot arm.



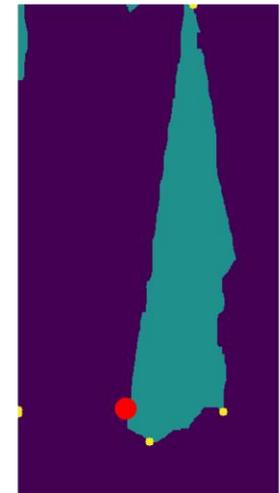
Clothing area extraction



Background removal



Erosion and polygon approximation



Select second farthest point

Framework of the grasp point detection method

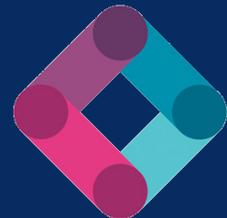
Future Vision and Conclusion

- **My primary research focus has been the development of deep learning-based perception techniques for robotic systems.**
- **I have been concentrating on shape estimation and control strategies for Deformable Linear Objects (DLOs).**
- **I aim to integrate robotic control strategies for 2D deformable objects, such as fabrics, into my research framework.**
- **Based on this winter school project, i aspire to develop advanced techniques that leverage garment topology to achieve precise shape transformations.**

Thank you

Julia Lopez Gomez

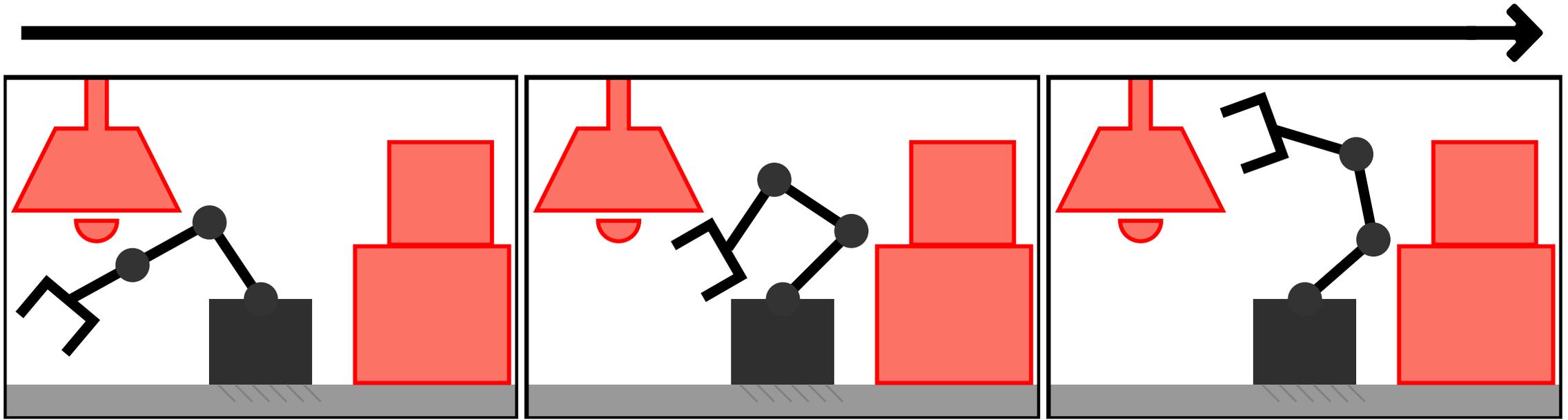
Optimisation-Based Manipulation Planning in Convex Decompositions of C-Free



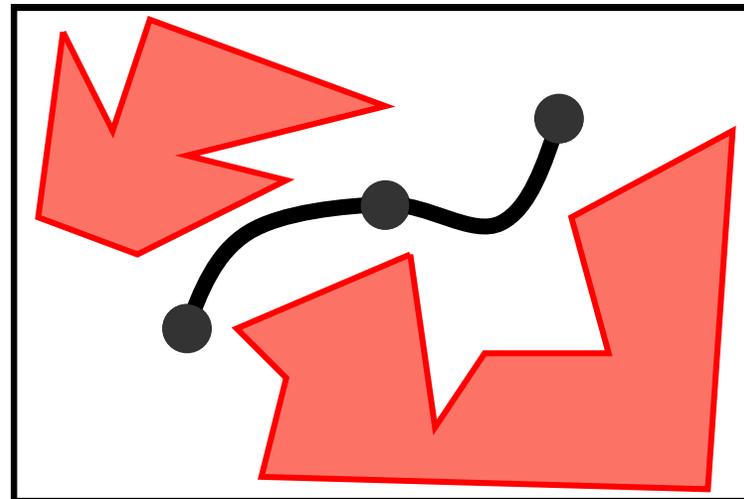
Edinburgh Centre for
Robotics

Julia López Gómez

Year 1 PhD Student - UKRI AI CDT-D2AIR

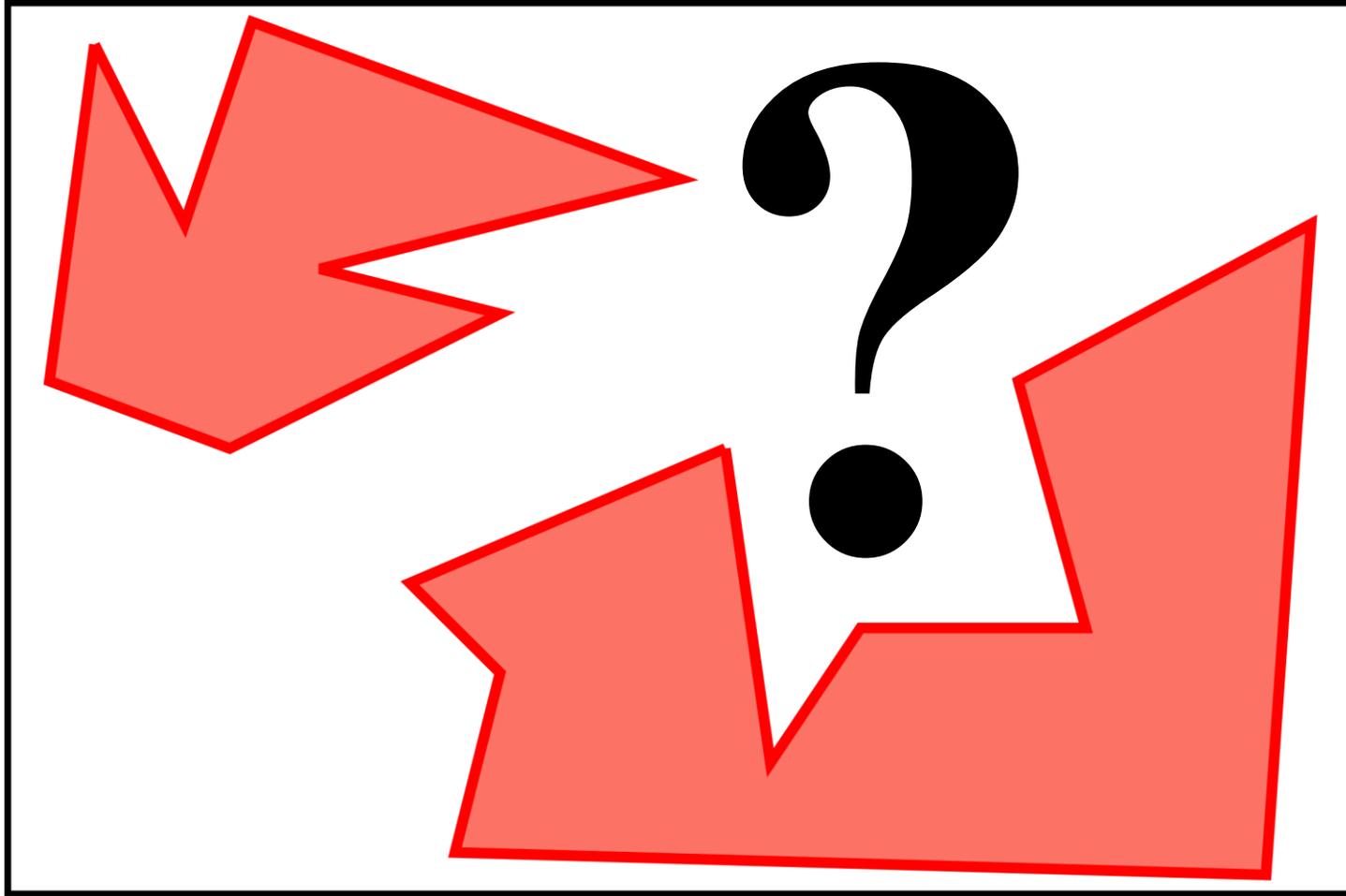


Trajectories in C-Space



- Robot in C-free
- Obstacle

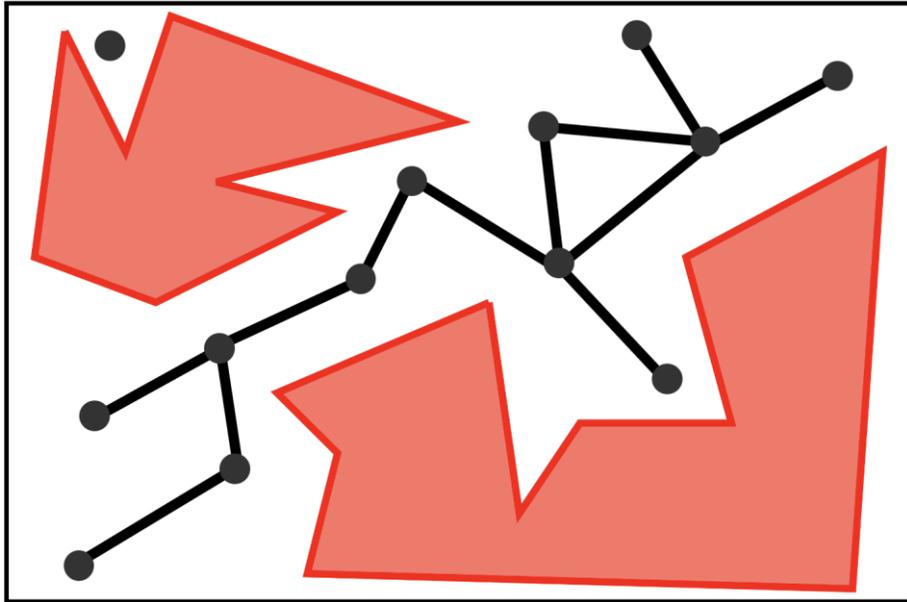
Collision-Free Configuration Space (C-free)



- How can we describe C-free?

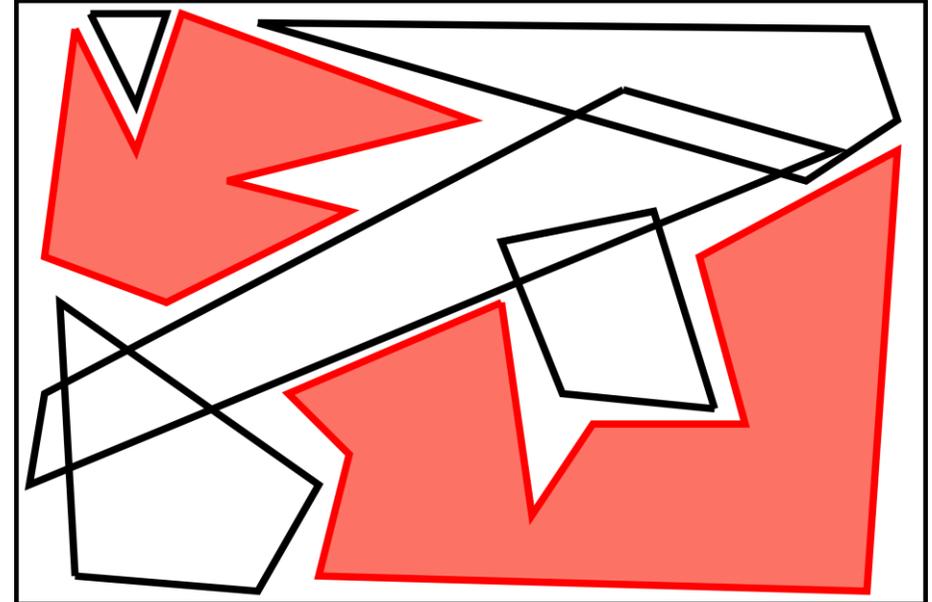
Collision-Free Configuration Space (C-free)

SAMPLING METHODS



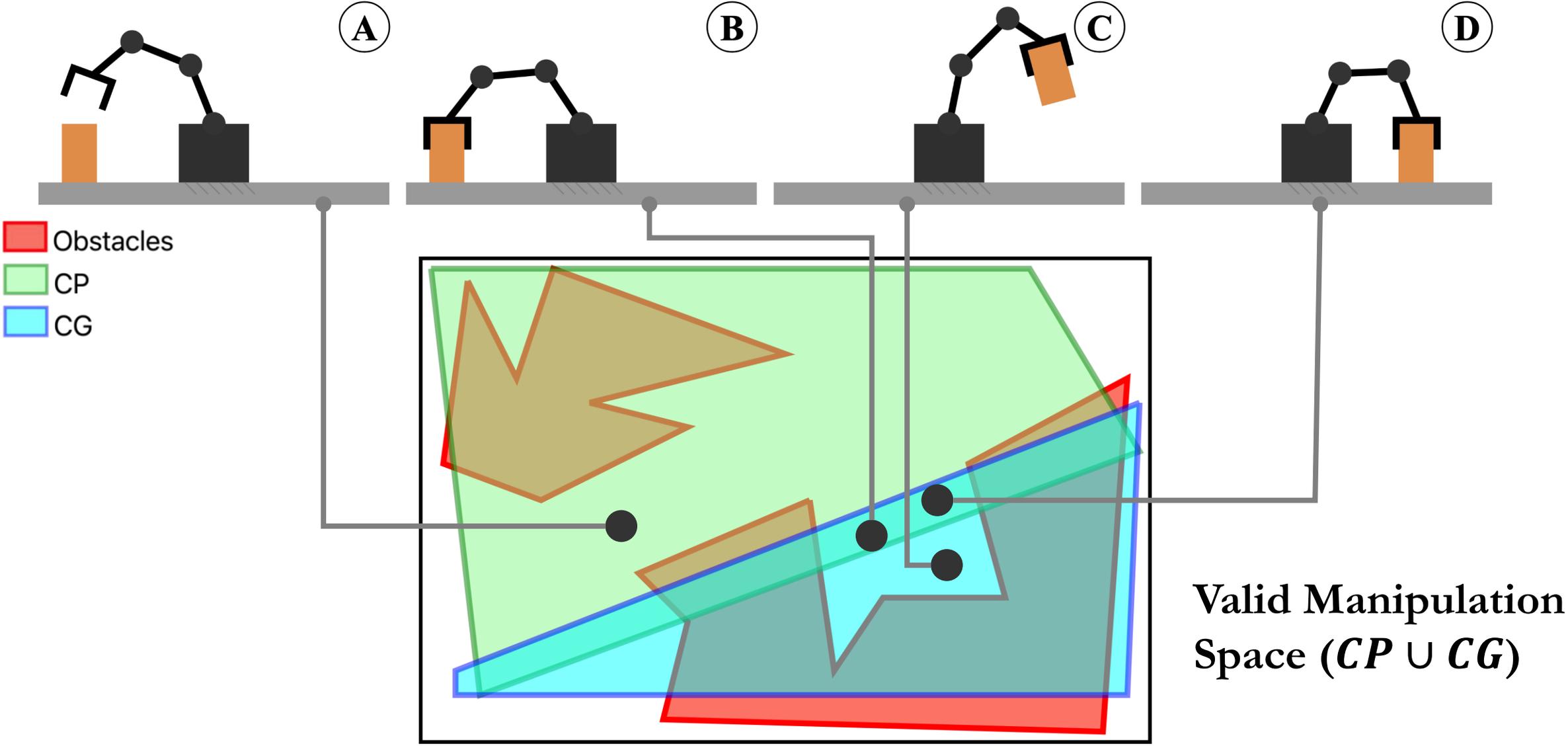
- Probabilistic Cert. of non-collision
- Probabilistically complete
- (At most) asymptotic optimality

CONVEX DECOMPOSITION

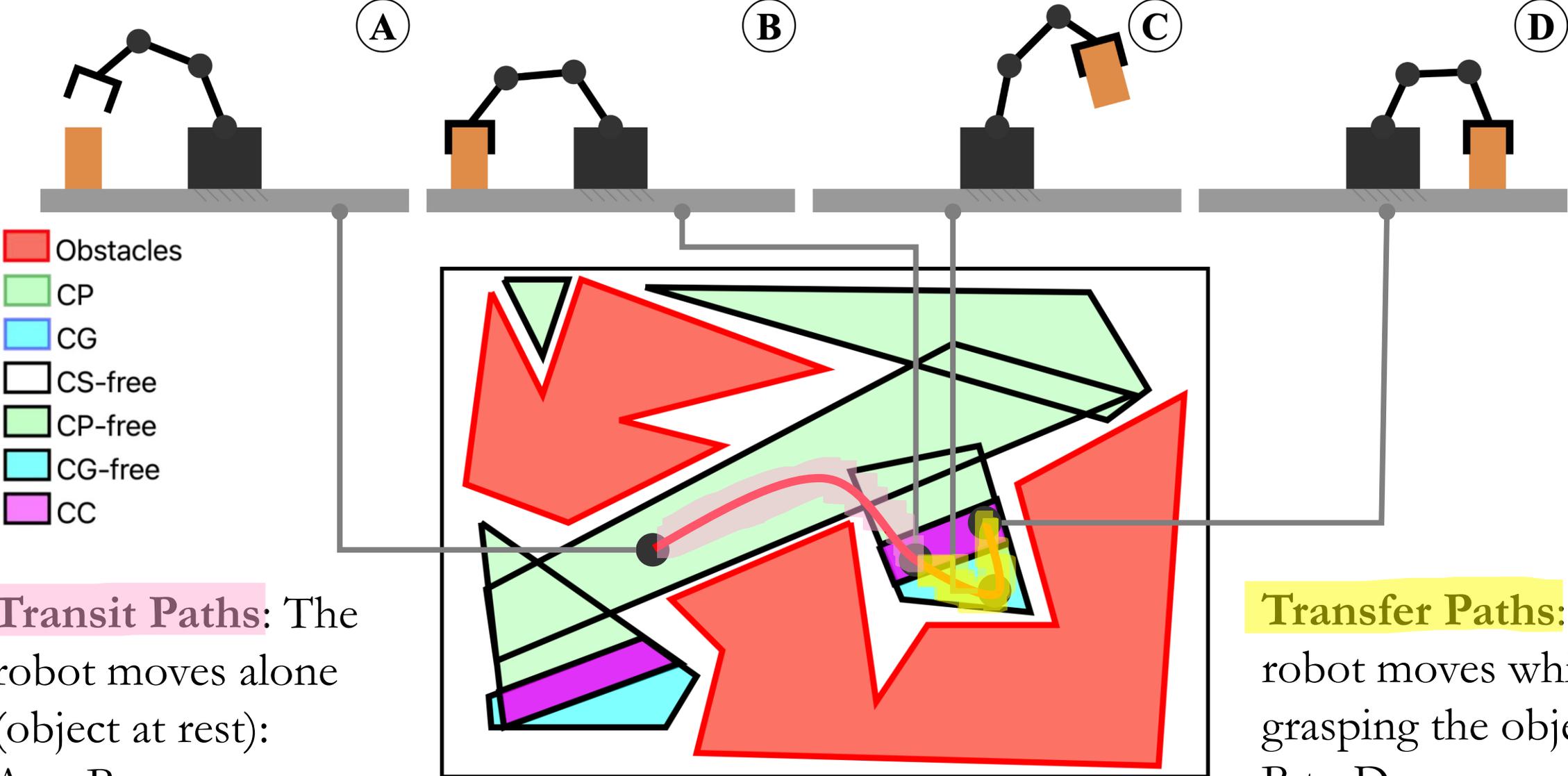


- Certificates of non-collision
- Completeness
- Global optimality [1]

Manipulation Planning in Convex Decompositions of C-Free



Manipulation Planning in Convex Decompositions of C-Free



Transit Paths: The robot moves alone (object at rest): A to B

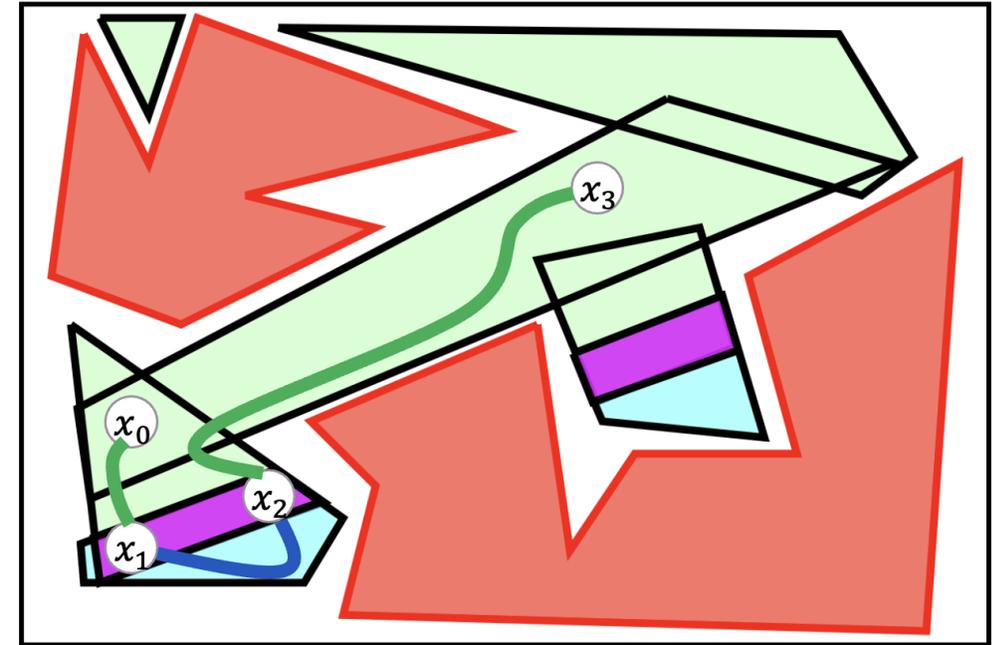
Transfer Paths: The robot moves while grasping the object: B to D

+ Trajectory Generation

1. Find Grasp-Release actions that solve the Manipulation Task

(actions that are both in placement and grasping space at the same time)

$$\begin{aligned} \min_{\mathbf{x}_0, \dots, \mathbf{x}_{2\ell+1}} \quad & \sum_{i=0}^{2\ell} \|\mathbf{x}_{i+1} - \mathbf{x}_i\|_2^2 \\ \text{s.t.} \quad & \mathbf{q}_{\min} \leq \mathbf{x}_i \leq \mathbf{q}_{\max} \\ & \text{Transfer Constraints} \\ & \text{Transit Constraints} \\ & \text{Connectivity Constraints} \end{aligned}$$



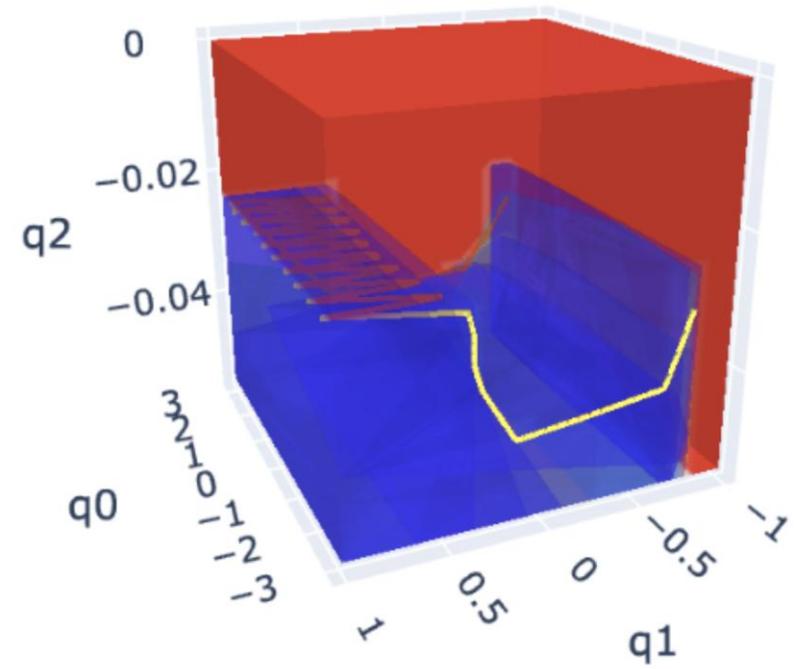
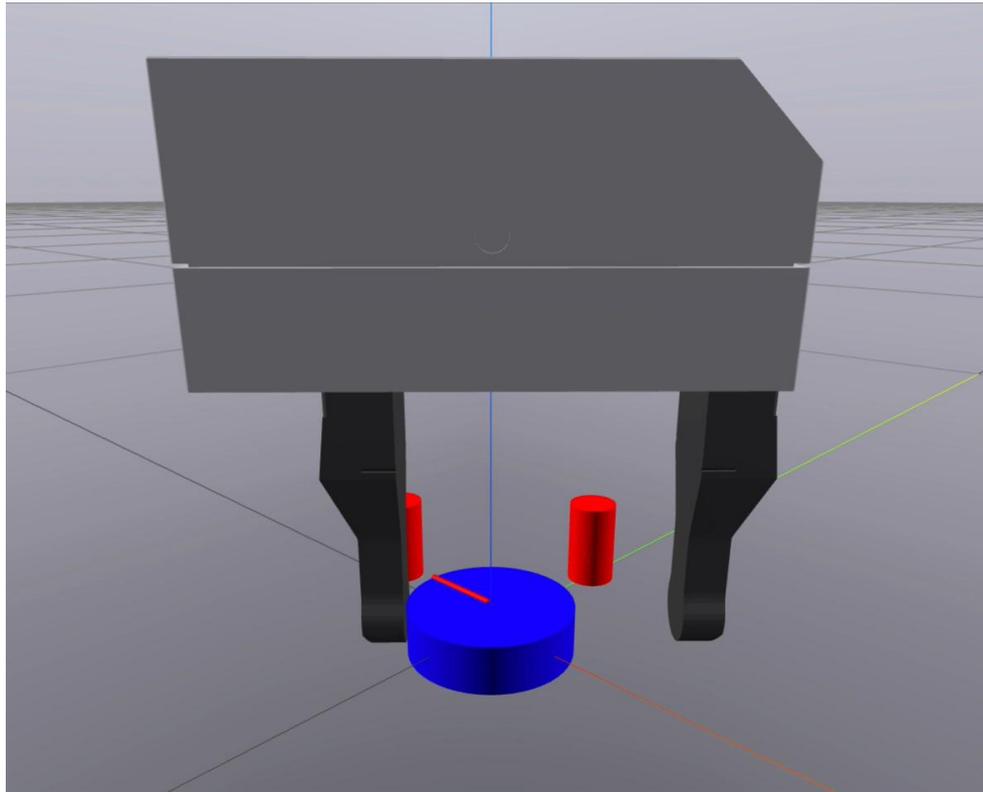
2. Find the transit and transfer trajectories that connect the grasp-release states

$$\tau = \bigcup_{i=0}^{2\ell} \tau_i \quad \text{where} \quad \tau_i = \text{GCS}(\mathbf{x}_i, \mathbf{x}_{i+1}), \quad \tau_i = \begin{cases} \text{Transit Path} & \text{if } i \text{ is even} \\ \text{Transfer Path} & \text{if } i \text{ is odd} \end{cases}$$

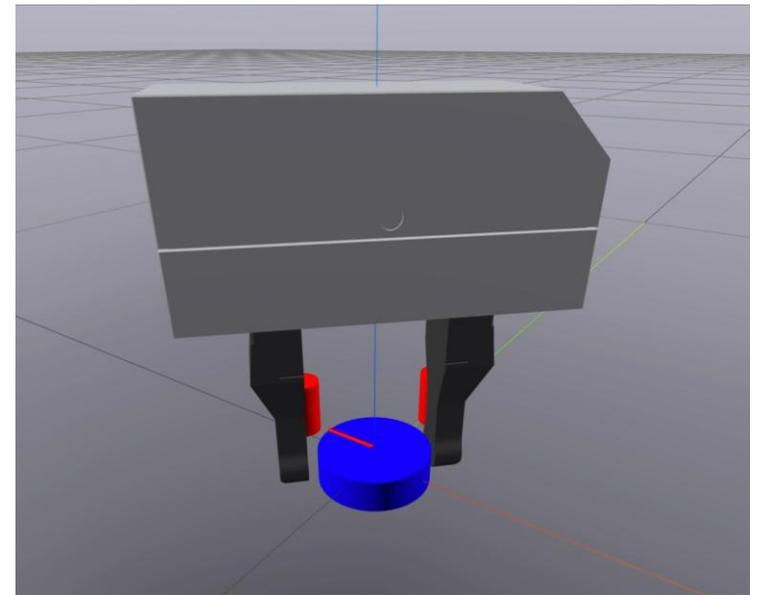


Results

4-DOF



3-DOF



Joana Plewnia



Memory and Imagination for Robot Action Prediction and Selection

Joana Plewnia

High Performance Humanoid Technologies Lab (H²T)

Institute for Anthropomatics and Robotics (IAR)

Karlsruhe Institute of Technology (KIT)

The Crumpled T-Shirt Problem



The Crumpled T-Shirt Problem



Same t-shirt, near infinite initial configurations!

Cloth Is Hard

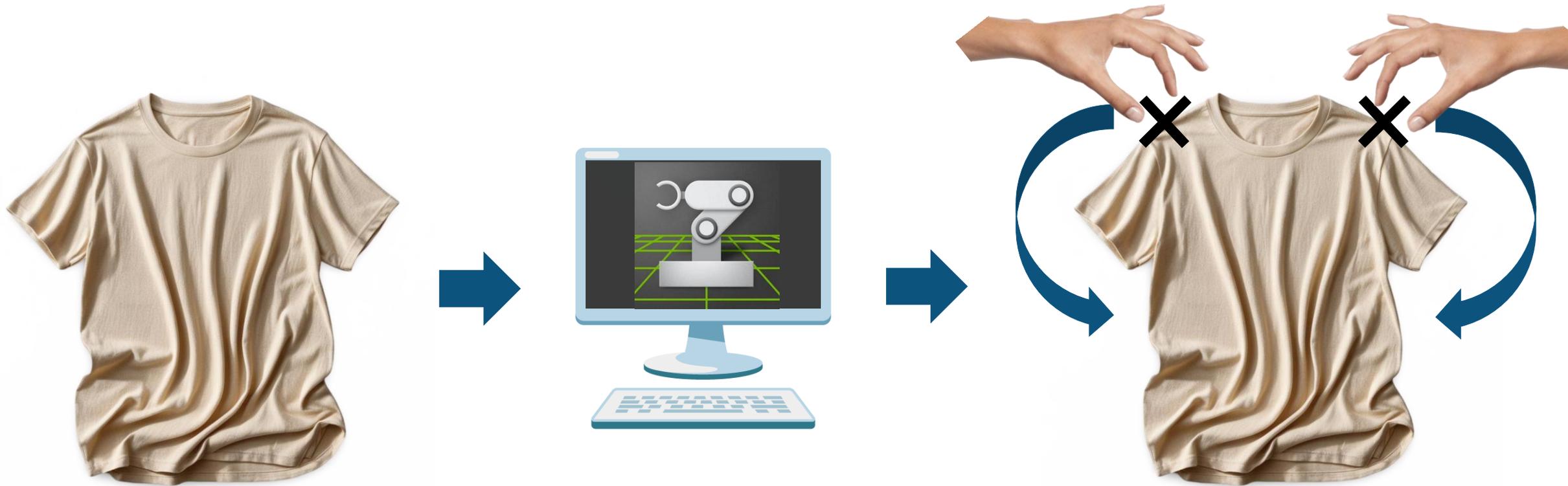


Cloth Is Hard



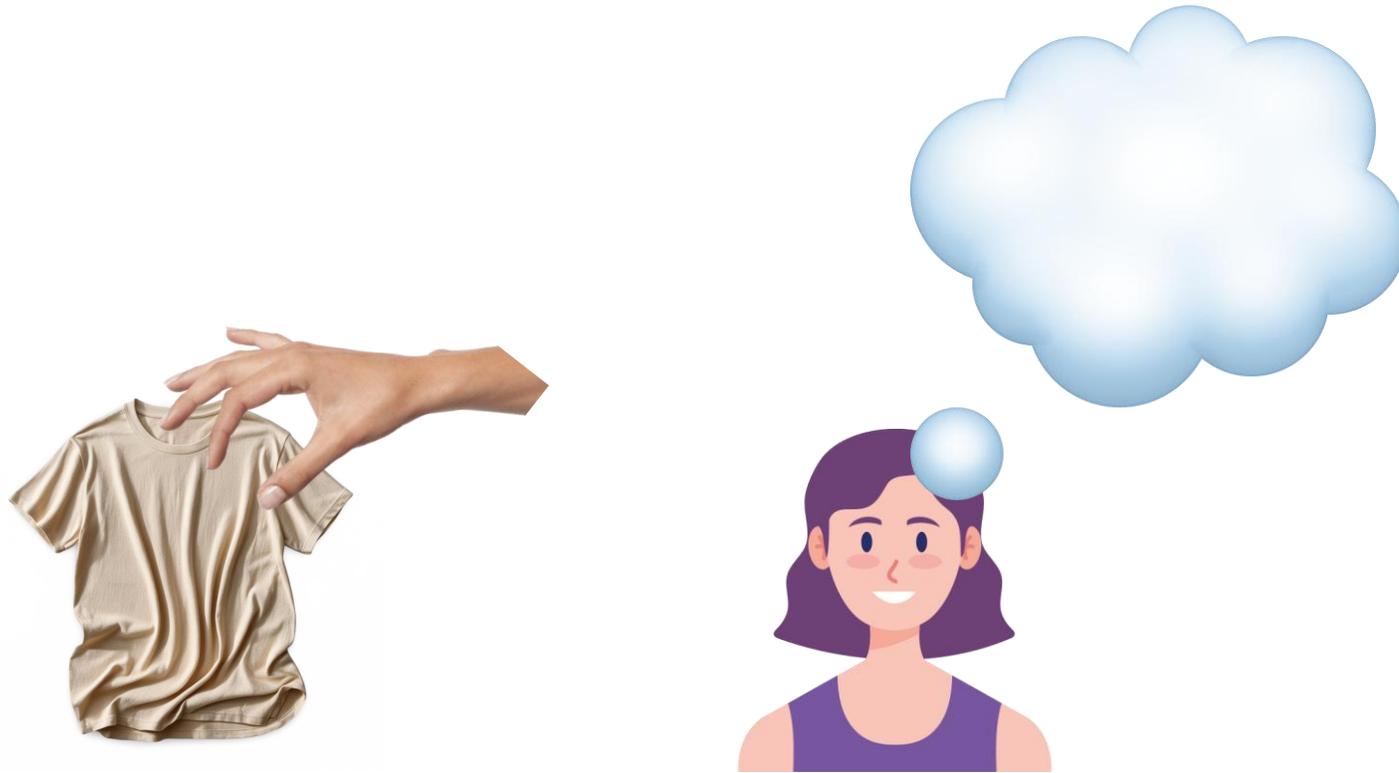
Same action
+
different initial
states
→
different
outcomes

Naive Solution: Simulate Everything



High Computational Costs
Sim-to-Real Gap

How Do Humans Handle This?



We don't simulate **everything**

How Do Humans Handle This?



Informed
Prediction

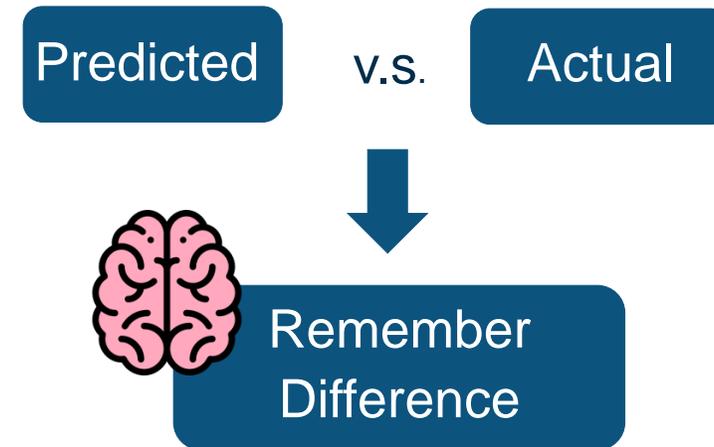
We don't simulate **everything**,
we remember what worked

Episodic Memory Enables ...

Leveraging prior knowledge to need fewer simulation starting points



Learning to know when simulation won't match the real-world



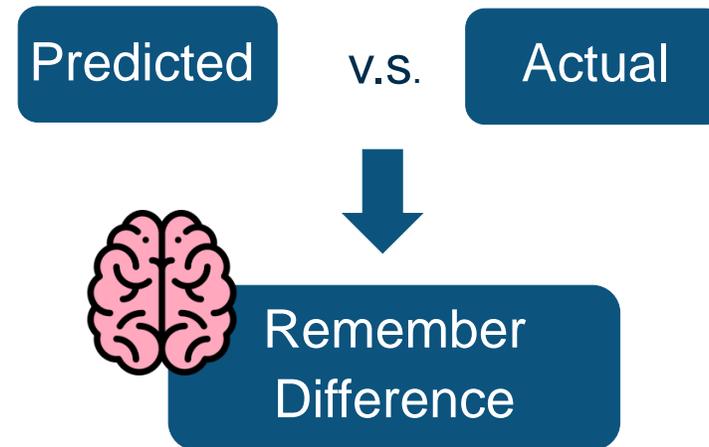
Episodic Memory Enables ...

Leveraging prior knowledge to need fewer simulation starting points

Memory provides Priors
→ Simulate only promising options

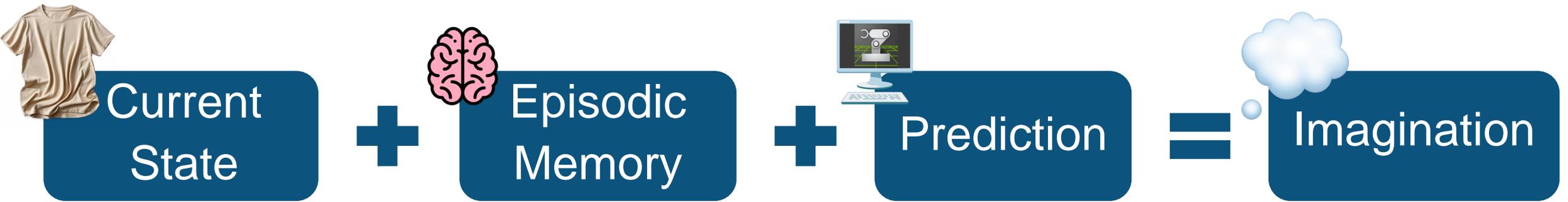


Learning to know when simulation won't match the real-world



know when to rely on simulation and when not to

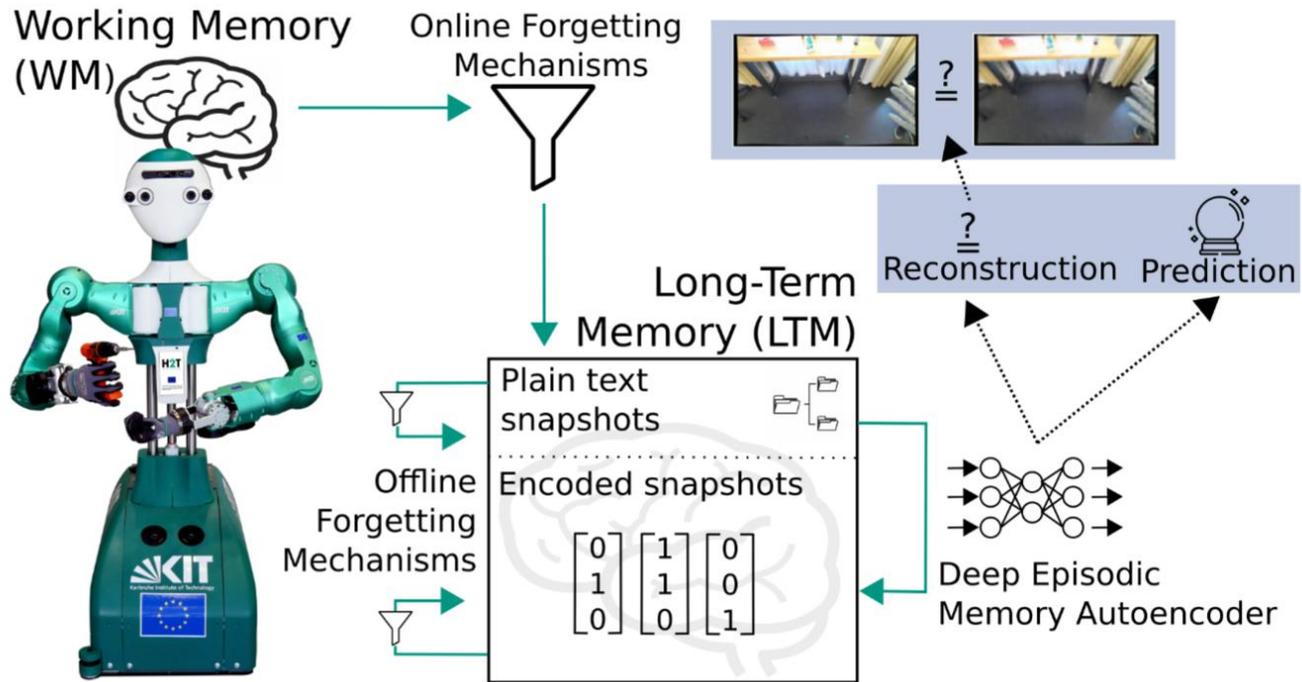
Imagination Draws on Memory



Imagination isn't random guessing, it's informed prediction based on remembered experiences

My Research

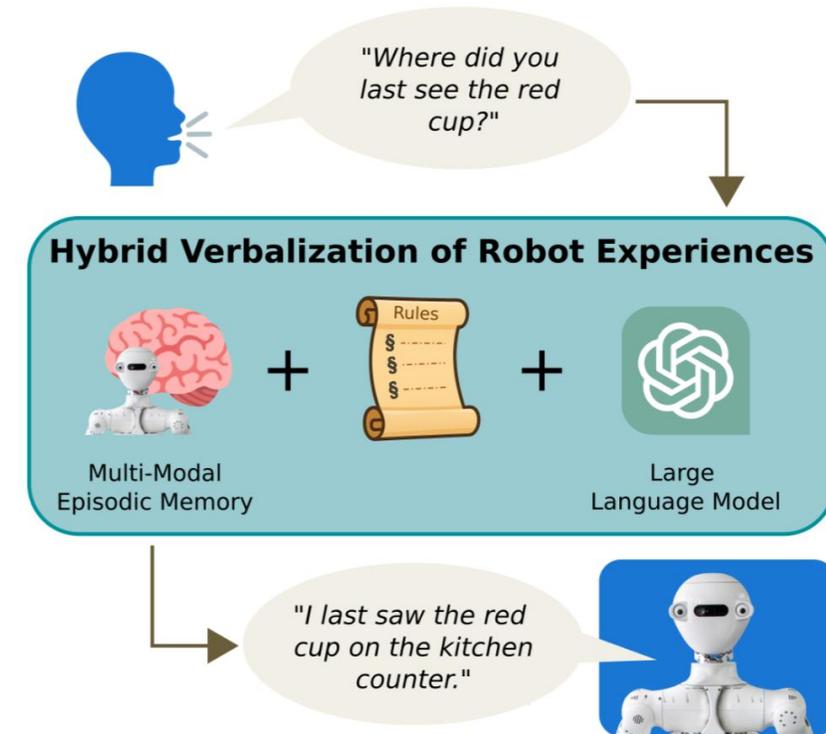
Forgetting



Plewnia, J., Peller-Konrad, F. and Asfour, T., *Forgetting in Episodic Long-Term Memory of Humanoid Robots*, IEEE International Conference on Robotics and Automation (ICRA), pp. 6711-6717, May, 2024

Plewnia, J., Peller-Konrad, F. and Asfour, T., *Beyond Recall: Evaluating Forgetting Mechanisms for Multi-Modal Episodic Robotic Memory*, German Robotics Conference (GRC), 2025

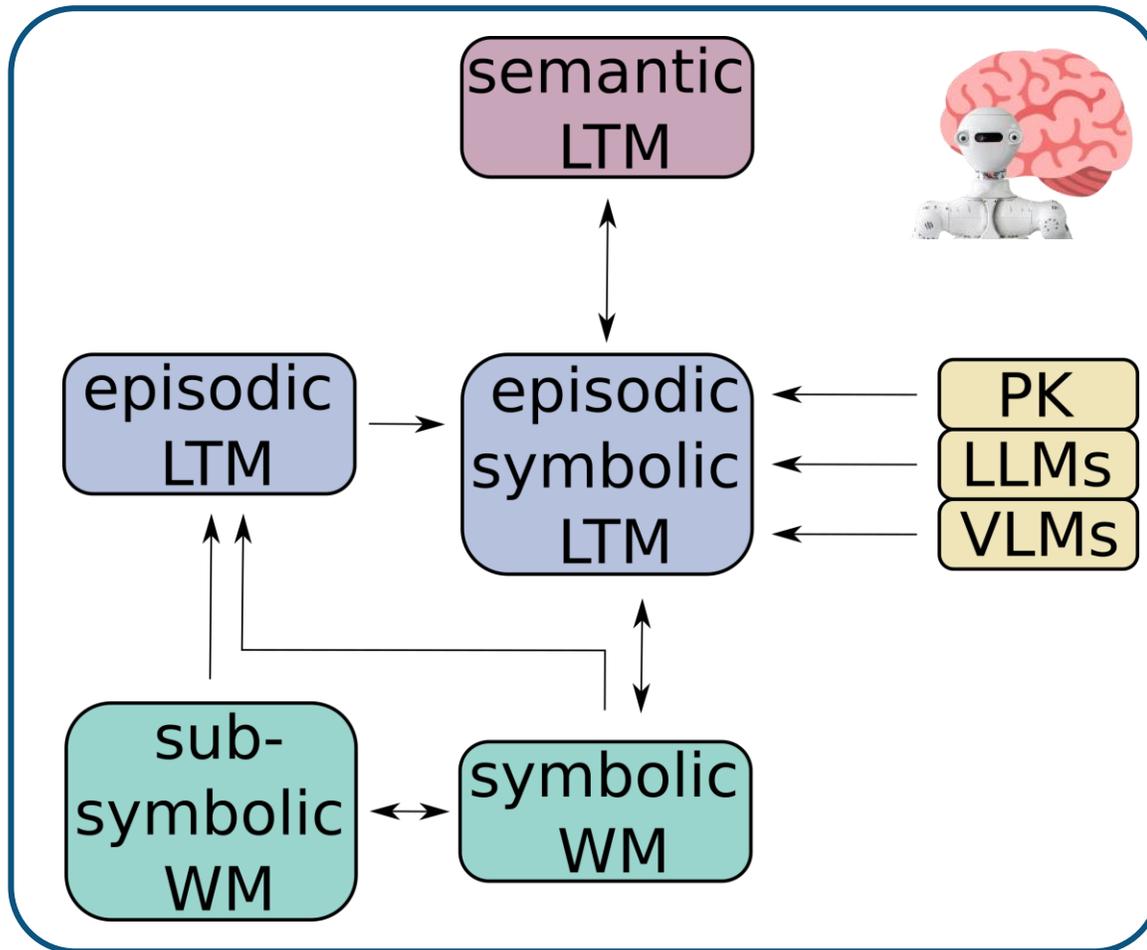
Verbalization



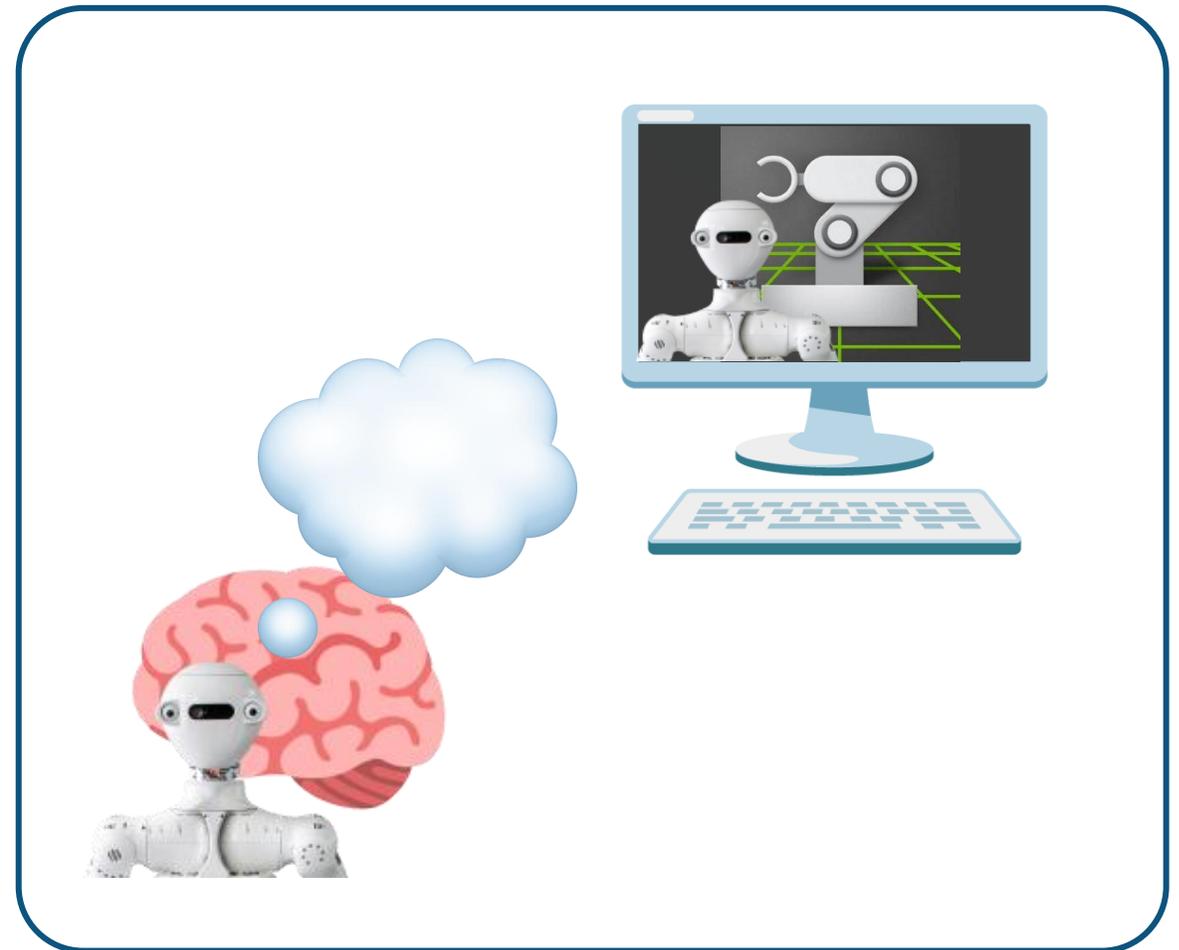
Plewnia, J. and Asfour, T., *Combining Episodic Memory and LLMs for the Verbalization of Robot Experiences*, IEEE/RAS International Conference on Humanoid Robots (Humanoids), September, 2025

My Current Research

LTM Architectures



Imagination





Joana
Plewnia



Tamim
Asfour

www.humanoids.kit.edu

Thank you!

Mahed Dadgostar

Interaction Stochasticity in Dynamic Cloth Manipulation

Presenter: Mahed Dadgostar

Supervisors: Júlia Borràs Sol, Guillem Alenyà



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Institut de Robòtica i
Informàtica Industrial



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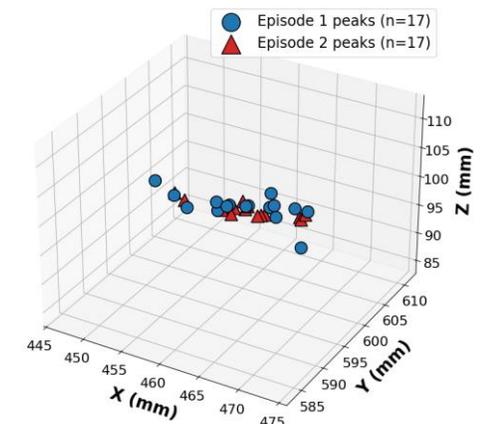
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DE CATALUNYA
BARCELONATECH

Why dynamic deformables break repeatability?

- Deformables: high-DOF + contact + partial observability
- Simulation: same start + same trajectory \Rightarrow same outcome
- Real world: outcomes diverge from micro-state + aerodynamics / unmodeled effects
- Key idea: treat outcome as a distribution (not a single rollout)
- Interaction Stochasticity: repeat N times \Rightarrow for outcome feature

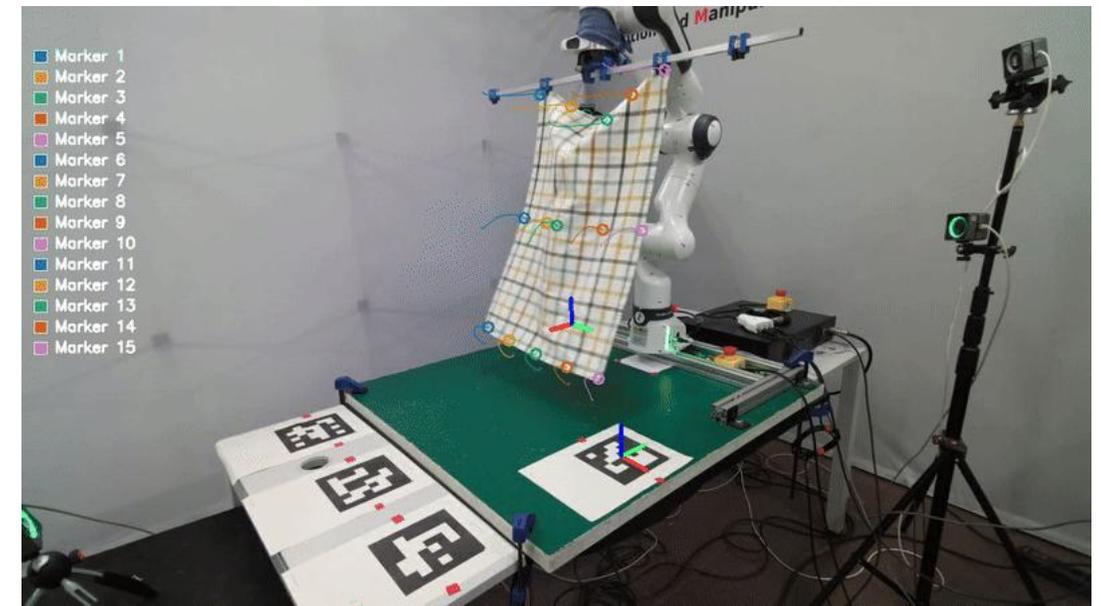
$$z = \varphi(y_{0:T})$$

$$\text{Var}[z|\pi] > 0$$



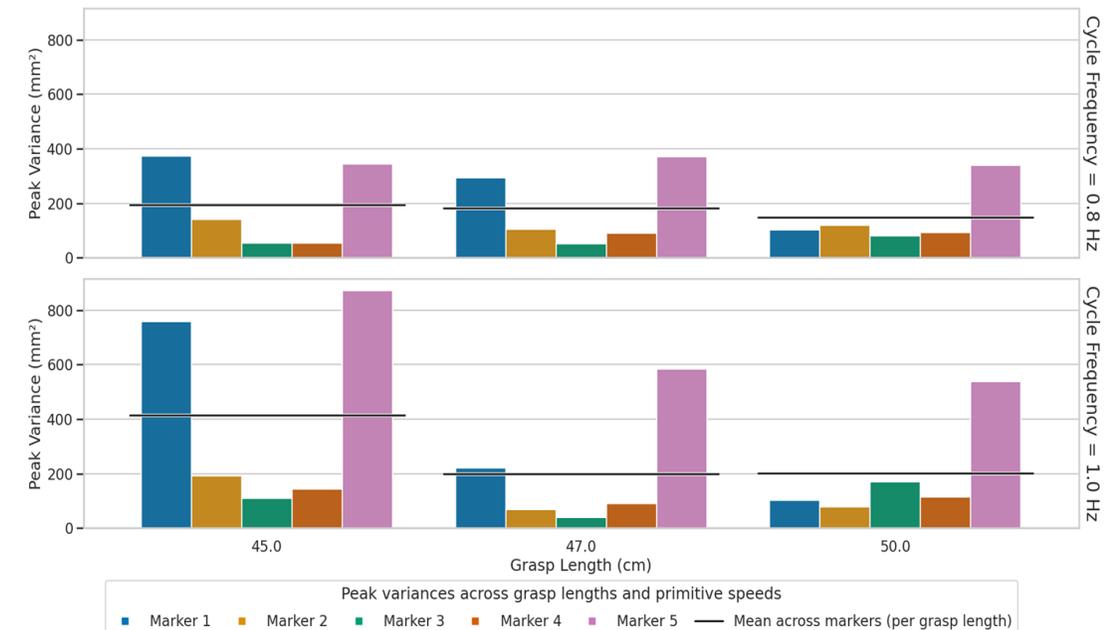
How to measure Interaction Stochasticity?

- Robot: Franka Research 3 + double-pinch grasp
- Perception : 360° OptiTrack + RGB camera aligned to same world frame
- Protocol: execute identical motion $N \geq 2$ times with nominally identical setup
- Change one factor at a time: speed, grasp distance, material, airflow, etc.
- Compute z (task feature): peak displacement, settling, fold/placement error → compare distributions



How to measure Interaction Stochasticity?

- Tasks:
 - Sine-wave swing (vary speed & grasp distance)
 - Swing and place-flat primitive
- Early results: faster motion and looser grasp \Rightarrow higher variability
- RQ1: which factors dominate Interaction Stochasticity in practice?
- RQ2: how to reduce it: training or runtime



Interaction Stochasticity in Dynamic Cloth Manipulation

Presenter: Mahed Dadgostar

Supervisors: Júlia Borràs Sol, Guillem Alenyà



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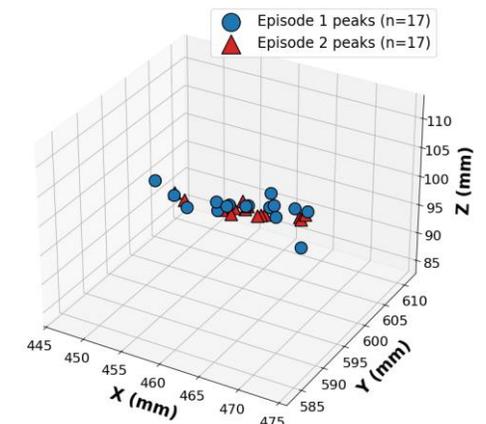
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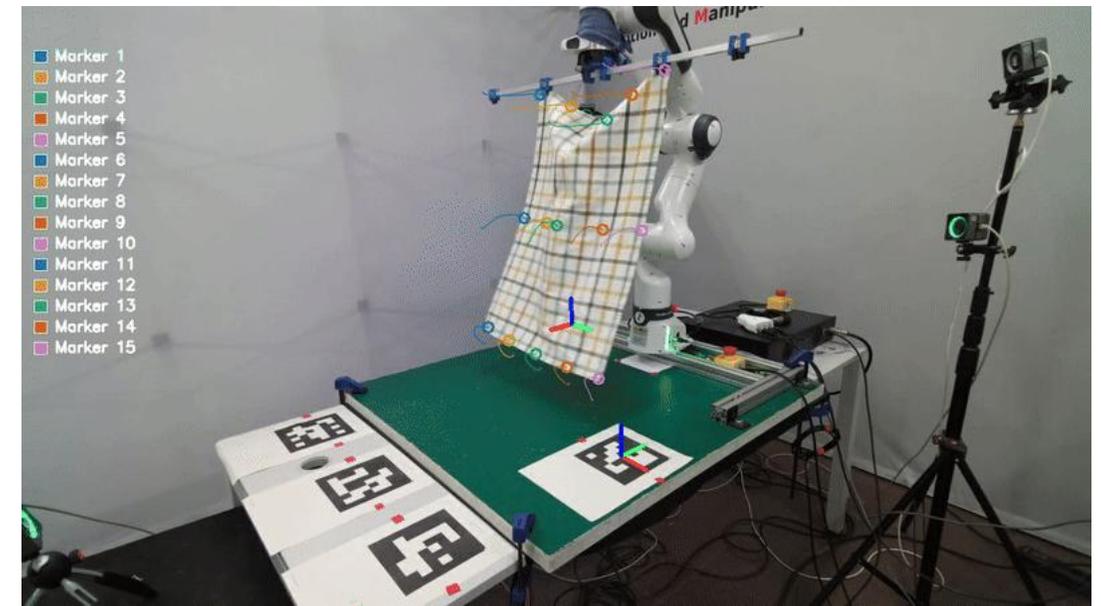
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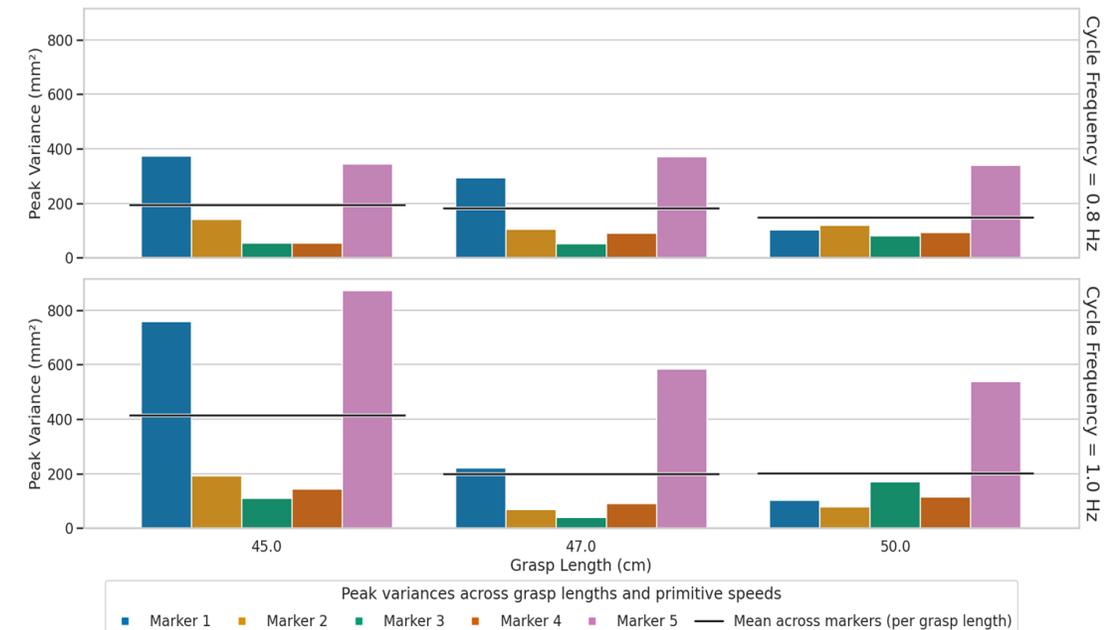
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Michel El Saliby



APPLIED DATA SCIENCE &
ARTIFICIAL INTELLIGENCE

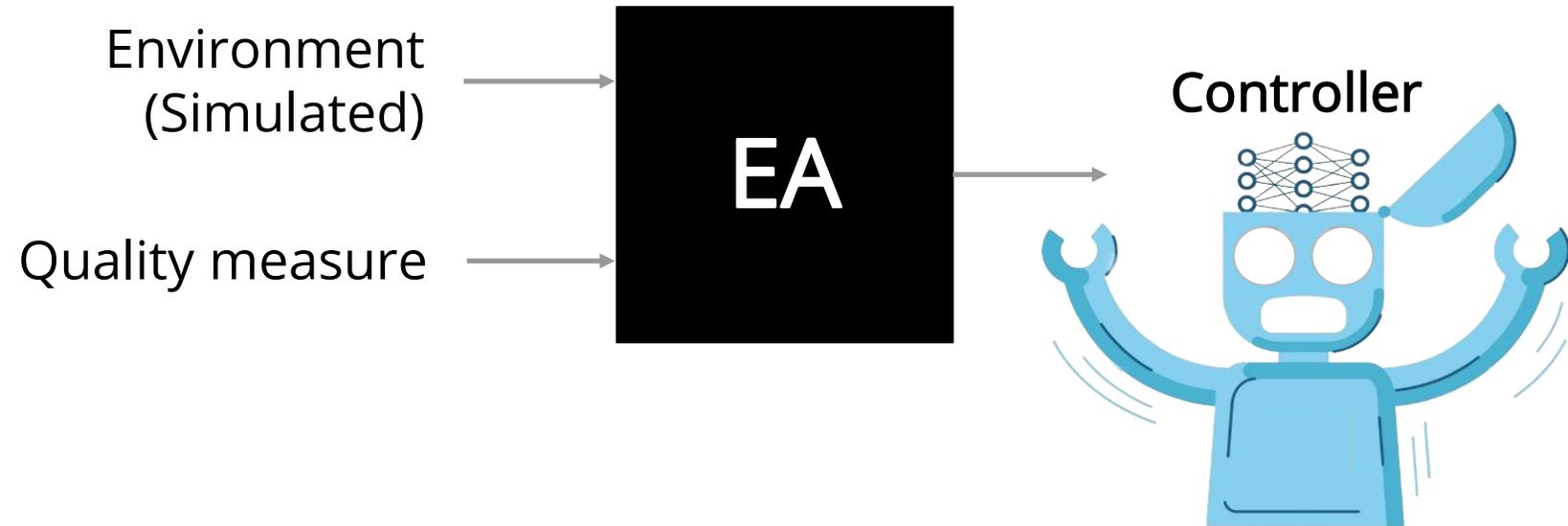


Towards Robust Embodied AI: Evolutionary Perspectives from Single to Multi-Agent Systems

Michel El Saliby

Eric Medvet, Erica Salvato

General focus



- Evolutionary robotics
- Neuro-evolution
- Embodied AI

More in detail

Intelligent behavior emerges from the **interactions between body, brain, and environment**

- ↳ Evolutionary algorithms allow to optimize agents **without a reward signal**

My research so far

¿ How to improve joint body-
brain optimization ?

Genotype



Phenotype

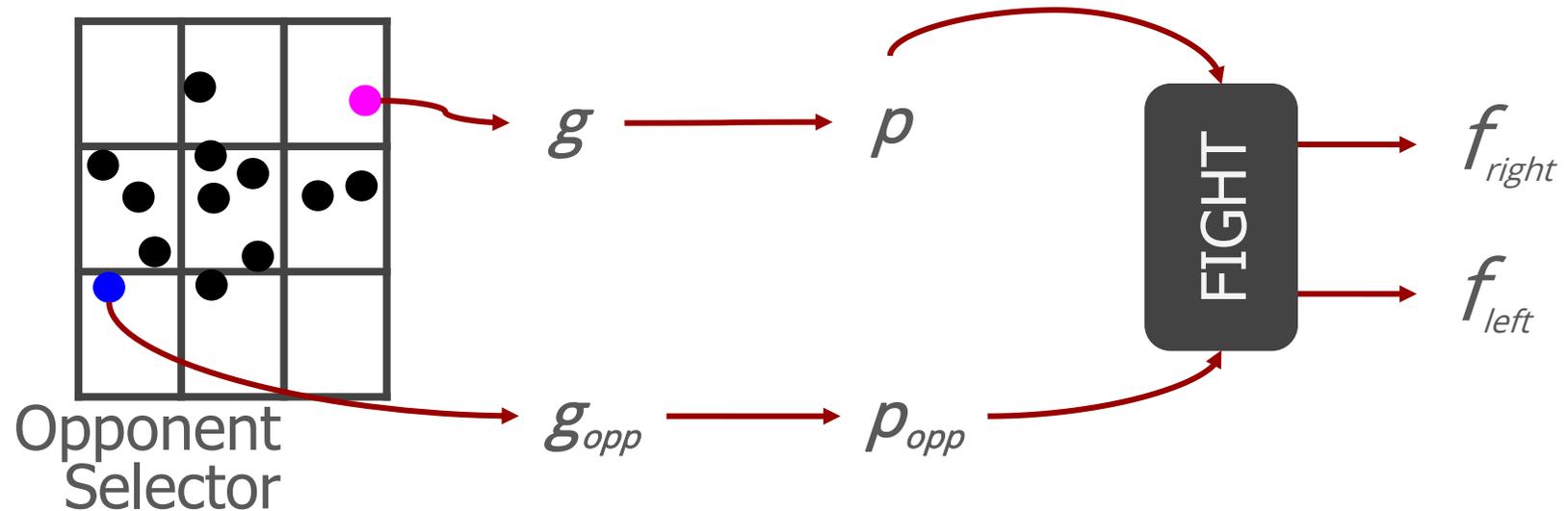
Trait 1

Trait 2

Trait 3

My research so far

¿ How to evolve general strategies in competitive multi-agent settings ?



EVOLUTIONARY
ROBOTICS
ARTIFICIAL
LIFE
LAB



APPLIED DATA SCIENCE &
ARTIFICIAL INTELLIGENCE



Towards Robust Embodied AI: Evolutionary Perspectives from Single to Multi-Agent Systems

Meet me at the poster session for
more details 😊



Miha Dežman



Exoskeleton Design for Enhanced Movement and Adaptability

Miha Dezman

High-Performance Humanoid Technologies (H2T)
Institute for Anthropomatics and Robotics (IAR)
Karlsruhe Institute of Technology (KIT)

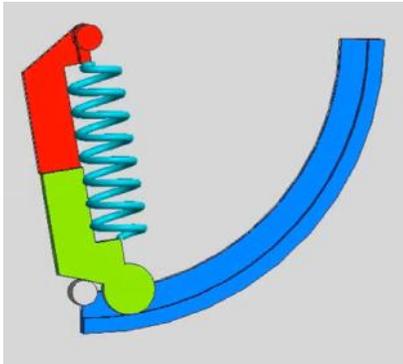
My Research Journey

Passive ankle



2016

Mechanical compliance



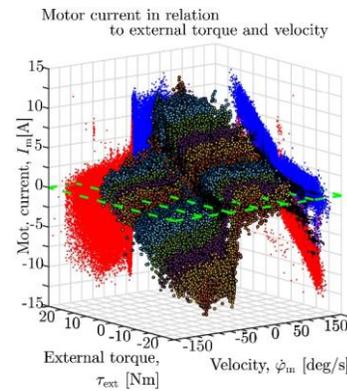
2018

Upper-limb exoskeleton



2020 

Friction analysis



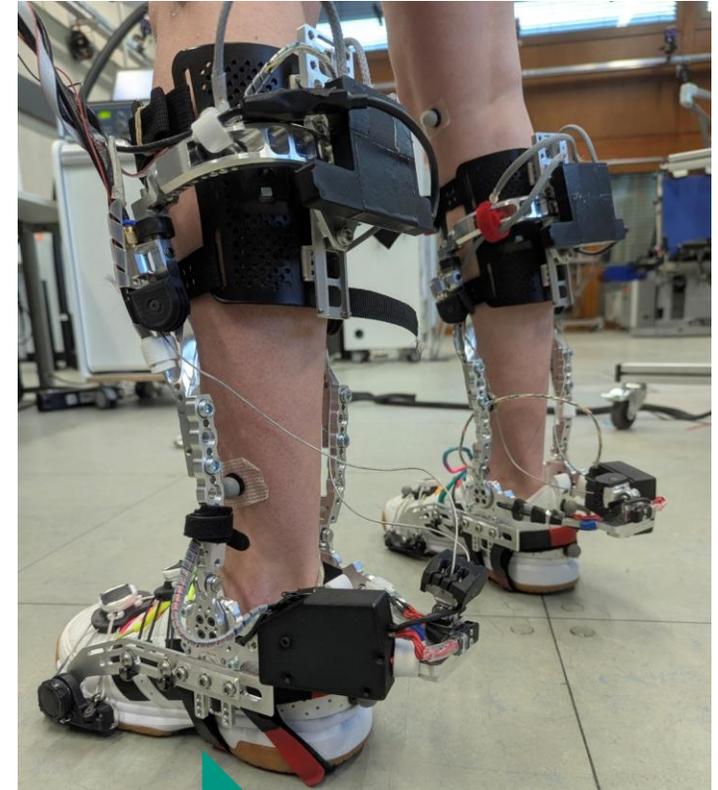
2022 

Leg replica



2023

KIT EXO 2



2024 

How do we balance rigidity and comfort?

- Novelty of the KIT-EXO-II



Field testing: 11.5 km health run (2024)



©Krebs, Dezman



Miha
Dežman



Charlotte
Marquardt



Tamim
Asfour

www.humanoids.kit.edu



Thank you!

Pietro Dardano



Pietro Dardano

PhD Candidate in Robotics-Ai

**BMW
GROUP**



Rolls-Royce
Motor Cars Limited



**RoboTac
Lab**

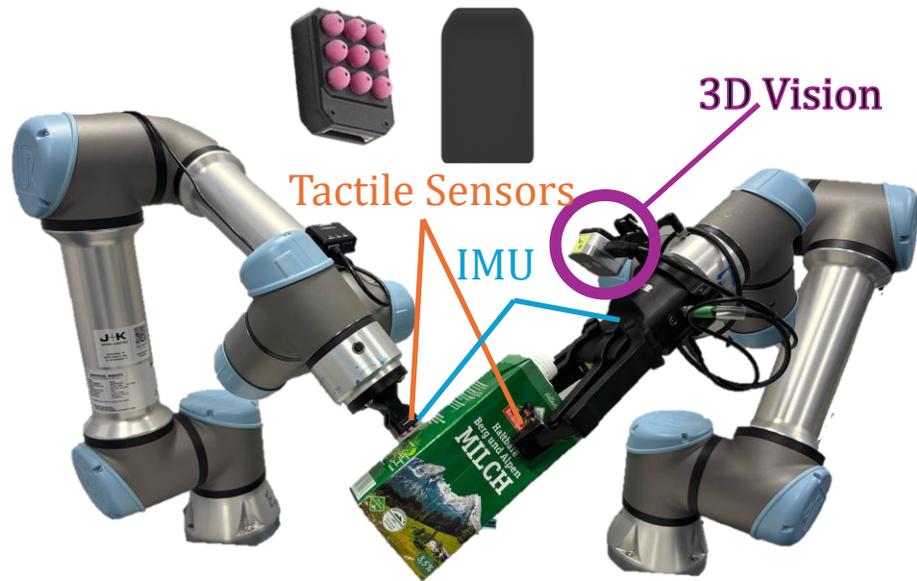
TU/e

**EINDHOVEN
UNIVERSITY OF
TECHNOLOGY**

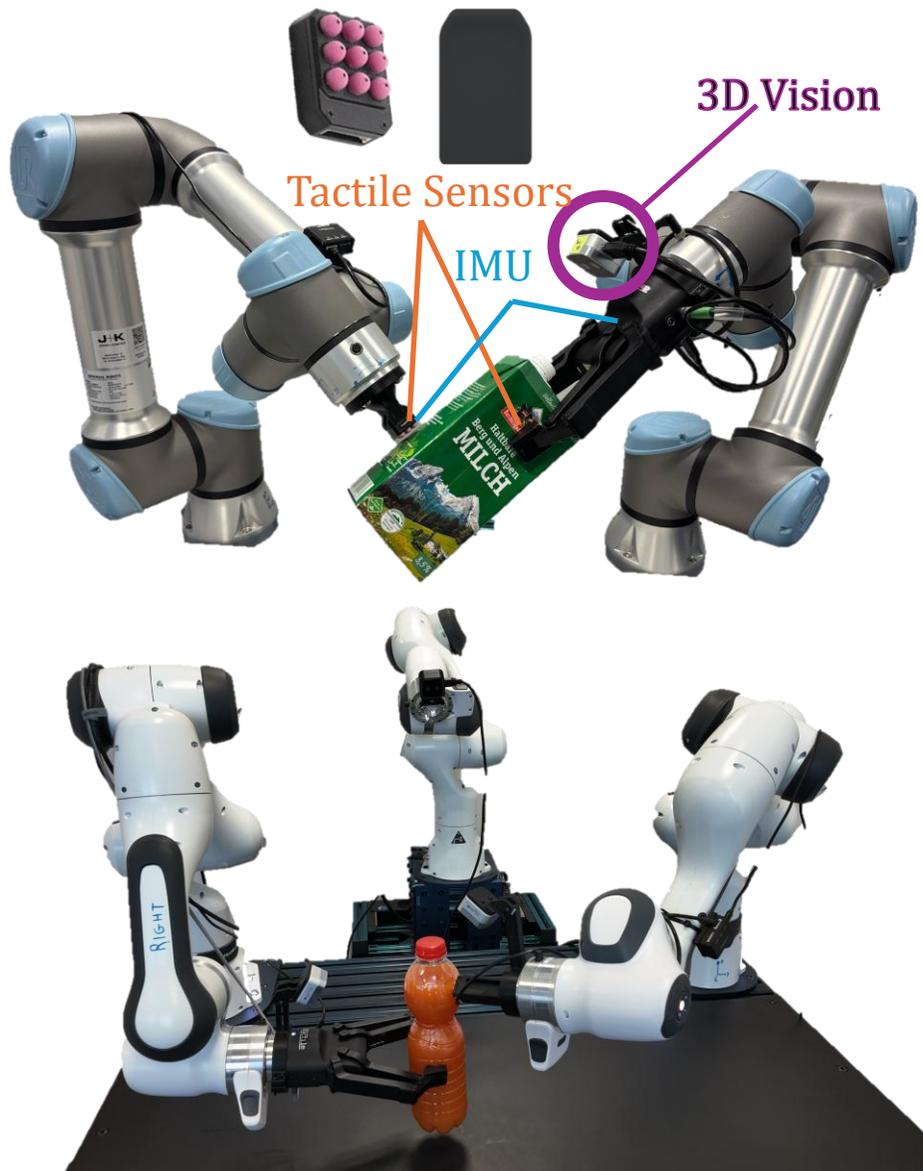


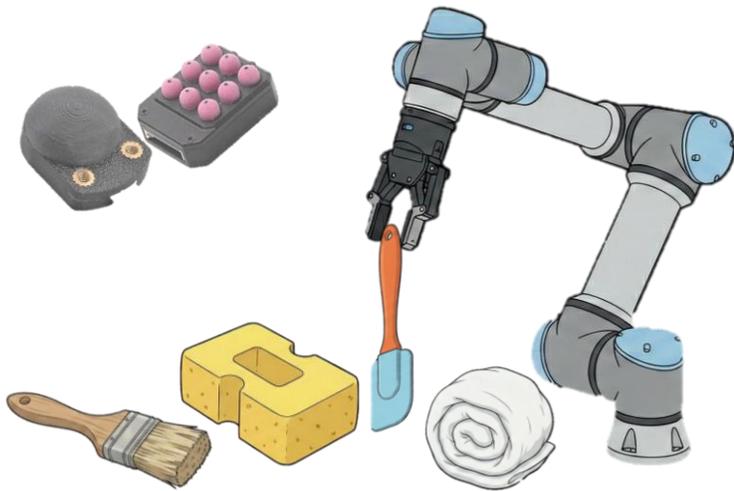
CONFIDENTIAL

Robust Multi-Modal Perception in Robotics and Intelligent Vehicles

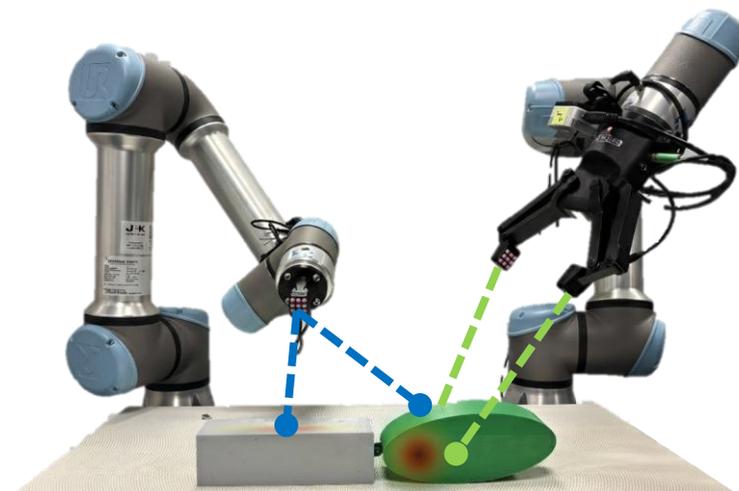


Robust Multi-Modal Perception in Robotics and Intelligent Vehicles

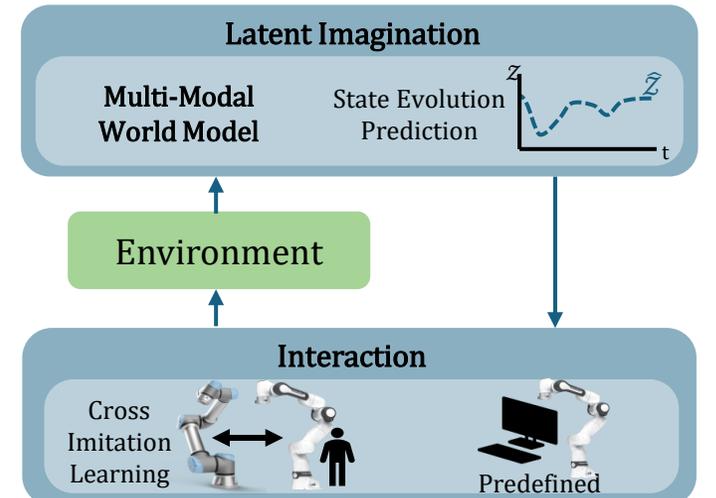




Embodiment Disentanglement



Affordances for Active Exploration



Prediction and World Models

Simone Rotondi



Shape Visual Servoing of Deformable Objects Robust to Model Uncertainties



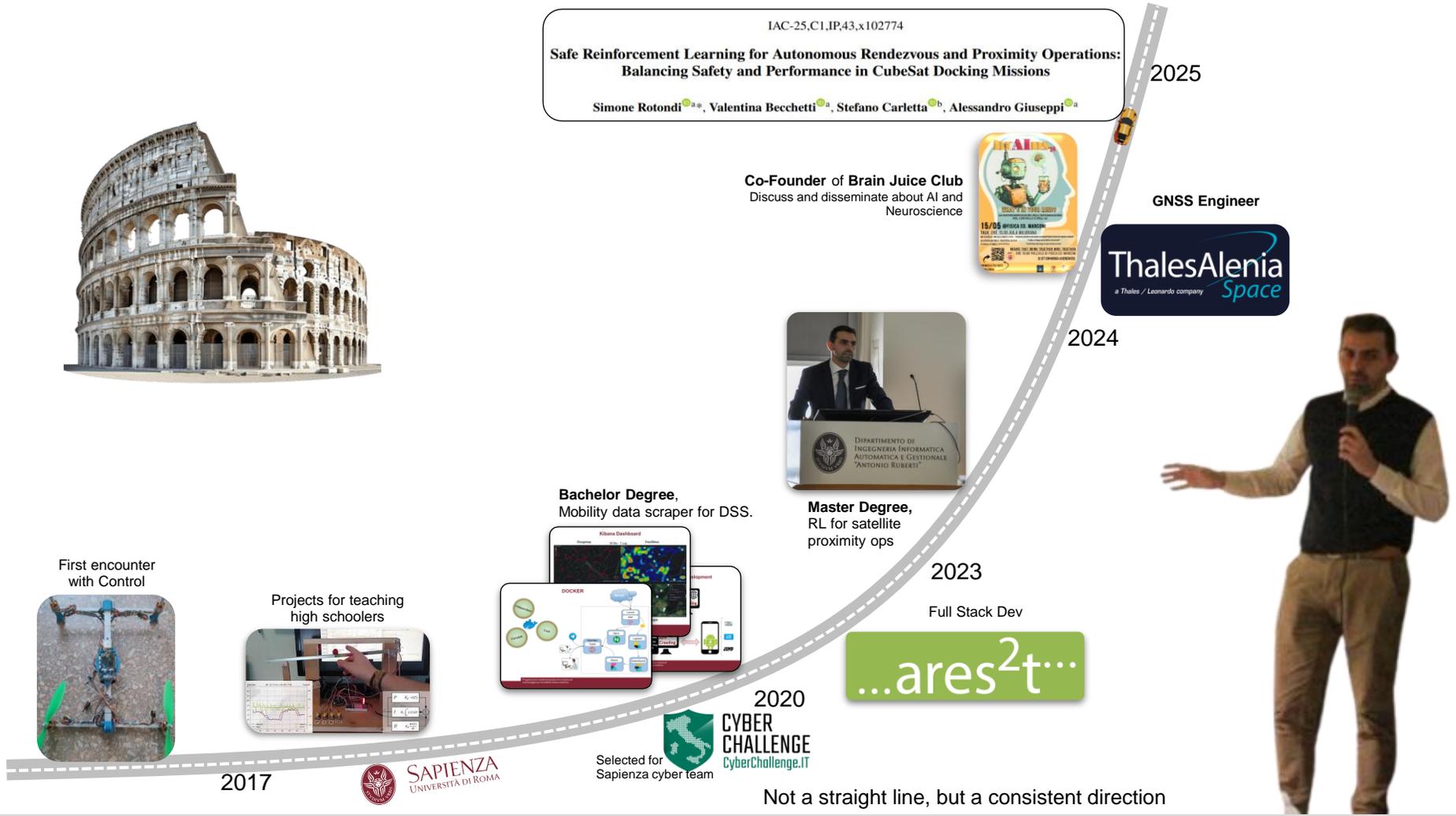
Simone Rotondi

PhD @ Rainbow Team
Inria – University of Rennes,
Britann, FR



Supervisors:
Paolo Robuffo Giordano
Alexandre Krupa
Tommaso Belvedere

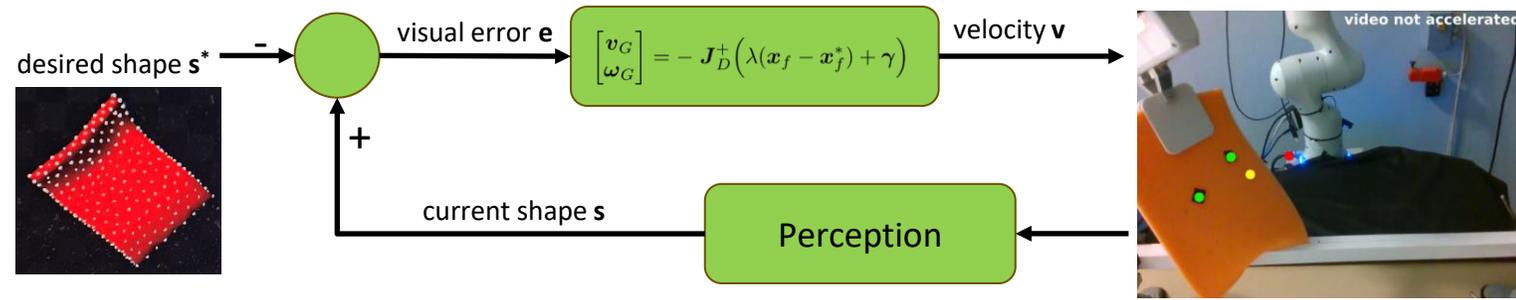
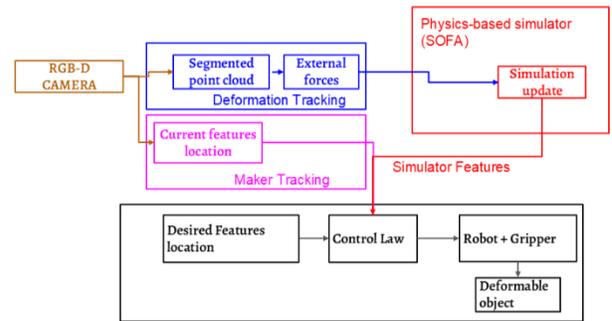
Get to know me (shortly)



Not a straight line, but a consistent direction

Shape Visual Servoing of Deformable Objects Robust to Model Uncertainties

- **Challenges**
 - **Complex Dynamics:** Soft objects are non-linear, hard to model accurately, and **parameters are uncertain.**
- **How**
 - **Perception:** RGB-D cameras to track the object's deformation in real-time
 - **Modelling:** use Finite Element Methods to predict deformation



- **WIP**
 - The integration of the **closed loop sensitivity** calculation to optimize trajectory and grip, making it intrinsically robust to material parameters and grip position uncertainty.

$$\Pi(t) = \left. \frac{\partial q(t)}{\partial p} \right|_{p=p_n} \quad \Pi(t) \in \mathbb{R}^{n_q \times n_p}$$



Hvala za
Thank you for your
pozornost
attention



Julia Hohensee



Bimanual Taxonomy for Deformable Objects

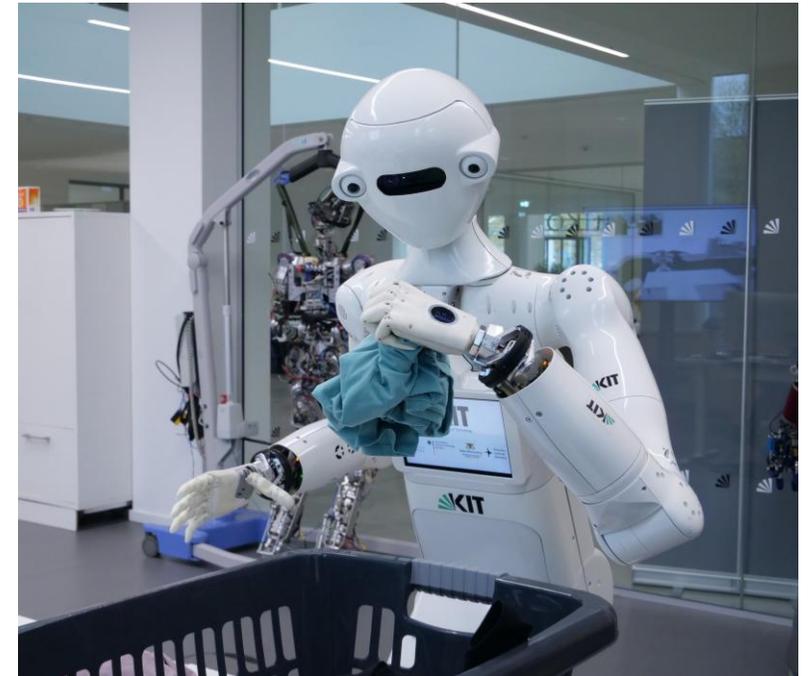
Julia Hohensee

Karlsruhe Institute of Technology (KIT)
High Performance Humanoid Technologies (H²T)

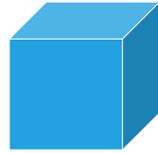


Problem Statement

- Existing taxonomies are insufficient for deformable object manipulation
- What is the right taxonomy for mastering robotic manipulation?
- Taxonomies represent constraints!



Constraints Rigid vs. Deformable Objects



Rigid Objects

- Spatial constraints
Position, orientation
- Temporal constraints
Synchronized motions



Deformable Objects

- Spatial constraints
Position, orientation
- Temporal constraints
Synchronized motions
- Deformation constraints
Bending, tension, compression
- Deformable object manipulation presents unique challenges:
Infinite DOF, complex deformations, bimanual coordination

Deformation Constraints

Deformation State

Deformable objects shape changes constantly

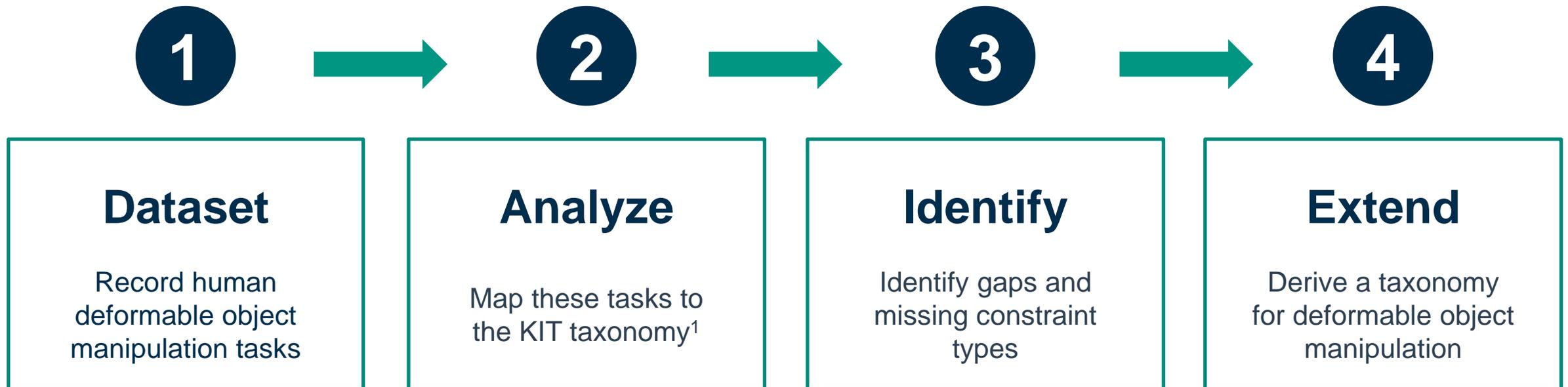
Environmental Contacts

Tables, surfaces or robot as 'third hand'

Grasp Types

Changes during manipulation

Roadmap



Validation: Analyze recordings with extended taxonomy and repeat step 3 & 4

[1] Krebs, F. and Asfour, T., *A Bimanual Manipulation Taxonomy*, IEEE Robotics and Automation Letters (RA-L), vol. 7, no. 4, pp. 11031-11038, 2022



Julia
Hohensee



Tamim
Asfour

www.humanoids.kit.edu

Thank you!

Srđan Apostolović

Personal presentation

Winter School 2026
Kranjska Gora, Slovenia



ROMANDIC

Srđan Apostolović

M.Sc. Student - Artificial Intelligence and Machine Learning in Robotics



Faculty of Technical Sciences
University of Novi Sad
Novi Sad, Republic of Serbia



ROMANDIC

About me



 Novi Sad, Republic of Serbia

EDUCATION:

B.Sc. Mechatronics, robotics and automation

Faculty of Technical Sciences, University of Novi Sad

ACADEMIC APPOINTMENTS:

Faculty Associate - Mechatronics, robotics and automation

Faculty of Technical Sciences, University of Novi Sad



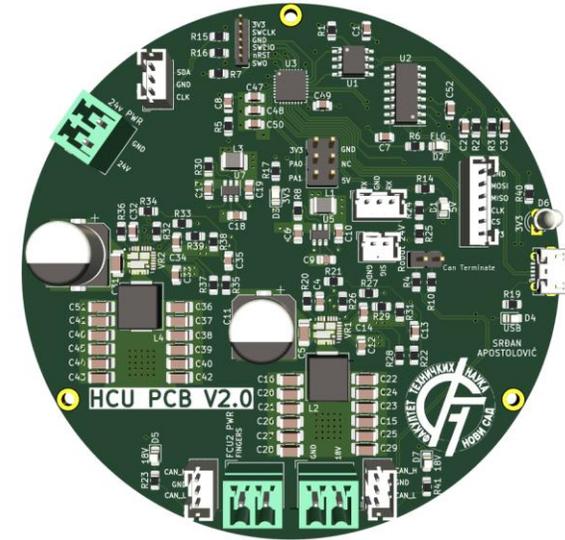
Faculty of Technical Sciences
University of Novi Sad
Novi Sad, Republic of Serbia



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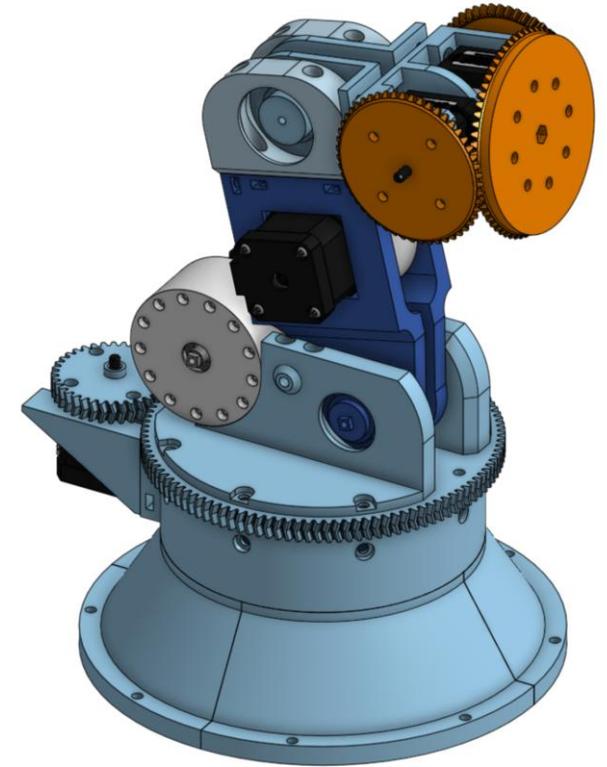
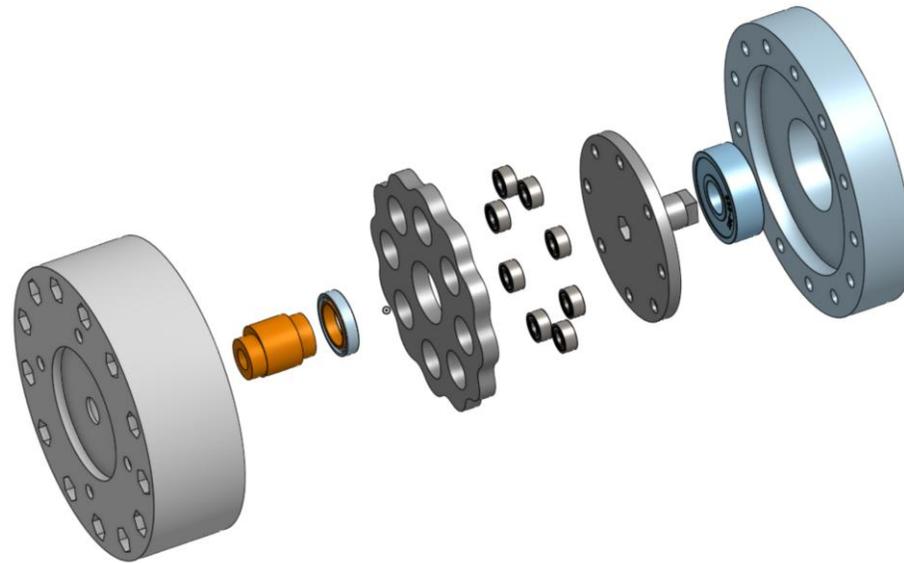
HRC Hand

- Three-fingered, underactuated, collaborative robotic hand
- PCB design
- System Control, firmware and Python interface



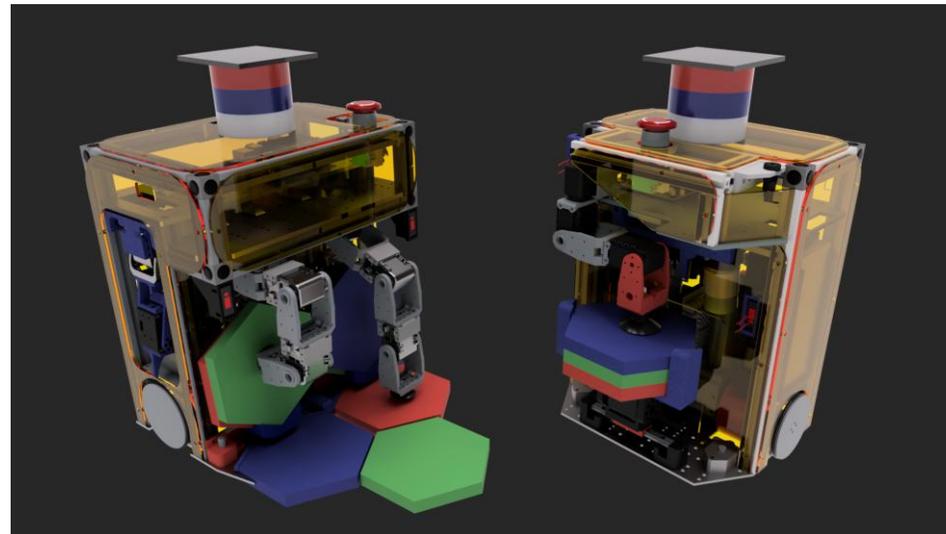
Project YARA

- Yet Another Robotic Arm
- 3D printed cycloidal drive
- ROS2/MoveIt2



Eurobot

- Robotics competition for students
- Software/firmware
- Mobile robots



Thank You for Your attention

- GitHub : aSrki
- e-mail : apostolovic@uns.ac.rs
- I am open to any questions and comments :D



Faculty of Technical Sciences
University of Novi Sad
Novi Sad, Republic of Serbia



ROMANDIC

Veljko Todić

Veljko Todić, Junior Research Assistant

- Institution: **University of Belgrade – School of Electrical Engineering (ETF)**
- Department: **Signals & Systems**
- Location: **Belgrade, Serbia**
- Application areas: **Industrial, Service, Healthcare**
- Research interests: **Human-Robot Collaboration**
- Website: <http://robot.etf.rs/>
- Contact: toveljko@gmail.com / robot@etf.rs



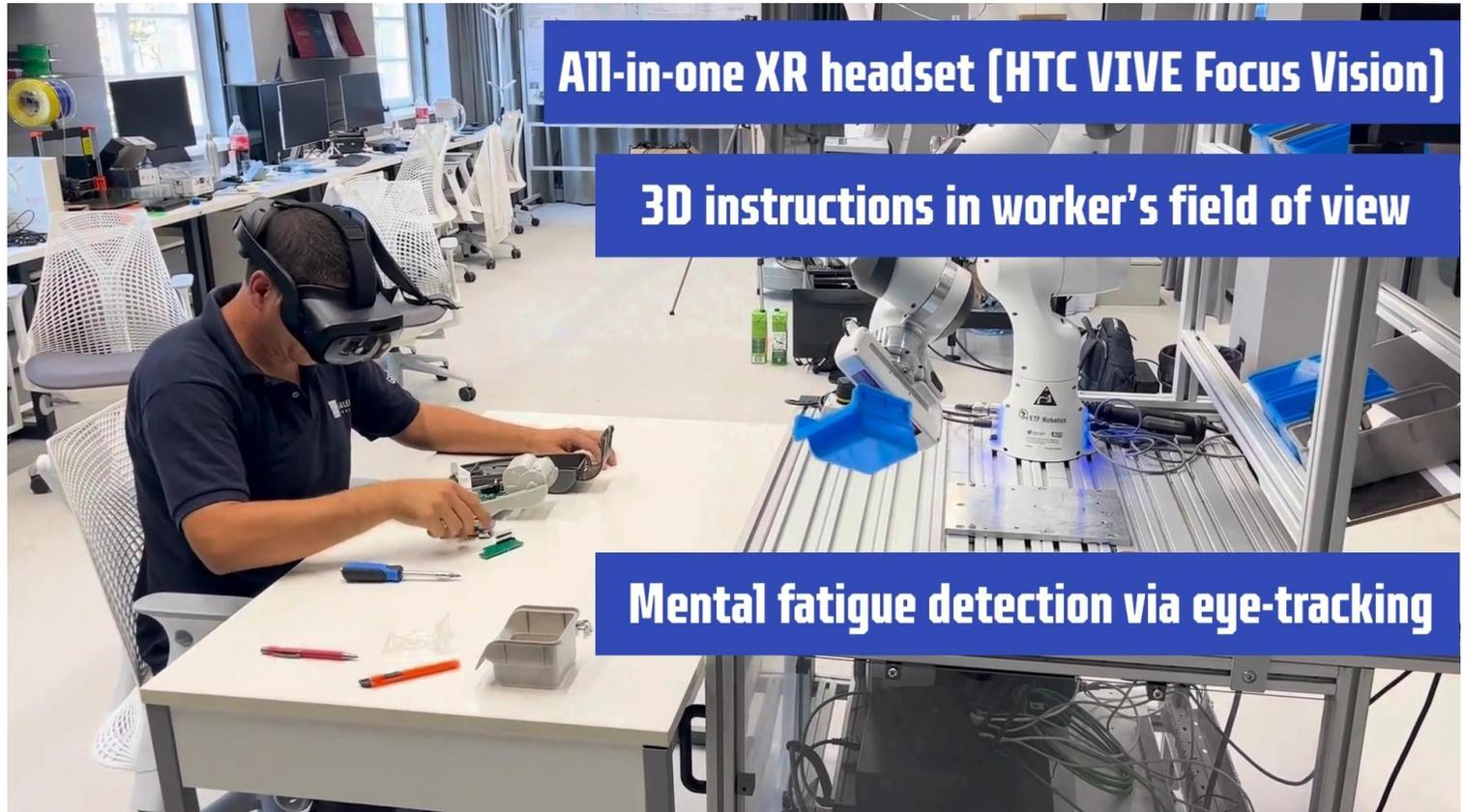
Extended Reality as an Intelligent Interface for Human-Robot Collaboration in Industry

XR serves as Bidirectional Interface:

- Human → Robot
(Intuitive programming)
- Robot → Human
(Real-time state visualization)

Technical Contributions:

- XR Programming
- Robot State Visualization
- Multimodal Interaction
- Learning Integration



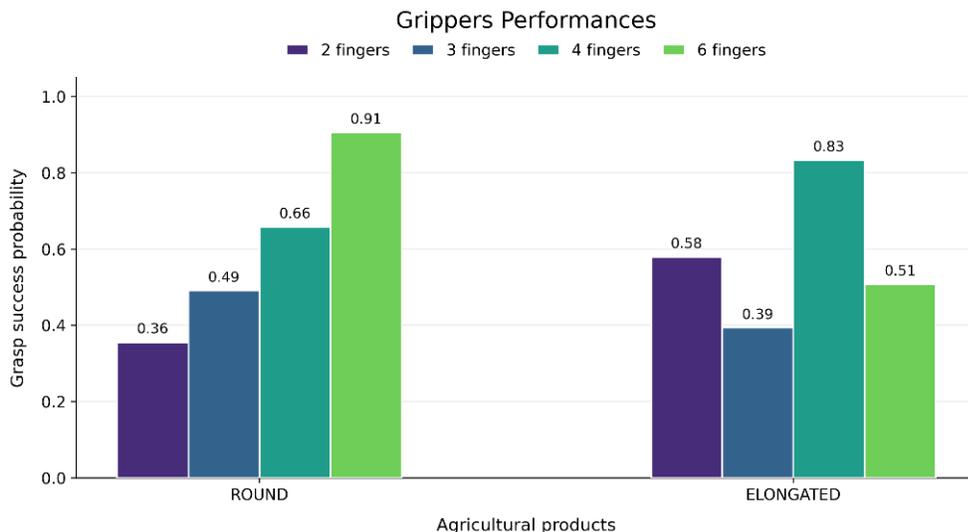
Uncertainty-Aware Multi-Robot Greenhouse Harvesting

The Platform:

- RB-Kairos mobile manipulator with Franka Research 3
- Autonomous multi-robot navigation in greenhouse environment

Quantifying grasp reliability - Experimentally measured grasp success probabilities for:

- 2, 3, 4, and 6 fingers grippers
- Round and Elongated agricultural products



Thank you for your attention!

website: <http://robot.etf.rs/>

e-mail: toveljko@gmail.com, robot@etf.rs

Vinayvivan Pedrick Rodrigues



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DI TECNOLOGIA
HUMAN-ROBOT INTERFACES
AND INTERACTION



Università
di Genova



I-RIM

Shape Control of a Deformable Linear object (DLO) using Reinforcement Learning (RL) Method

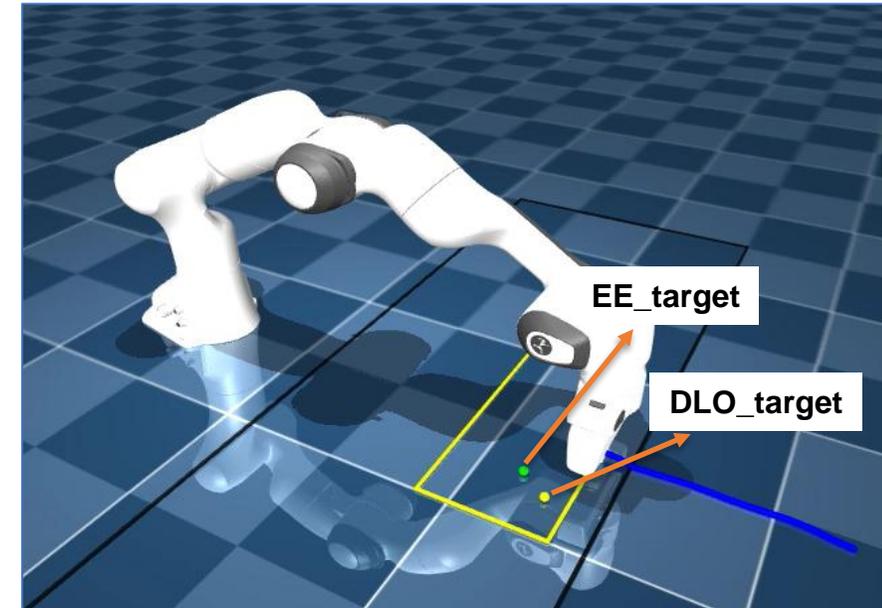
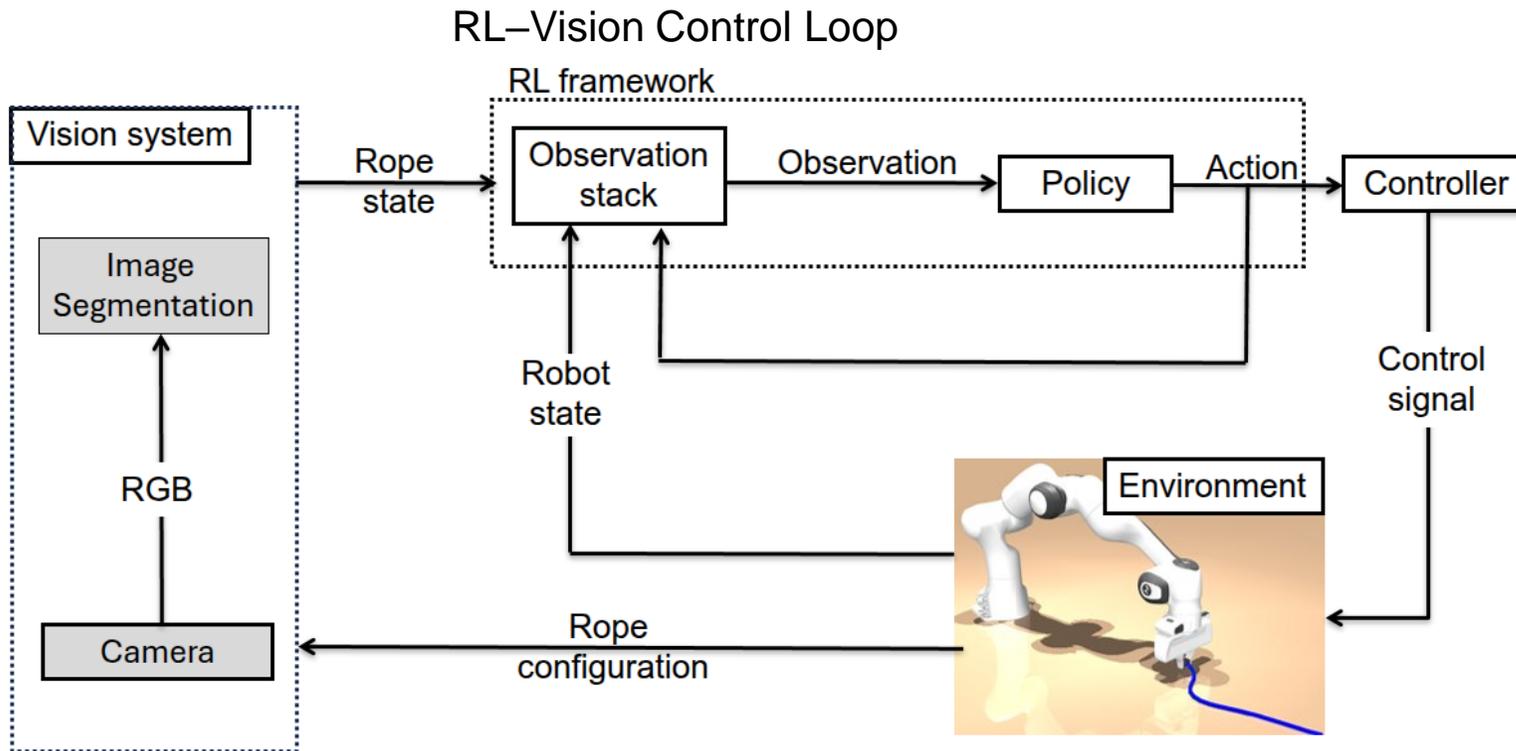
Vinay Rodrigues

Motivation & Objective

- **Challenge:** Deformable objects are **high-dimensional, contact-rich**, and hard to model reliably.
- **Goal:** Achieve **rope shape objectives** via **waypoint tracking** (start: rope tip reaching).
- **Key constraint:** No pick-and-place — rope stays **gripped at the end-effector**.
- **Approach:** Deep RL policy learns **quasi-static manipulation** to move rope configuration toward goals.



Framework & Demo



Take aways:

- **Coordinated shaping:** not dragging—policy learns motion patterns that steer rope geometry.
- **Goal-conditioned behavior** handles **two targets** (tip + near-grasp segment).
- **Roadmap:** multi-point tracking for **full shape control** (more waypoints, dynamic motions later).



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AND INTERACTION



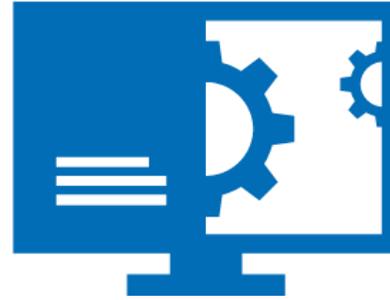
Università
di Genova



I-RIM

Thank You
&
See you at the Poster!

Vishnu Nair



Development of a Robotic Soft Gripper for Harvesting Berries

Vishnu P. Nair

Supervisor: Dr. Mathias Brandstötter

Agenda of Presentation

- Introduction
- Objective
- Concept development
- Design and control system development
- Simulation
- Demonstration Video
- Conclusion



Introduction

Supervisor: Dr. Mathias Brandstötter

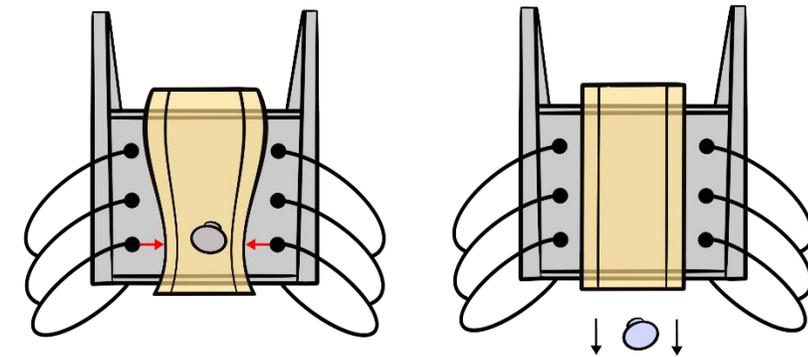
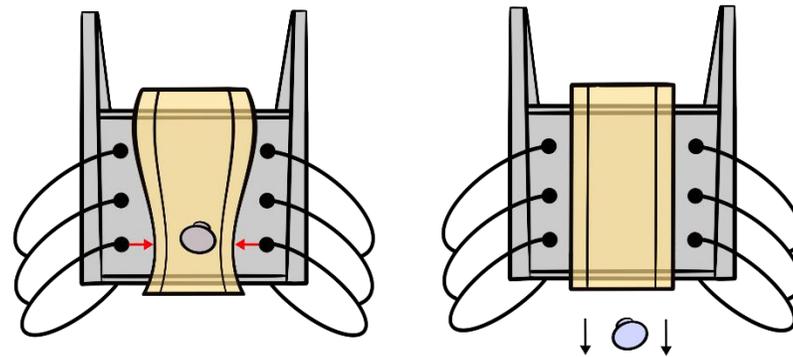
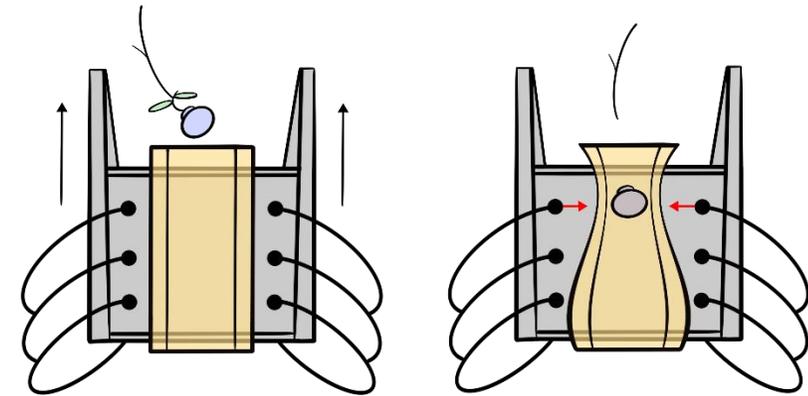
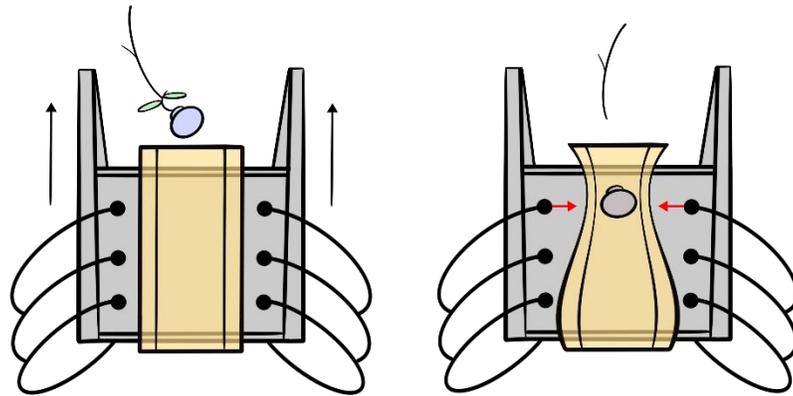
Client: Robokraft



Objective

Development and research to implement and evaluate a working prototype of a Soft Robotic Gripper specifically tailored for harvesting fruits (berries) but can also be used to harvest certain vegetables if needed.

Concept development

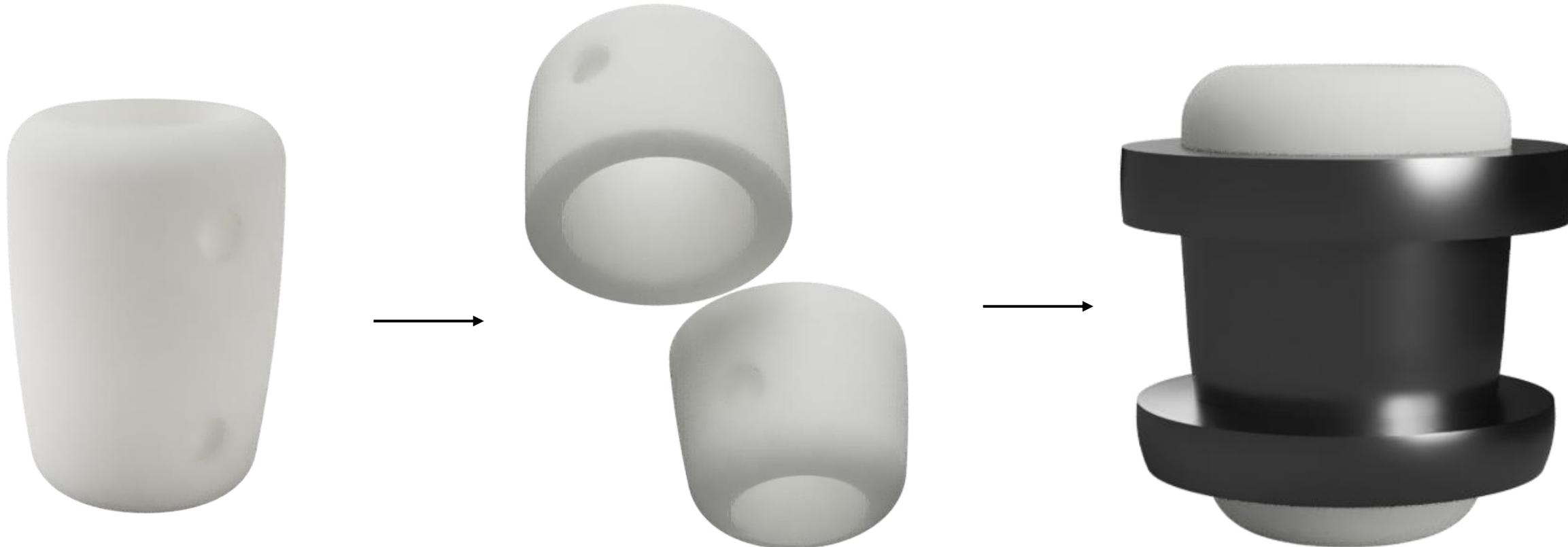


Leveraging Suction-based actuation

Leveraging SMA-based actuation

Design and AM

Different stages of design and actuation process



Soft inflatable shell made of
TPEs due to its (>100%) strain

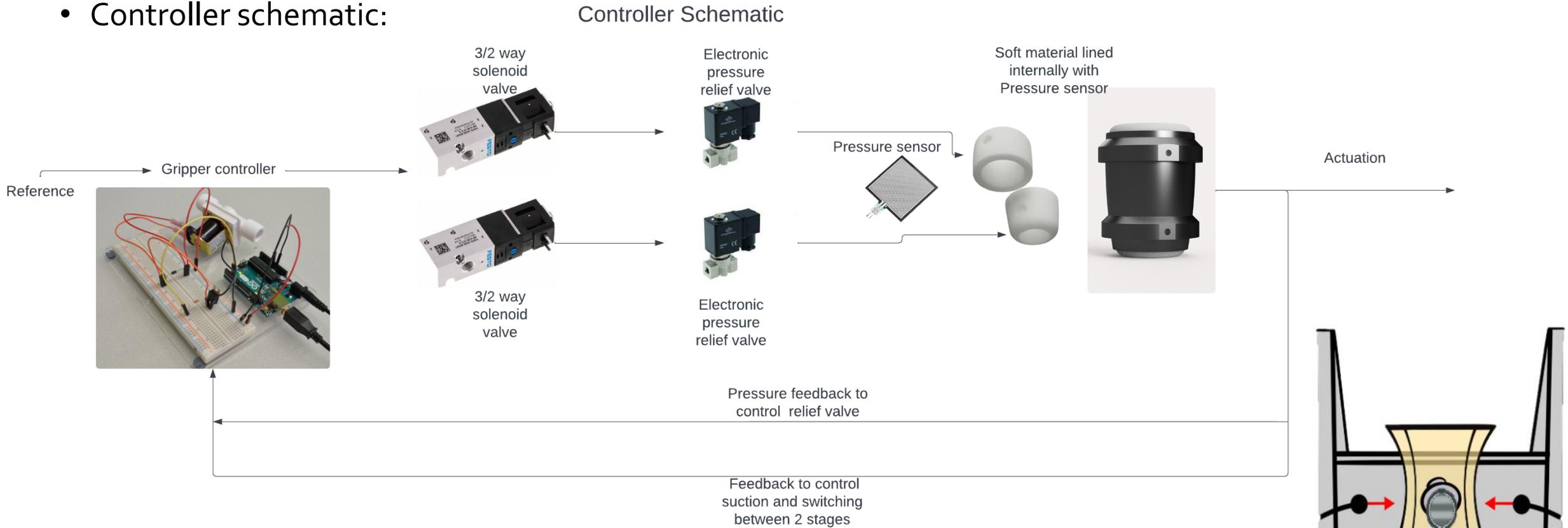
Soft shell split into two
independent sections for
multi-stage control

Hard outer shell made of
ASA to enable internal
inflation of soft shell

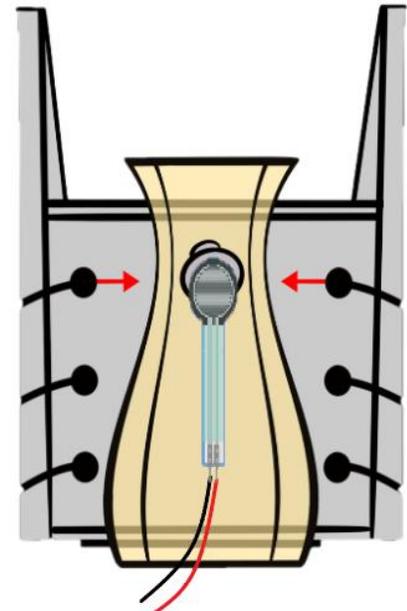


Control system development

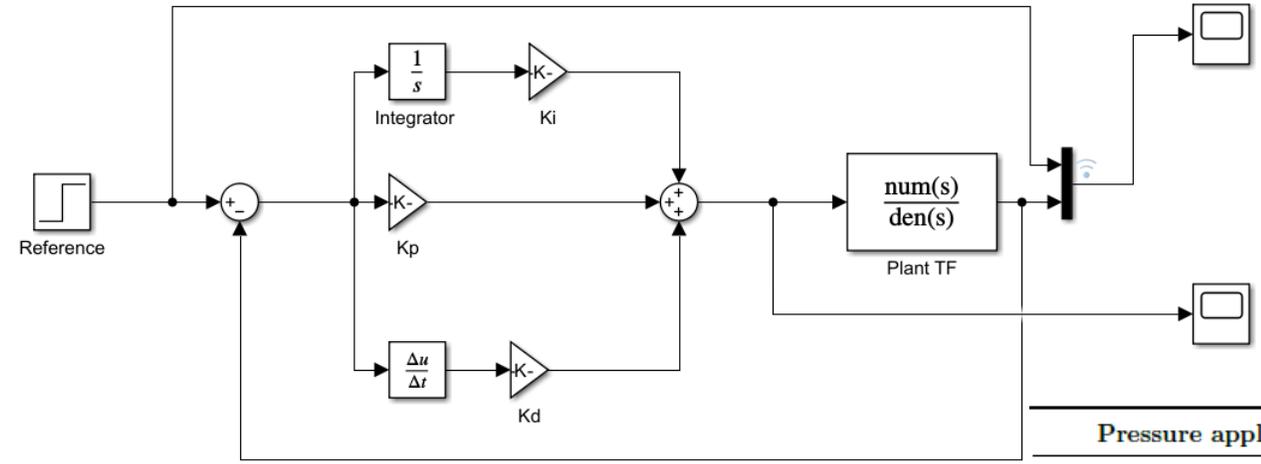
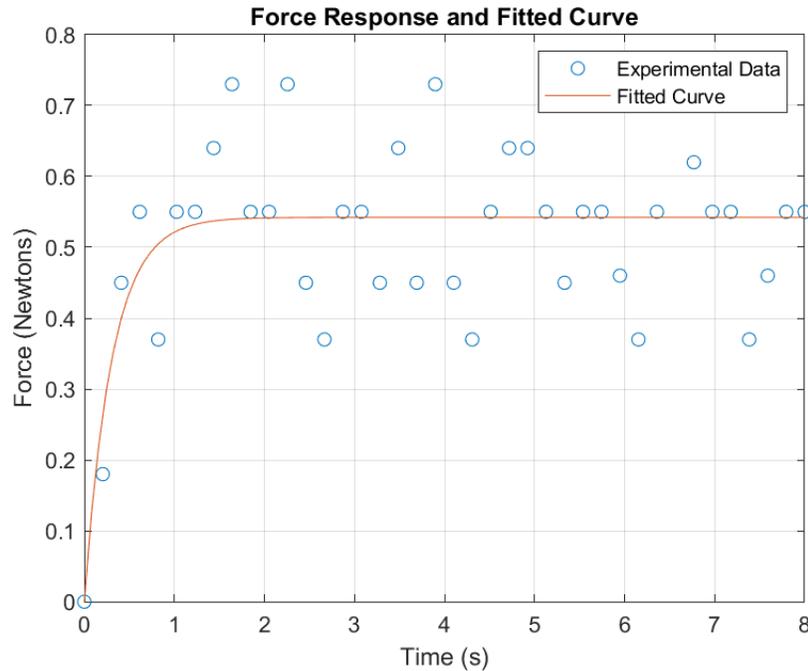
- Controller schematic:



- PID Control: Proportional Integral Derivative controller was chosen as a mode of control as compared to some of the other options due to its compatibility with the application use case.



Simulation:



Model function for curve fitting:
 $F(t) = F_{steady}(1 - \exp(-t/\tau))$

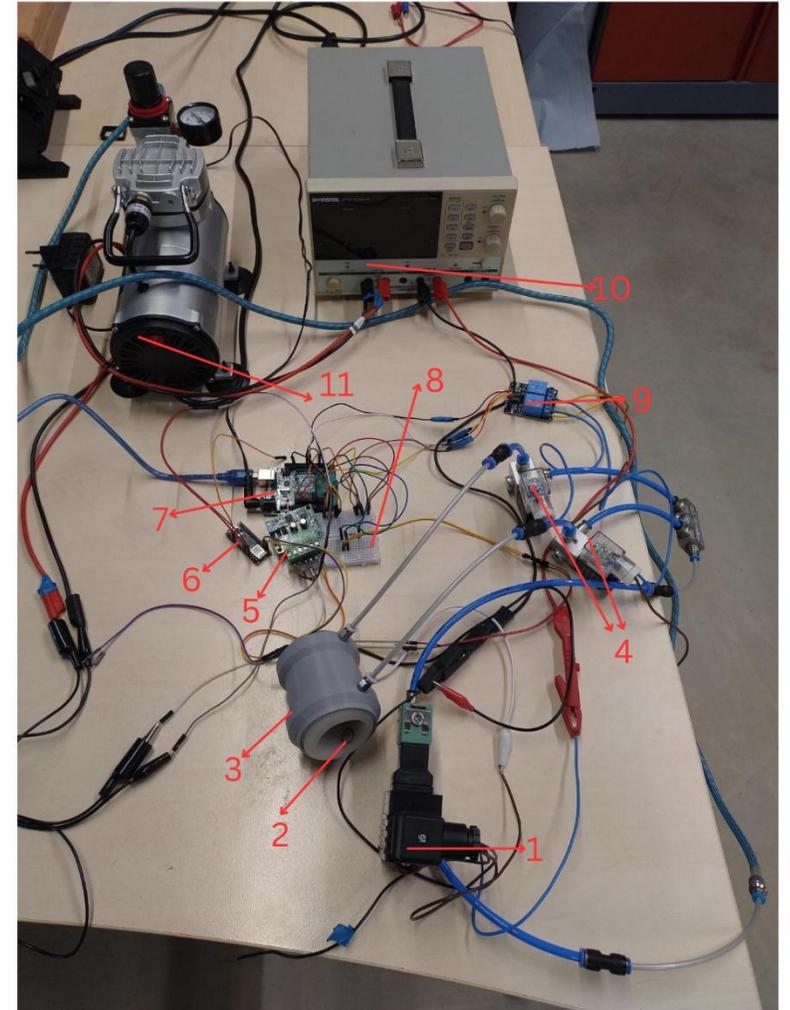
Plant model to be controlled:

$$\tau \frac{dP_o}{dt} + P_o = KP_{ref} \quad \longrightarrow \quad \frac{K}{\tau s + 1} \quad \text{[Frequency domain]}$$

$$= \frac{1.47}{0.31s + 1} \quad \text{Plant Transfer Function}$$

| Pressure applied in N | |
|-----------------------|----------------|
| Time intervals | Force measured |
| 0 | 0 |
| 0.2 | 0.18 |
| 0.4 | 0.45 |
| 0.6 | 0.55 |
| 0.8 | 0.37 |
| 1 | 0.55 |
| 1.2 | 0.55 |
| 1.4 | 0.64 |
| 1.6 | 0.73 |
| 1.8 | 0.55 |
| 2 | 0.55 |
| 2.2 | 0.45 |
| 2.4 | 0.37 |
| 2.6 | 0.55 |
| 2.8 | 0.55 |
| 3 | 0.45 |

Demonstration Video:



Conclusion:

- Final results

- Execution of test case of harvesting berries.
- Robustness of gripper.

- Enhanced understanding

- Tuned PID parameters from Simulink do not match actual parameters to control plant.
- Arduino UNO is typically used for single threaded control tasks. Timing issues due to multiple control tasks.

- Scope

- Potential to improve gripper parametrically to harvest other fruits. Incorporate better models and multi-threading to control tasks
- Integrate camera and vision to automate and trigger harvesting procedure.



References

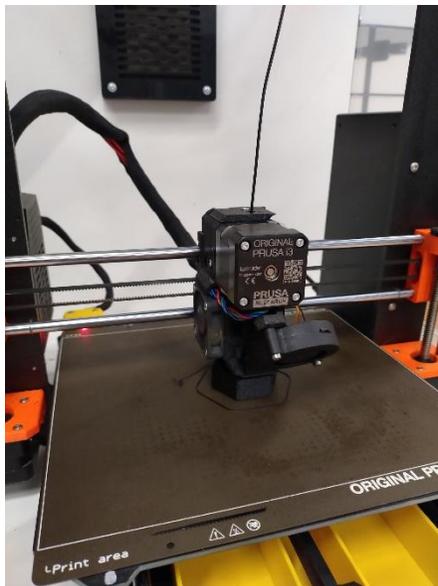
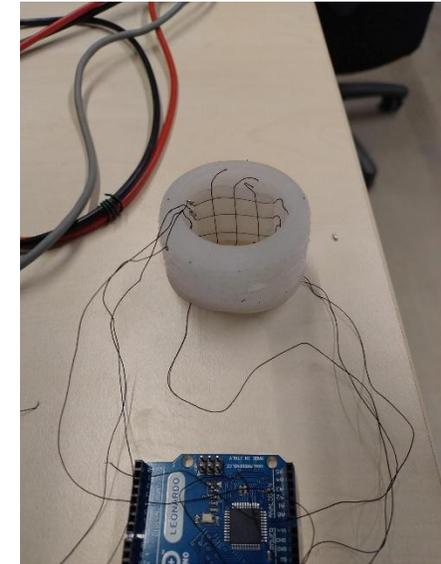
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- Mail, Mohd Fazly, et al. "Agricultural harvesting robot concept design and system components: A review." *AgriEngineering* 5.2 (2023): 777-800.
- Liu, Yuxuan, et al. "Intelligent soft robotic grippers for agricultural and food product handling: A brief review with a focus on design and control." *Advanced Intelligent Systems* 5.12 (2023): 2300233.
- Campos, Carlos Blanes, et al. "Technologies for robot grippers in pick and place operations for fresh fruits and vegetables." *Spanish Journal of Agricultural Research* 9.4 (2011): 1130-1141.
- Elfferich, Johannes F., Dimitra Dodou, and Cosimo Della Santina. "Soft robotic grippers for crop handling or harvesting: A review." *IEEE Access* 10 (2022): 75428-75443.
- Shintake, Jun, et al. "Soft robotic grippers." *Advanced materials* 30.29 (2018): 1707035.
- M. Laboratories, "Ziegler-nichols tuning rules for PID."





THANK YOU

QUESTIONS ?



Yu Li

Tension-Aware DLO Manipulation: A Structured Map & Open Questions

A perspective on control, optimization, and learning

Yu Li

Kranjska Gora, Slovenia, 11 Feb 2026



Who I am

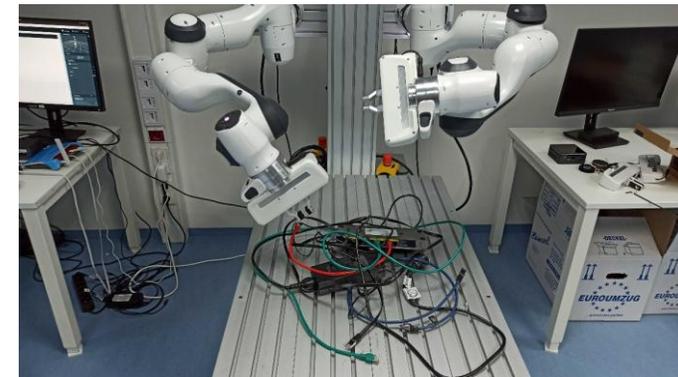
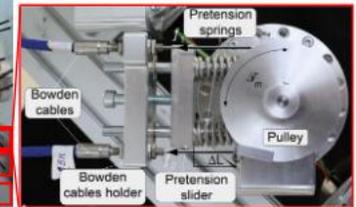
Yu Li

Doctoral Researcher at MIRMI, TUM



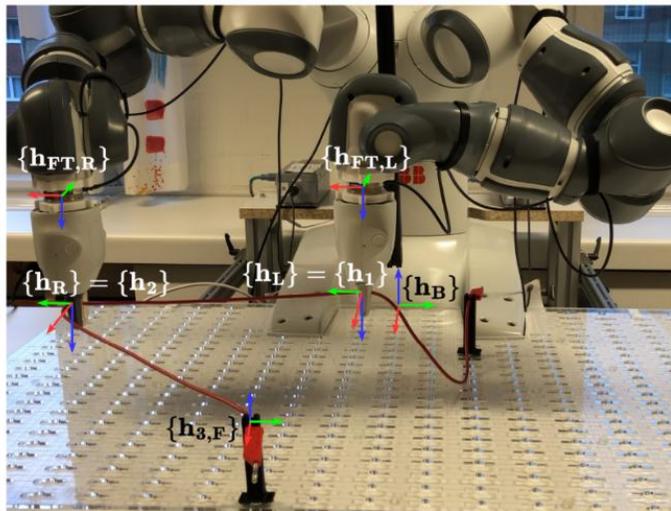
Working on control, modeling, and interaction of cable-driven and contact-rich robotic systems

My Background:



What I want to discuss here:

- I. Sequencing: events vs continuous tension—what works in practice?
- II. Sensing near fixtures: tactile vs wrist F/T vs vision—real bottlenecks?
- III. Benchmarks/demos: any coiling/bundling tasks with maintained tension?



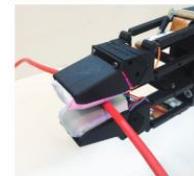
[ForceSem]

Perceive



[MovingCables]

Grasp/Pinch



[TacGripper]

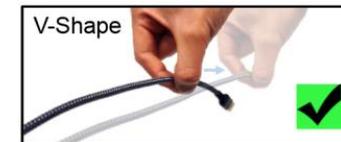
Recovery

Insert and Release



[TacMP]

Follow Sliding



[InHandFol]

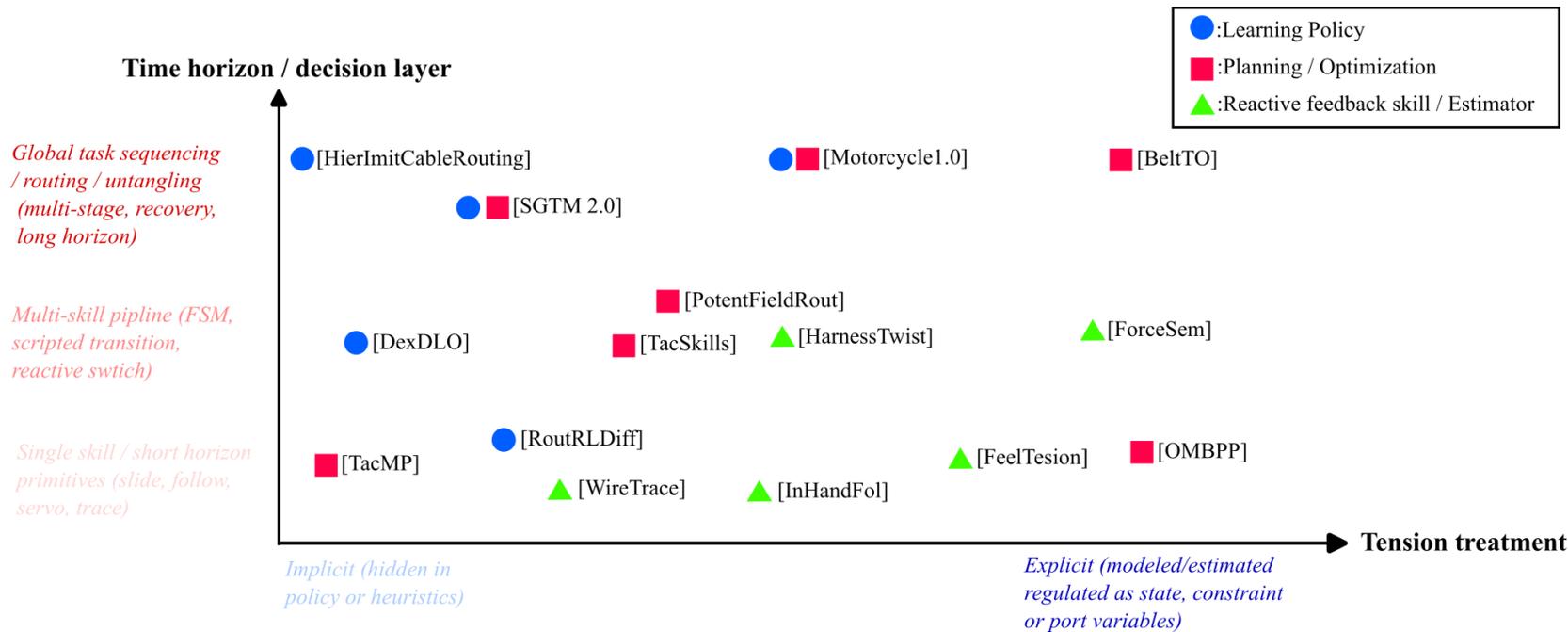
Route around Fixture



[FeelTension]

Landscape map: horizon × tension explicitness

Reading guide: vertical = decision horizon (skill → pipeline → sequencing). Horizontal = how explicitly tension is represented/regulated.



Reading guide: vertical = decision horizon (skill → pipeline → sequencing). Horizontal = how explicitly tension is represented/regulated.

Three Takeaways

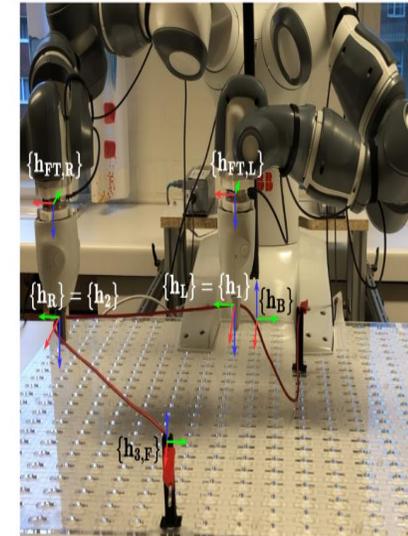
1) Tension-aware execution is strong at the skill level (tactile/force following).

2) Long-horizon success often depends on transitions, recovery, and observability—not only the planner/policy.

3) Key gap: what tension-relevant signals/parameters should be exposed across layers to make skills composable?

Questions I'd like your input on

- Event-based vs continuous tension for sequencing?
- Best sensing stack around fixtures?
- Any benchmark/task board recommendations?



[ForceSem]

Perceive



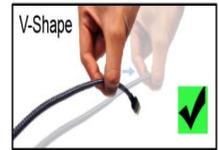
[MovingCables]

Grasp/Pinch



[TacGripper]

Follow Sliding



[InHandFol]

Recovery

Route around Fixture



[FeelTension]

Insert and Release



[TacMP]

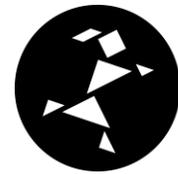
Thank you for attention!



Lets connect!

Also happy to discuss
“**contact-rich control**”
“**trajectory optimization**”
“**generative policies for manipulation**”

ROMANDIC winter school is supported by



FRANKA ROBOTICS



Grant agreement ID: 101070596



**Funded by
the European Union**

Project ROMANDIC Grant agreement ID: 101159522



ROMANDIC



CSIC
CONSEJO SUPERIOR DE INVESTIGACIONES CIENTÍFICAS



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