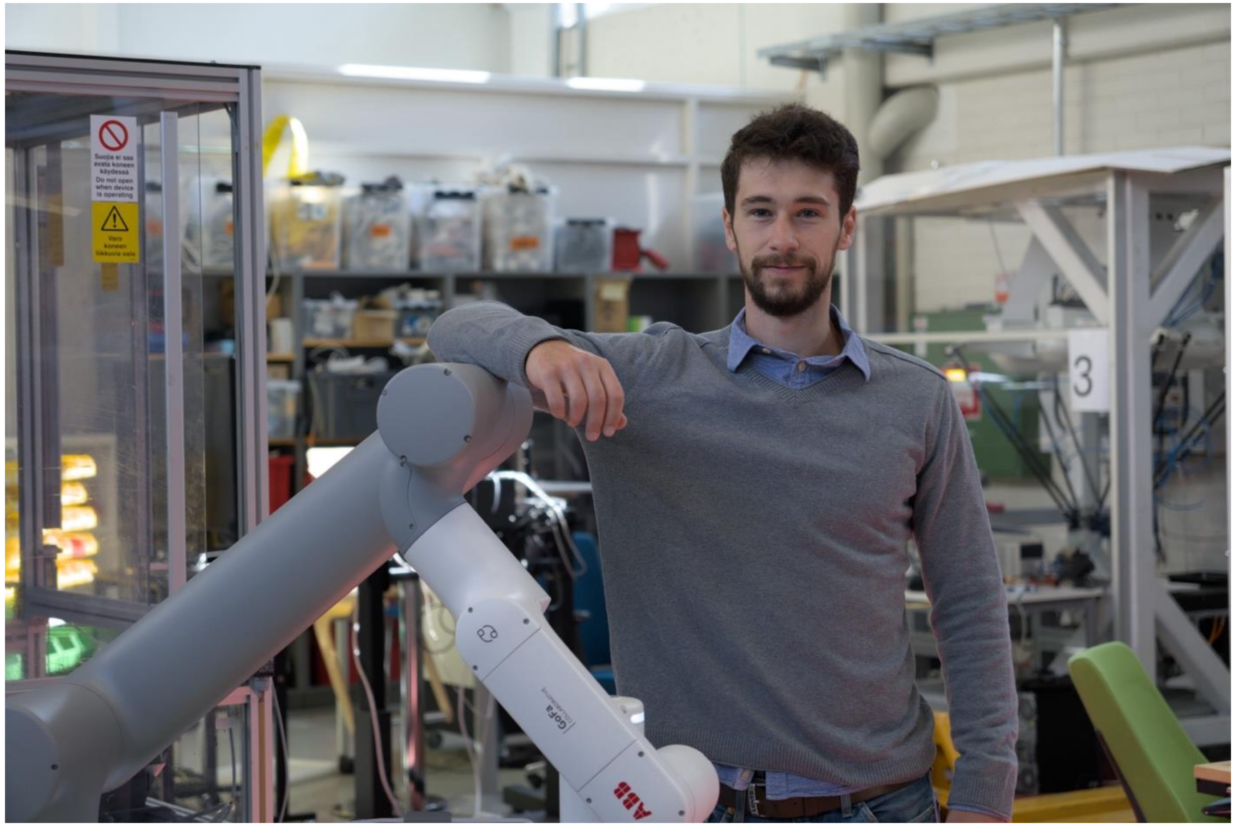
Perception and planning for dual-arm robotic manipulation of multi-deformable linear objects in wire harness assembly

ELLIIT Focus period Lund 2025

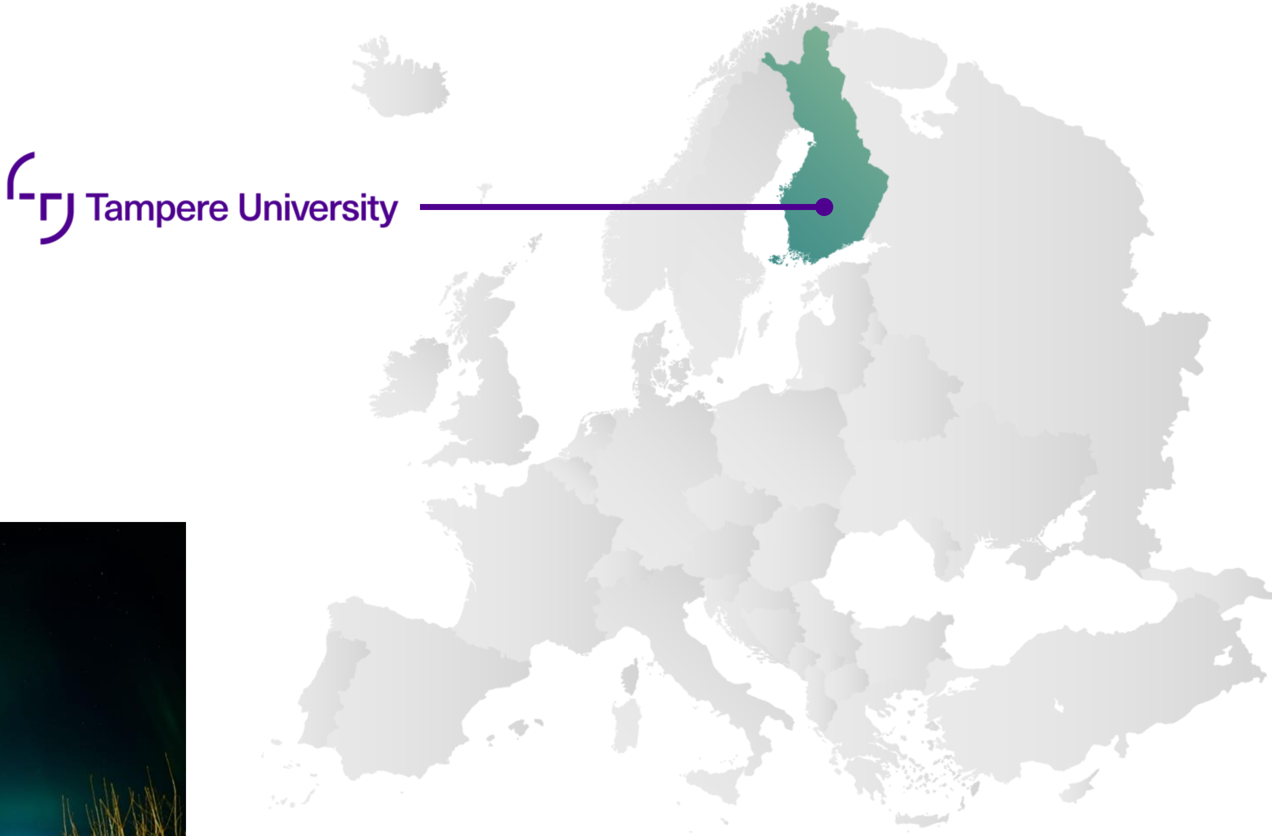
Pablo Malvido Fresnillo – Tampere University

About me



- PhD in Automation Science and Engineering (2025)
- Tampere University
- Research Interests:
  - DLOs robotic manipulation
  - Computer vision
  - Dual-arm motion planning
  - Programming by Demonstration

About me – Tampere University



About me – FAST-Lab Research group

Scan Me

- Multicultural group: 27 researchers from 12 different countries
- 27 European projects
- Areas of expertise:
  - Robot manipulation of deformable materials
  - Human-robot interaction
  - Digital twins
  - AI for logistics and manufacturing

About me – My research

2020 – 2023

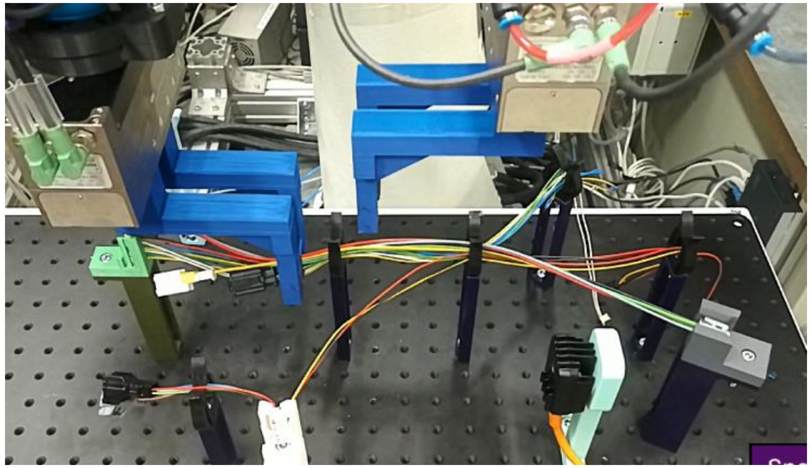
Robotic manipulation of DLOs

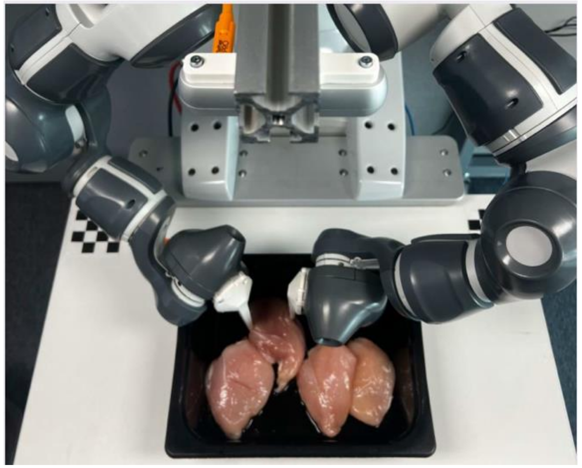
2023 – 2025

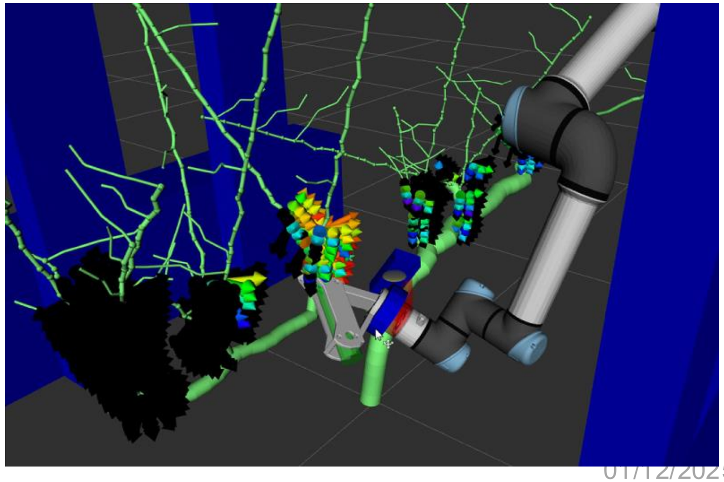
Robotic manipulation of food (Soft and deformable 3D objects)

2025 - …

Robotic vineyard pruning







Motivation

Perception and planning for dual-arm robotic manipulation of multi-deformable linear objects in wire harness assembly

Motivation

Perception and planning for dual-arm robotic **manipulation** of multi-deformable linear objects in wire harness assembly

Motivation

manipulation

Ability to intentionally alter or physically interact with objects in our environment to achieve a desired outcome

manipulation

Motivation

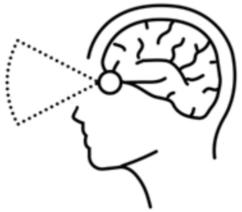
manipulation

Ability to intentionally alter or physically interact with objects in our environment to achieve a desired outcome

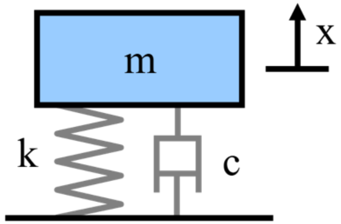
Robot manipulation

- Gripper

- Sensing and perception

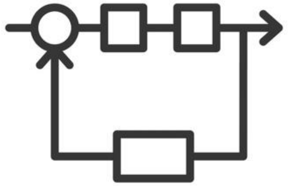


- Modeling



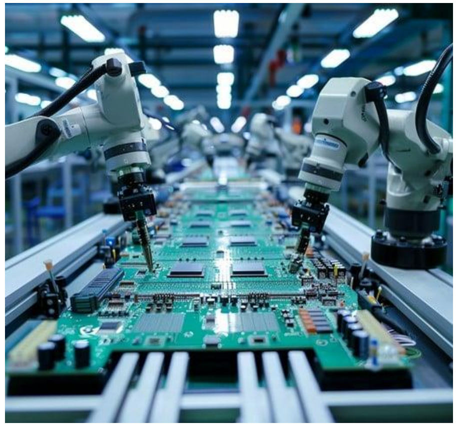
- Planning

- Control



Motivation

- Robots are very good at manipulating rigid objects
- Revolutionized many industries
- What about deformable objects?



Motivation

Deformable objects

- Their shape is not constant
- Studied differently depending on their topology

Linear (DLO)

Planar

Volumetric

Motivation

Deformable objects

not cc

ntly de

- Highly revelant (e.g., cables, ropes, hoses…)
- Entanglements
- Large deformations

Linear (DLO)

Linear (DLO)

Planar

Volumetric

Motivation

Deformable objects

Linear (DLO)

- Highly revelant (e.g., cables, ropes, hoses…)
- Entanglements
- Large deformations

But…
What if we have multiple DLOs?

Motivation

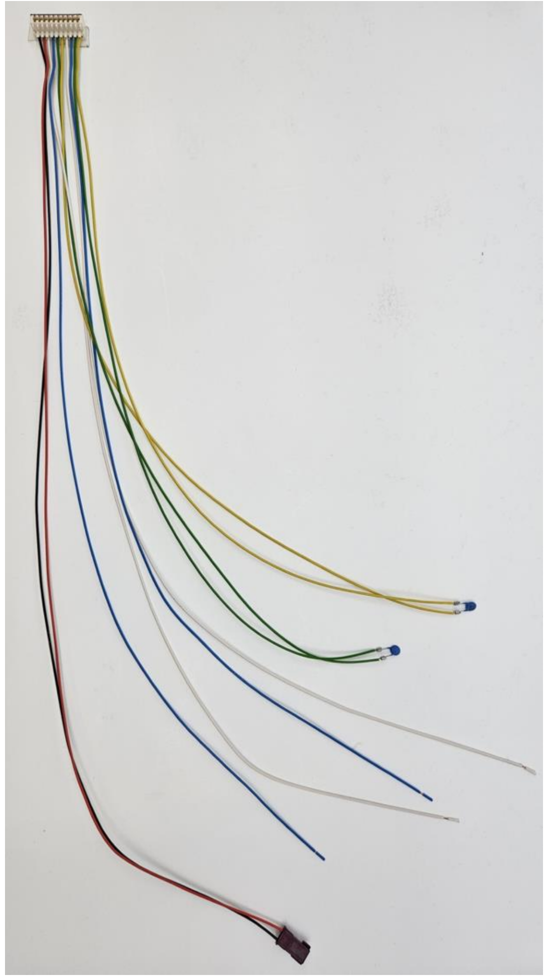
Deformable objects

Linear (DLO)

- Highly revelant (e.g., cables, ropes, hoses…)
- Entanglements
- Large deformations

Multiple DLOs (**MDLOs**)

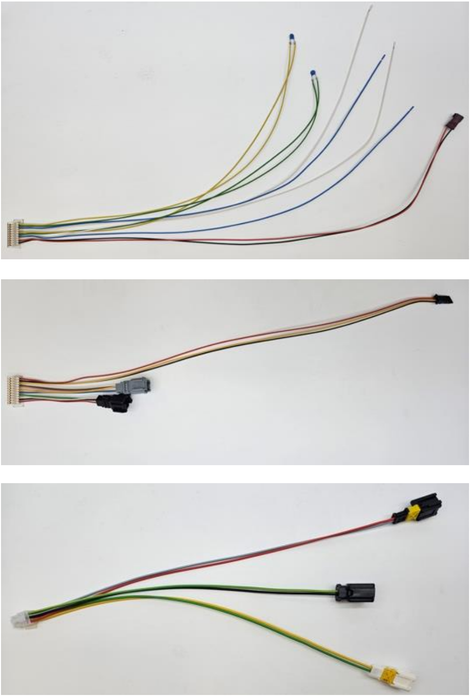
New challenges
- More entaglements
- Self-occlusions
- Adjacent DLOs



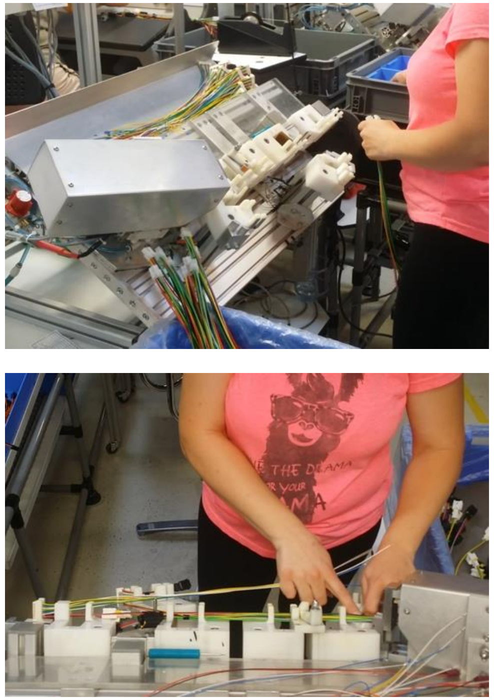
Wire harness

Motivation

Deformable objects: relevance of wire harnesses



Individual wire harnesses



Assembly (90% manual)

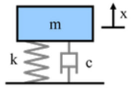
Assembled wire harness

Problem statement

Robot manipulation of MDLOs

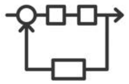

Gripper


Sensing and perception



Modeling


Planning


Control

RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

RQ2. What motion planning capabilities are necessary for effective manipulation of MDLOs?

Problem statement

- Complex advanced system
- Task and setup frequent changes
- End users with

RQ4. How can robotic systems be intuitively programmed and reconfigured to adapt to rapidly changing industry demands?

RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

RQ2. What motion planning capabilities are necessary for effective manipulation of MDLOs?

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

MDLOs perception

- Tactile
- Force
- Vision

Tactile, Force → Localized information on shape and contact

Vision → Global large-scale shape

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

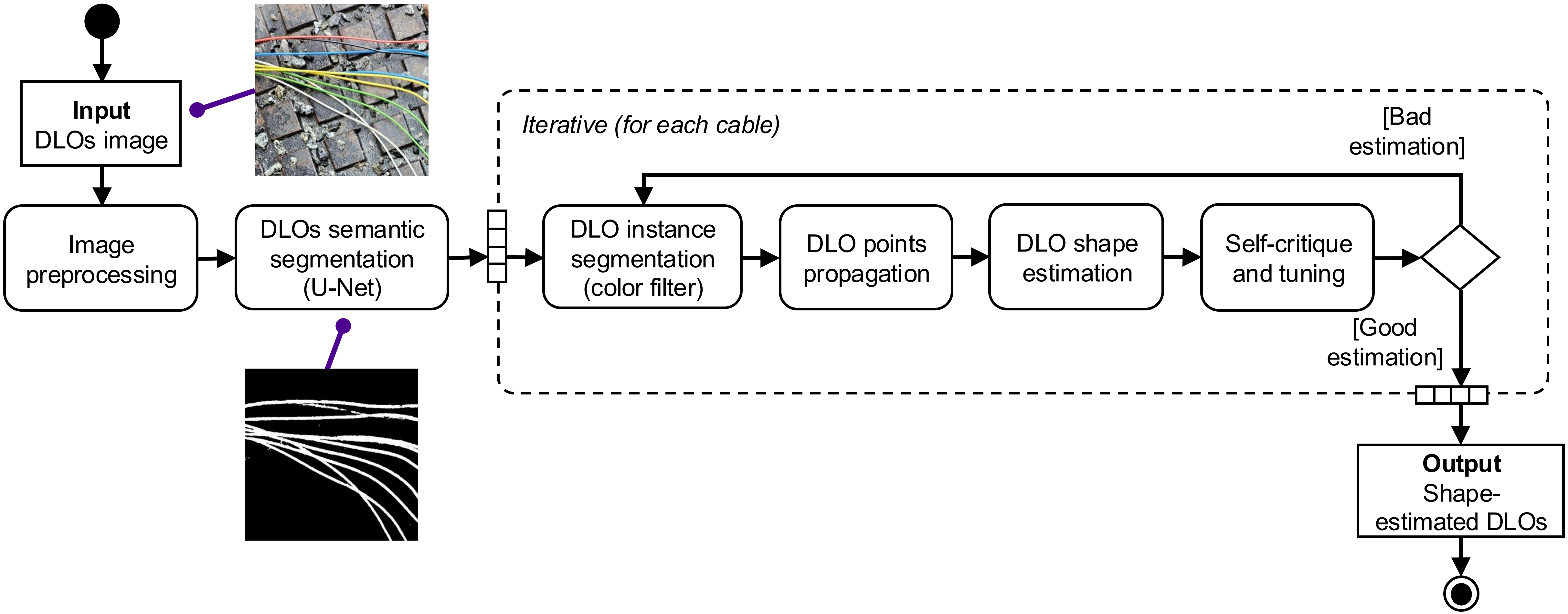
MDLOs perception

- Tactile
- Force

→ Localized information on shape and contact

- **Vision** → **Global large-scale shape** ✓

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?



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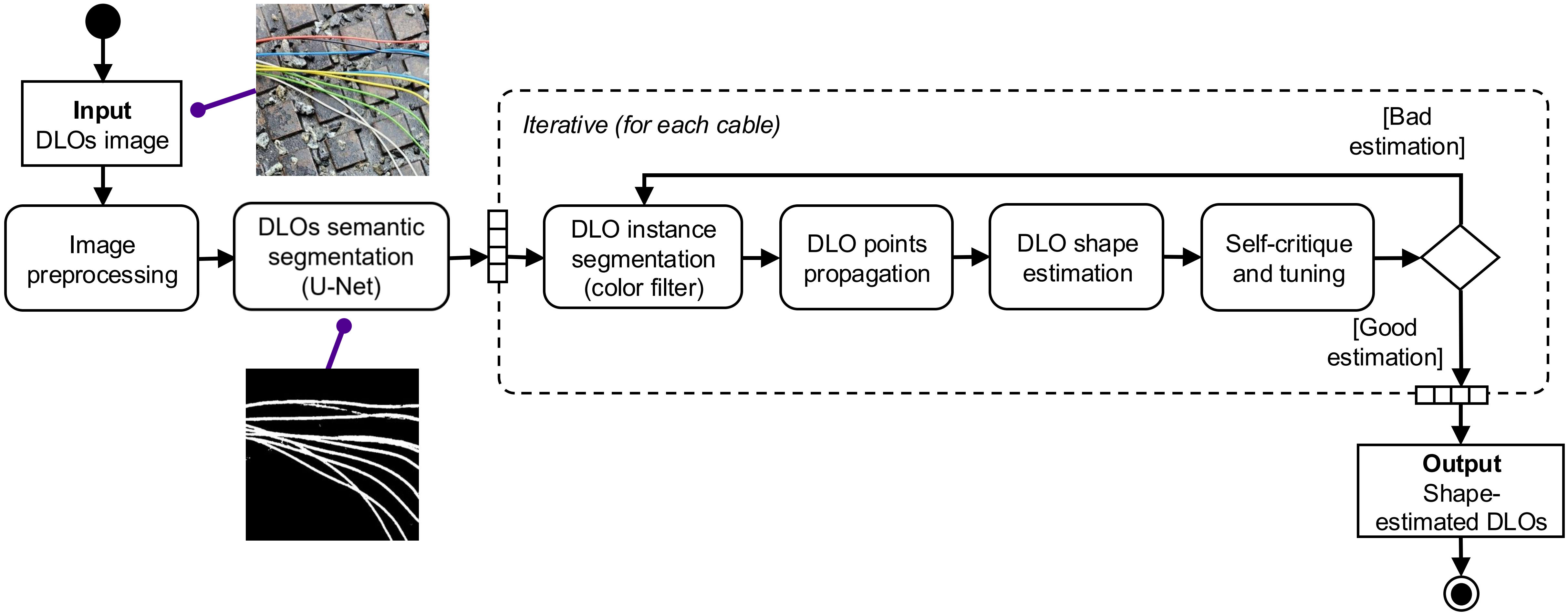
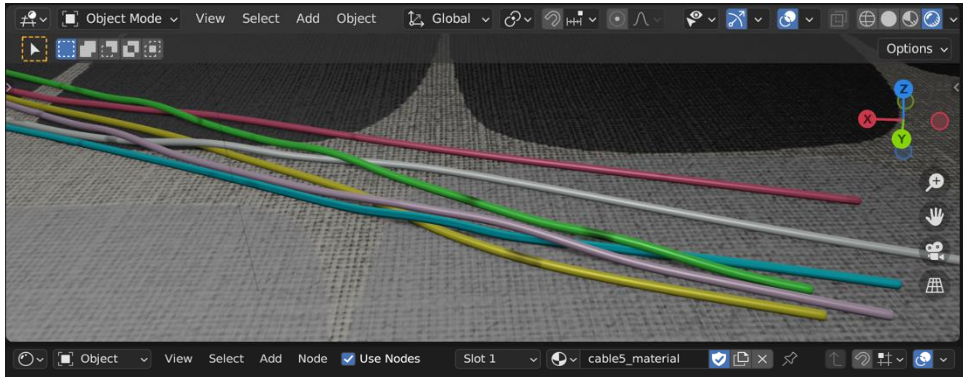
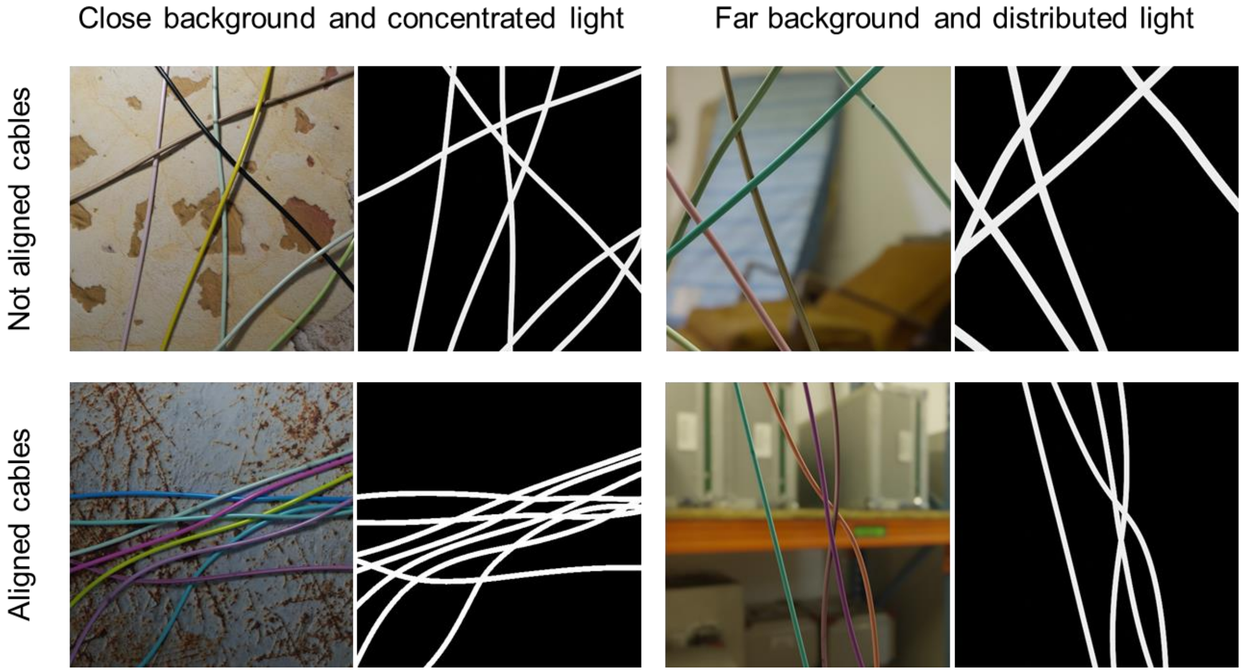


RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

MDLOs synthetic segmentation datasets generation

- Blender + scripting → Realism and variety
- Deep Learning models trained on purely synthetic datasets



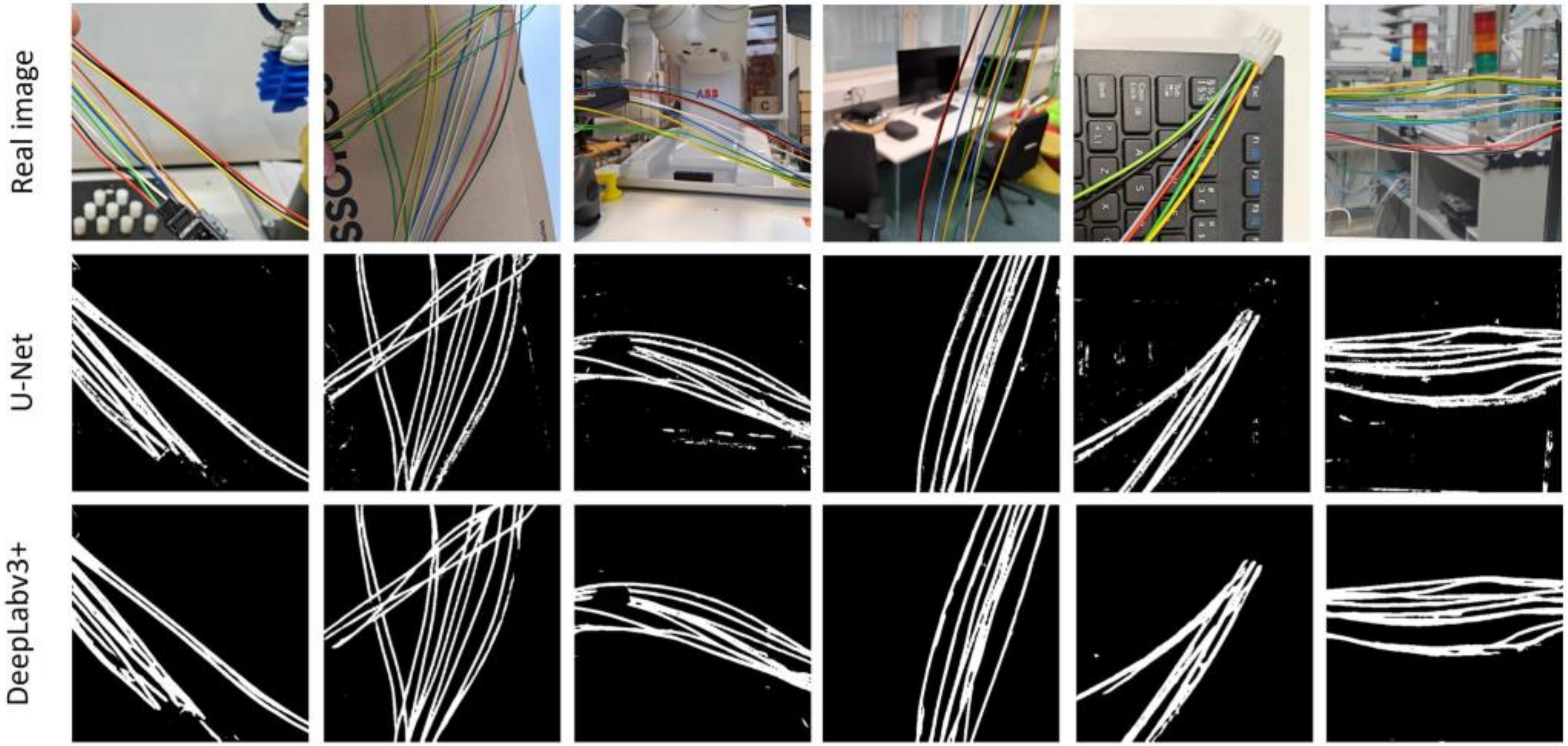


Examples of synthetically generated images and masks

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

MDLOs synthetic segmentation datasets generation

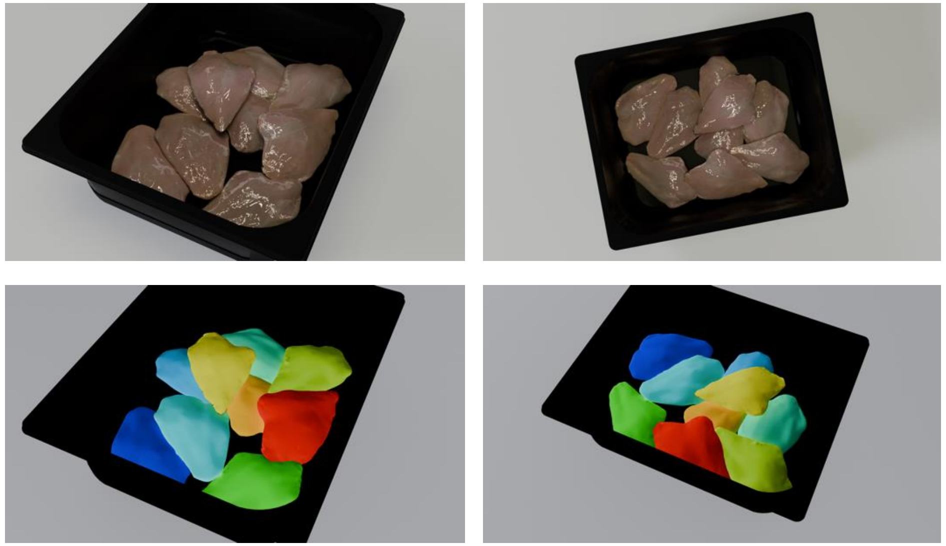
- Performance of models trained purely with synthetic images

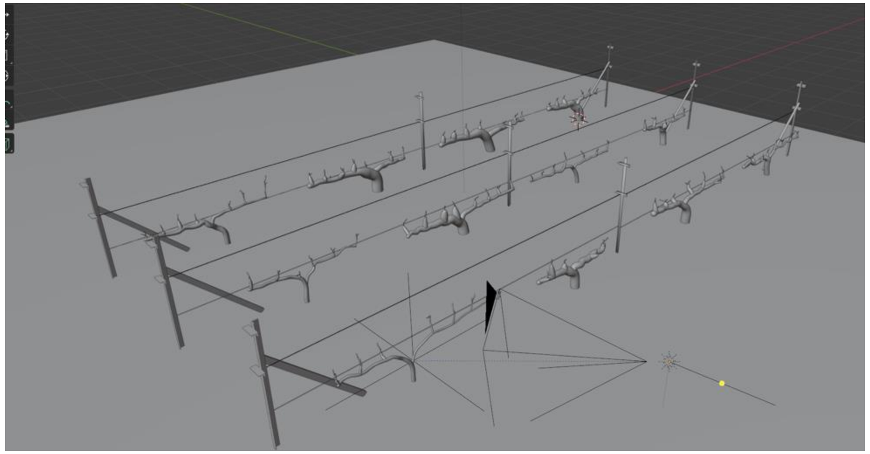


RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

MDLOs synthetic segmentation datasets generation

- Same technique applied for other objects and applications





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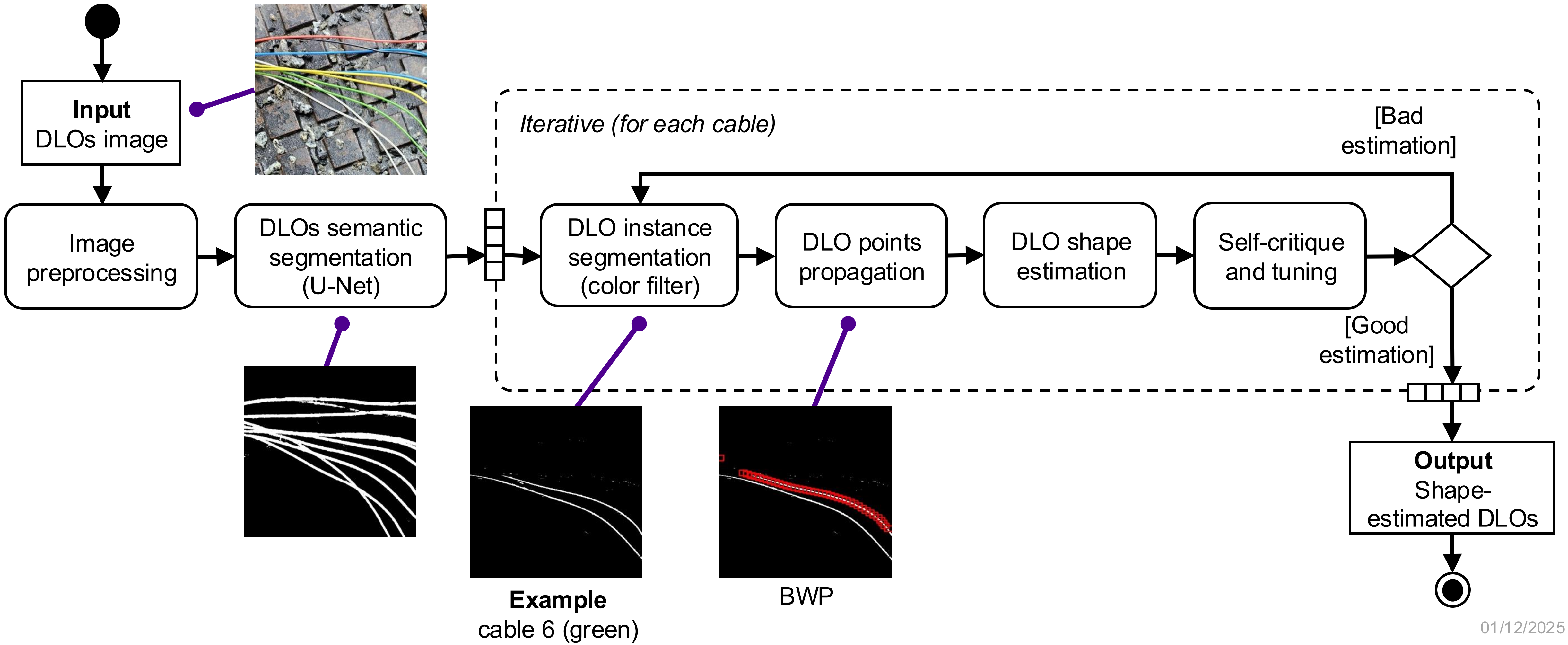

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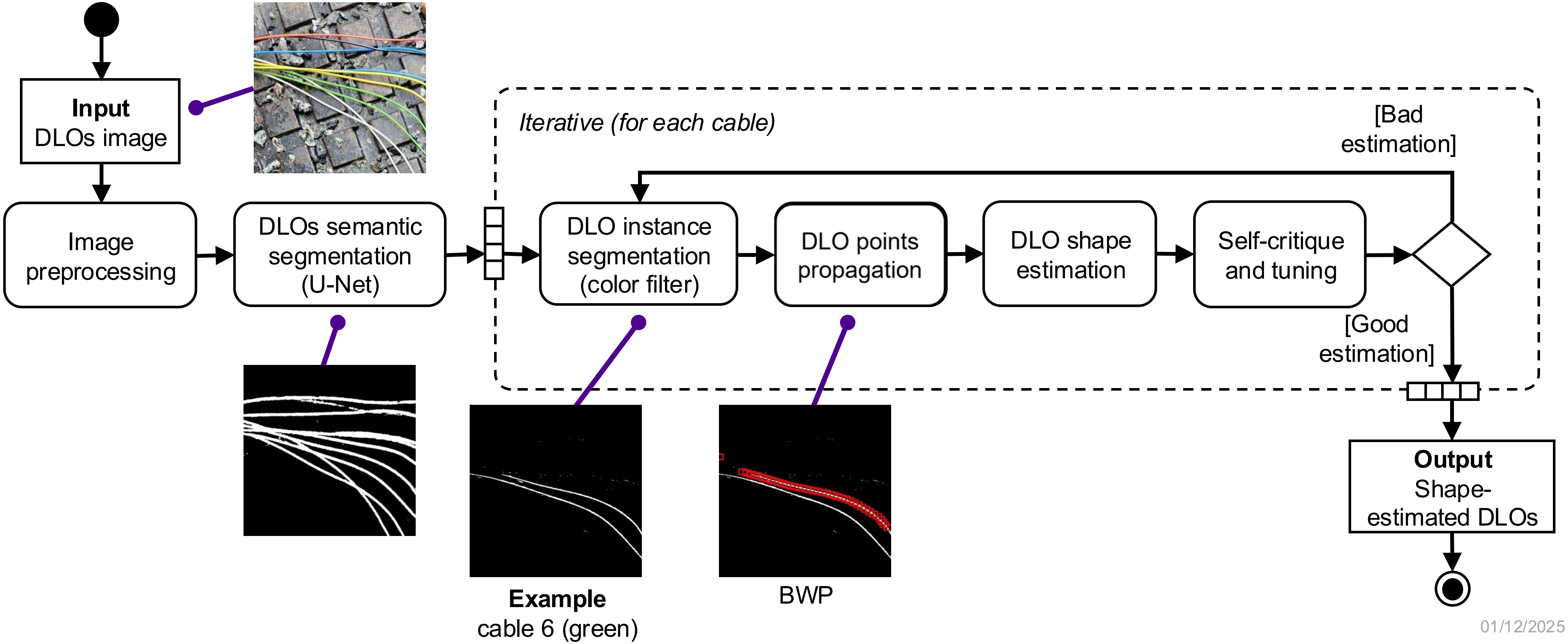
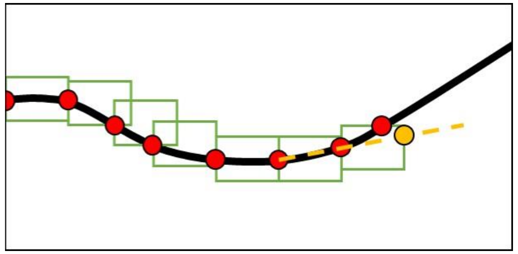
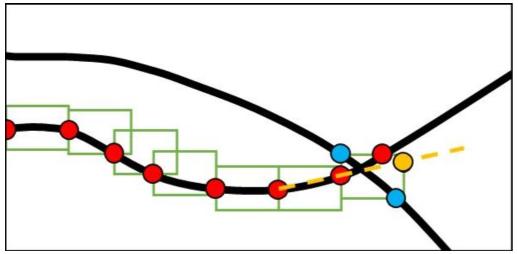
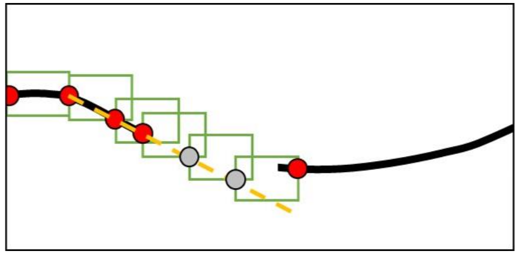


RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?

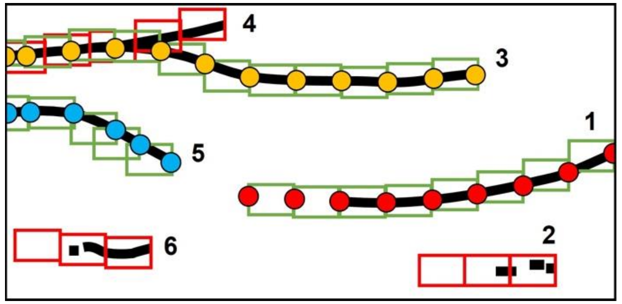
Forward points propagation (FWP)


Single DLO


DLOs entanglement

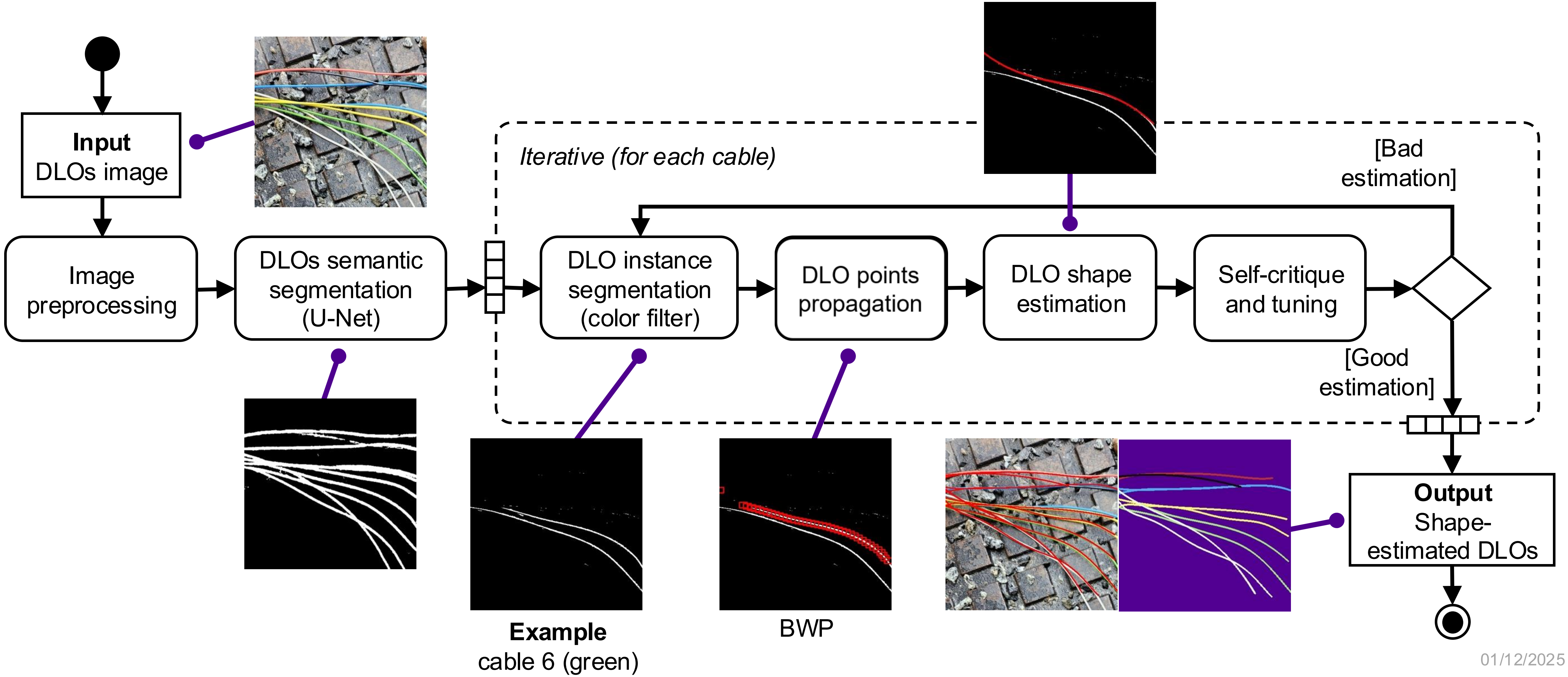

DLO occlusion

Backward points propagation (BWP)



- Apply FWP backwards for each potential DLO
- Evaluate all potential DLO candidates
- Identify the most likely DLO

RQ1. How can the shape of MDLOs be reliably estimated within industrial environments?



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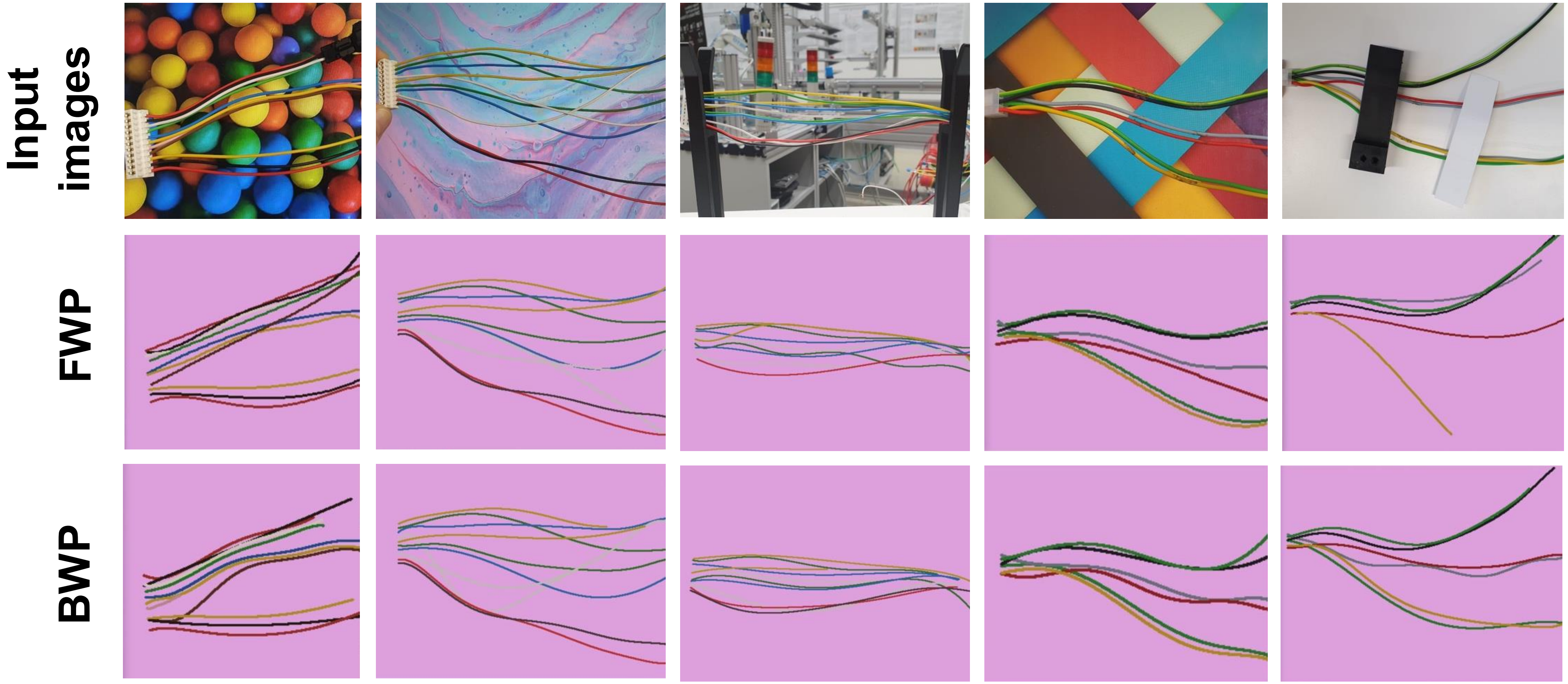

RQ2. What motion planning capabilities are necessary for effective manipulation of MDLOs?

Main MDLOs manipulation tasks

- Separate DLOs → Vision-based perception
- Routing in cluttered spaces → MDLO Tangle-free path planning algorithm
- Clip insertion → DLOs tensioning
- Shape modification → Dual-arm manipulation

RQ2. What motion planning capabilities are necessary for effective manipulation of MDLOs?

- 5 dual-arm synchronization policies
  i. Finish at the same time
  ii. Independent speeds
  iii. Reach waypoints at the same time
  iv. Leader-follower
  v. Close-chain
- Control of cartesian speeds
- Integration with MoveIt motion planner

RQ2. What motion planning capabilities are necessary for effective manipulation of MDLOs?

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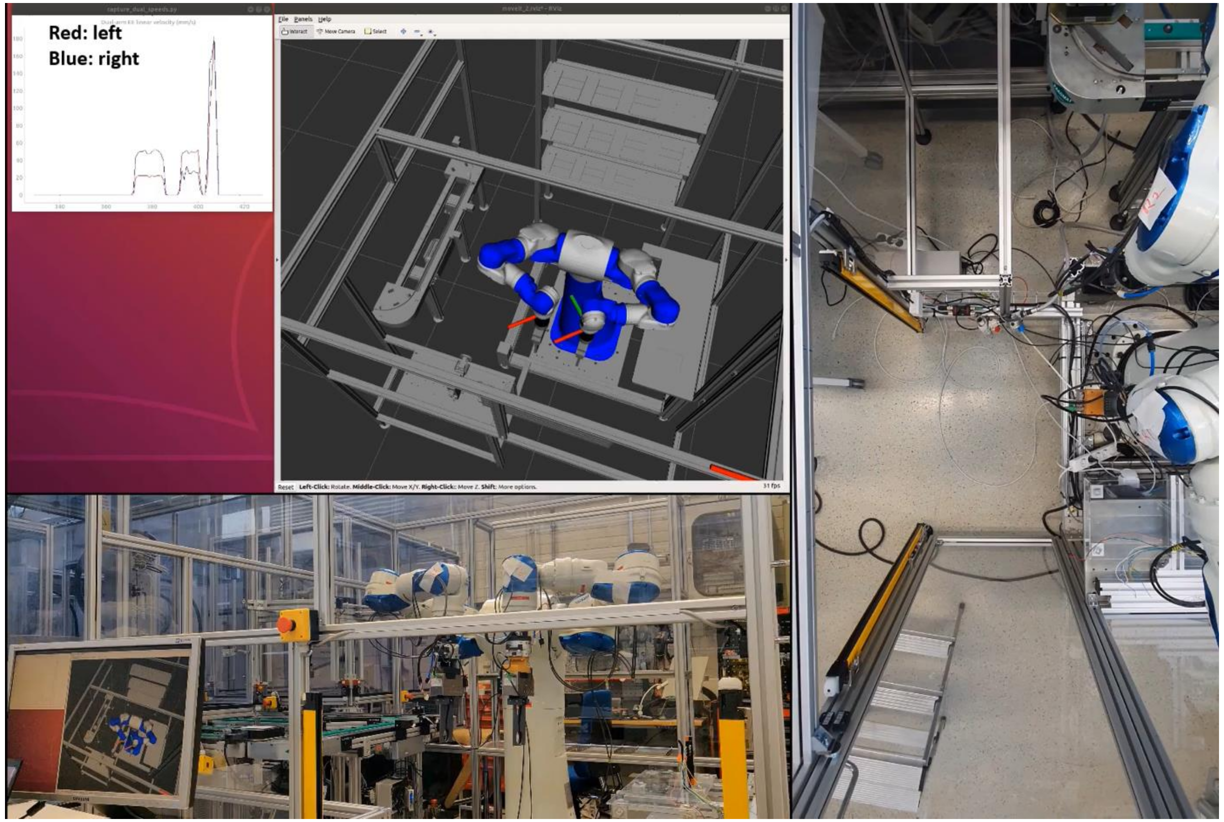
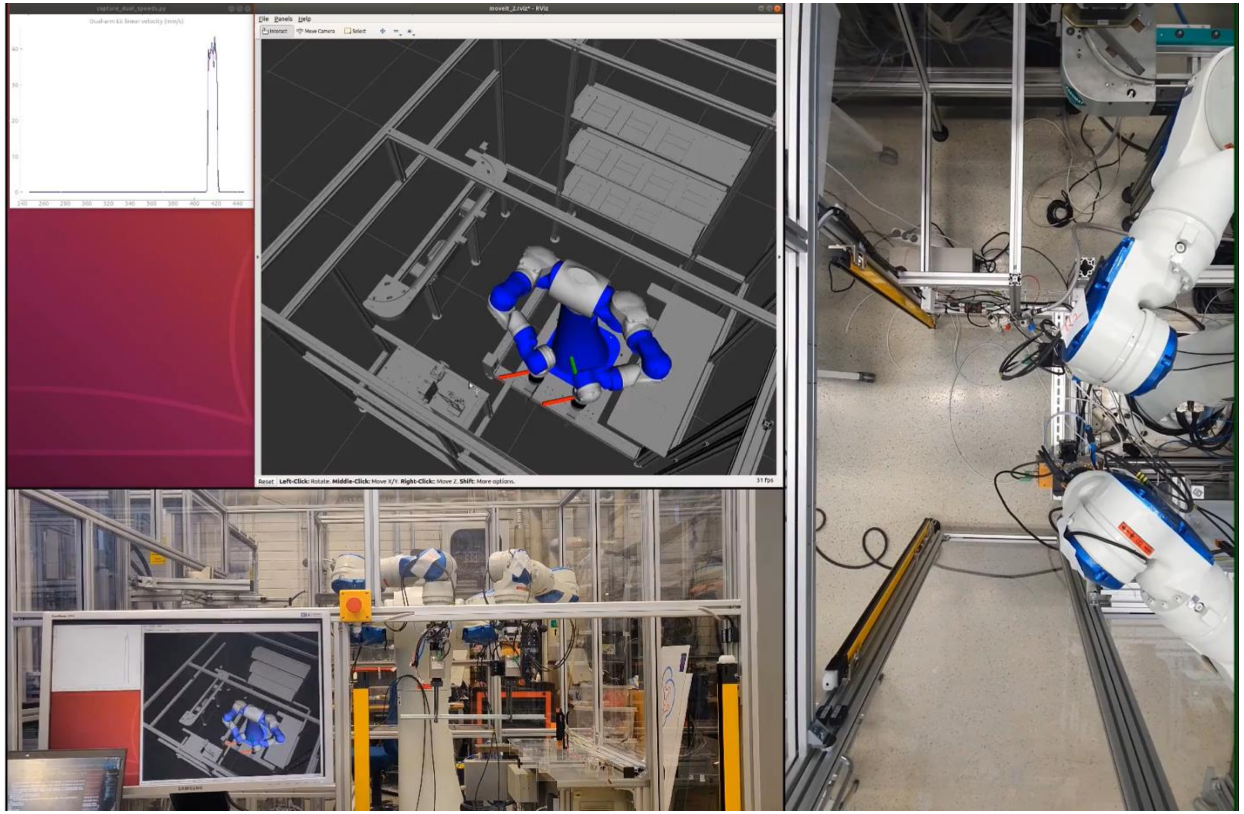


RQ2. What motion planning capabilities are necessary for effective manipulation of MDLOs?

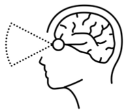
- 5 dual-arm synchronization policies
  1. Finish at the same time
  2. Independent speeds
  3. Reach waypoints at the same time
  4. Leader-follower
  5. **Close-chain**
- Control of cartesian speeds
- Integration with MoveIt motion planner

Master arm: Left

Master EEF speed:
- 40mm/s
- 60mm/s
- 30mm/s
- 30mm/s
- 40 mm/s



RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?



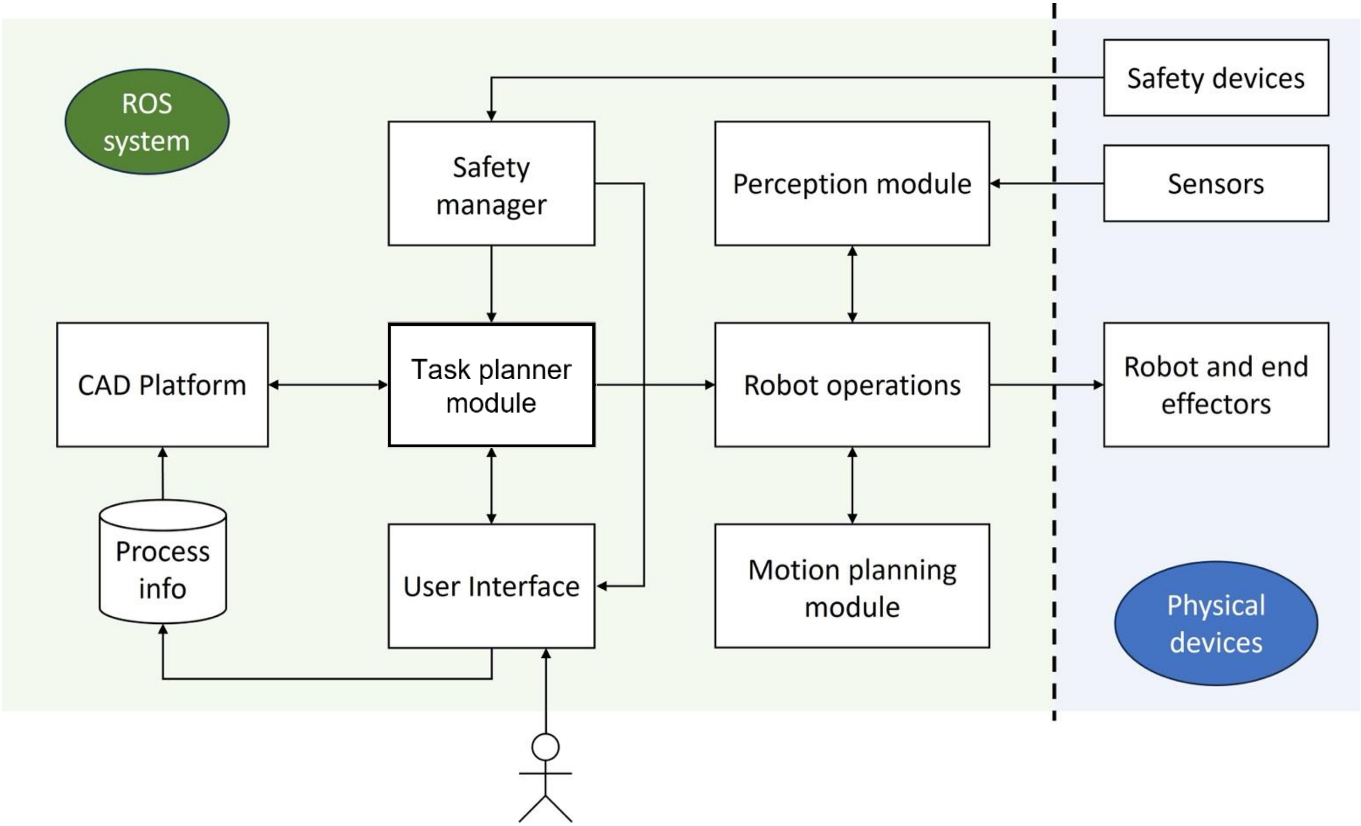
Sensing and perception ✓

Planning ✓

How to employ them to achieve specific goals? → **Task-level programming**

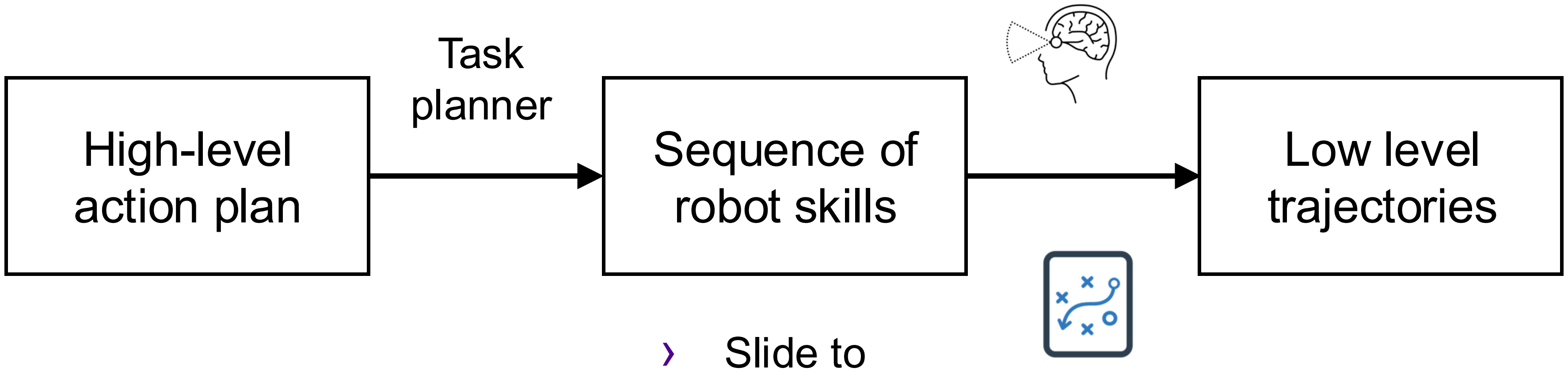
- Set of skills with perception and planning capabilities
- Skills are configurable and can be combined to achieve complex behaviors

RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?



Proposed Task-level programming system

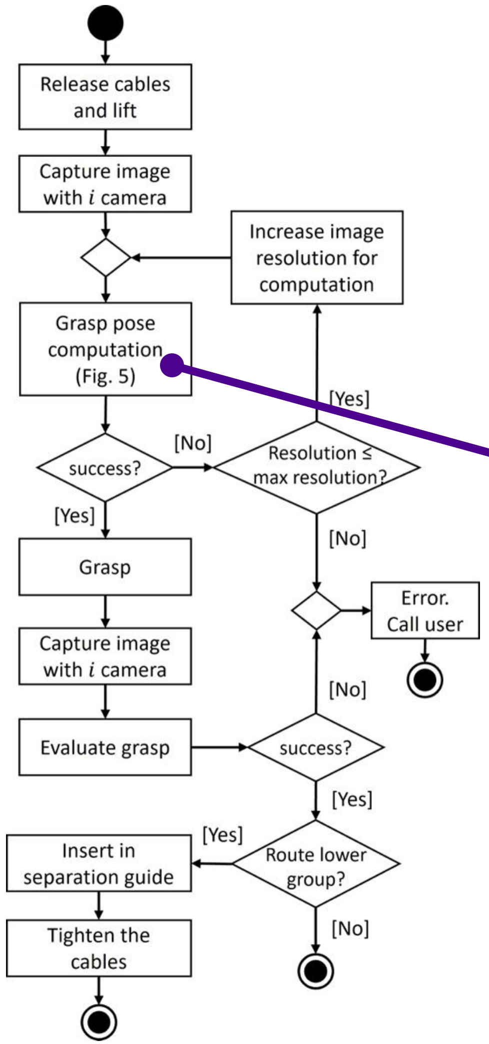
RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?

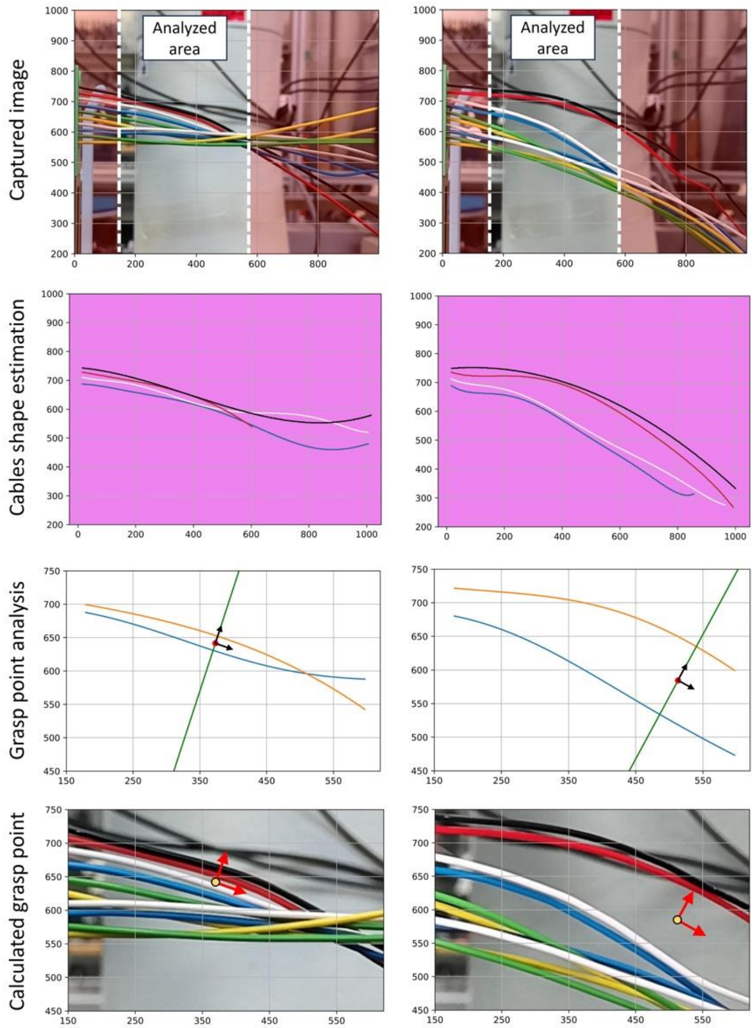


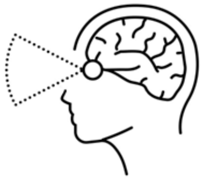
- Slide to
- Insert in
- Pivoting
- Separate
- …

RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?

- Skill example:
  Cable separation







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- Skill example:
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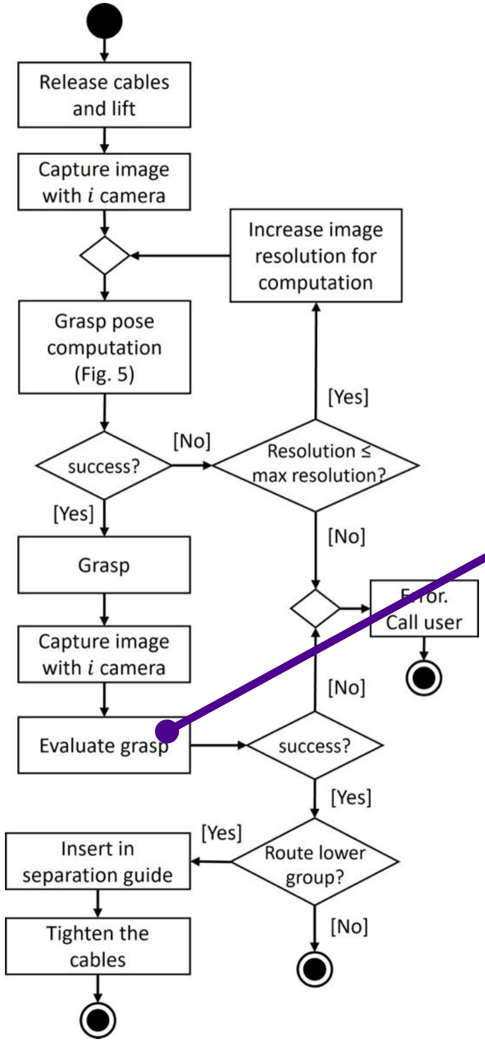
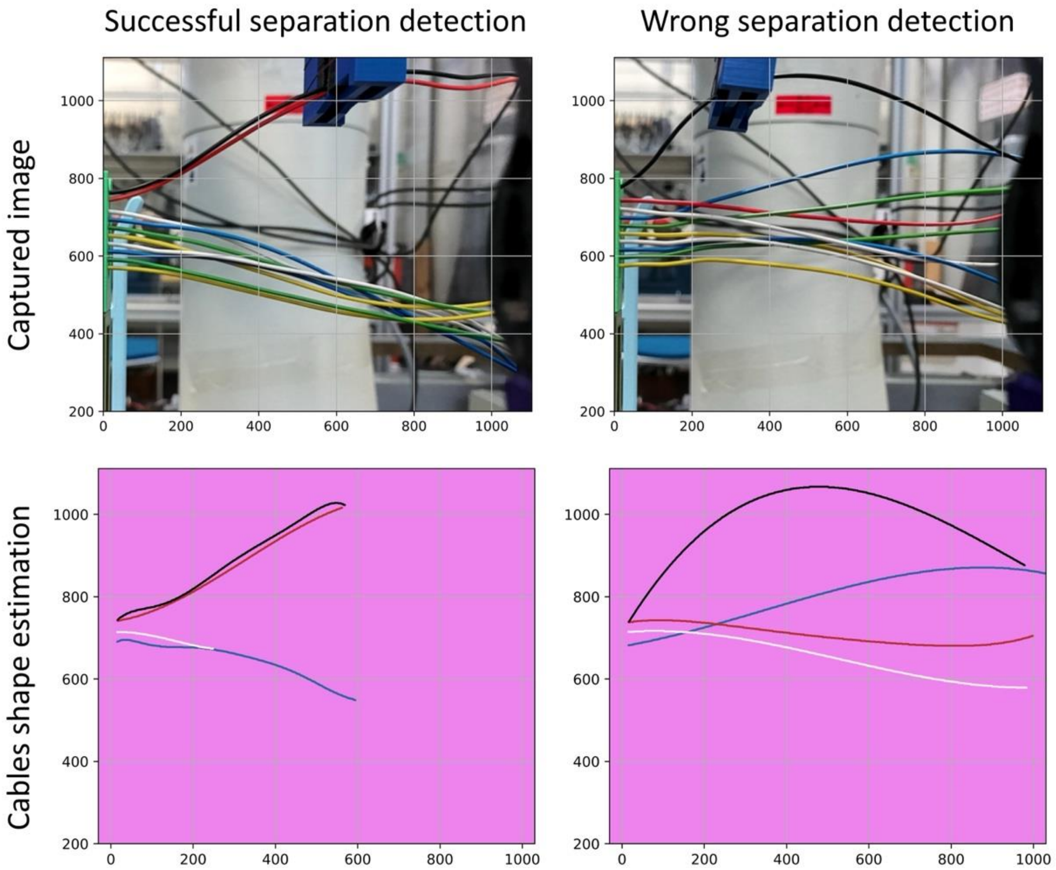
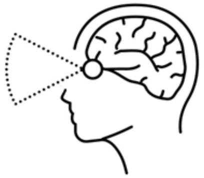
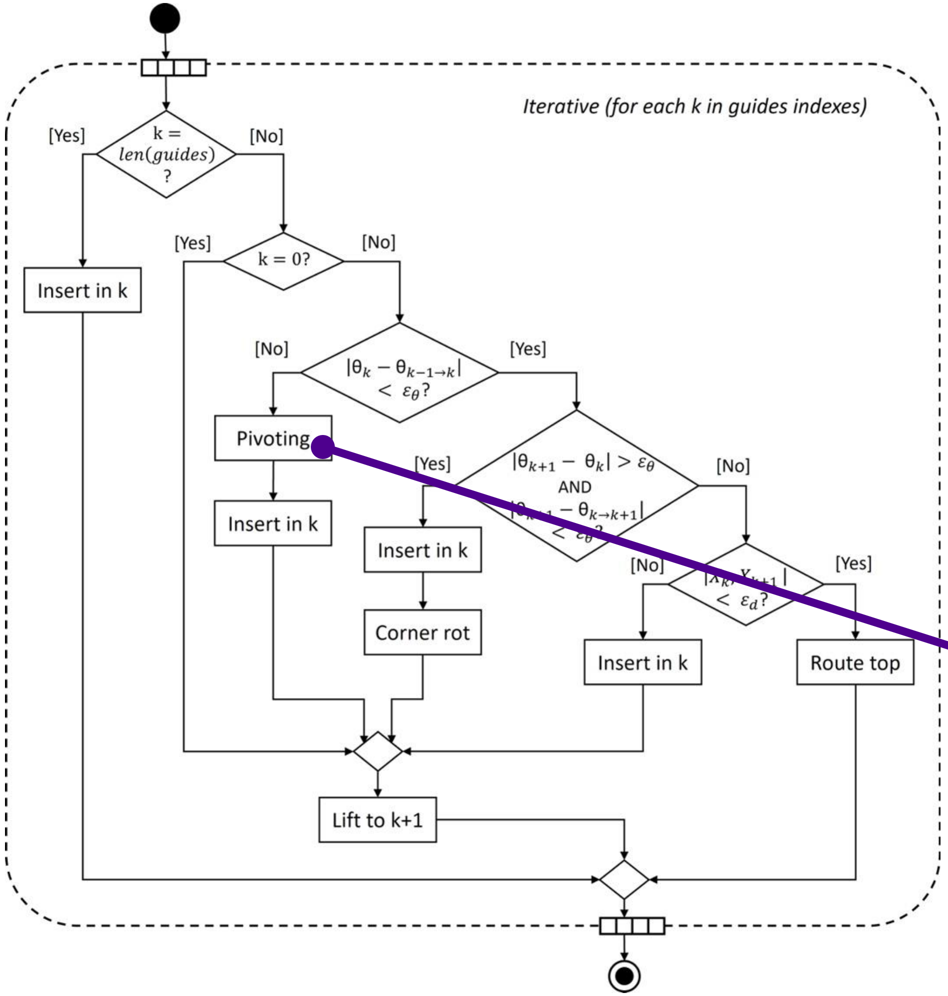


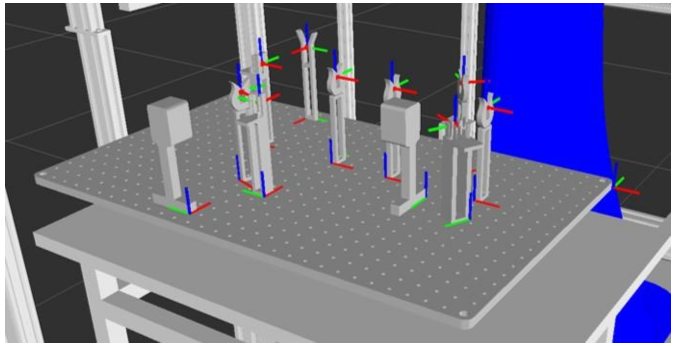


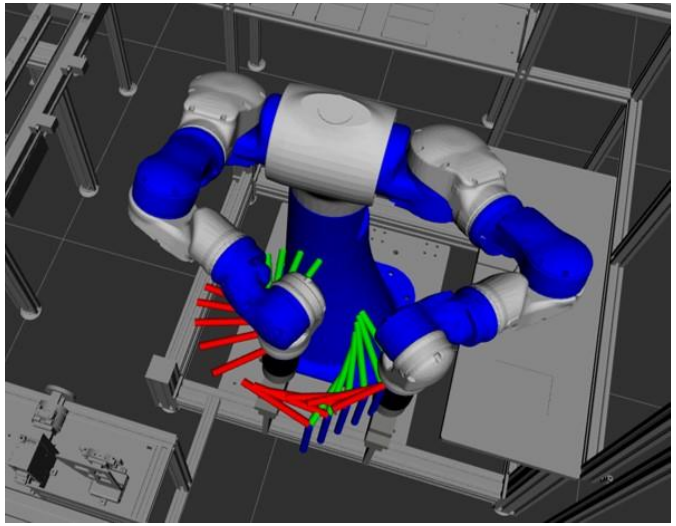


RQ3. How can perception and planning solutions be effectively integrated to achieve end-to-end automation in processes involving MDLOs?

- Skill example: **Cable pivoting**







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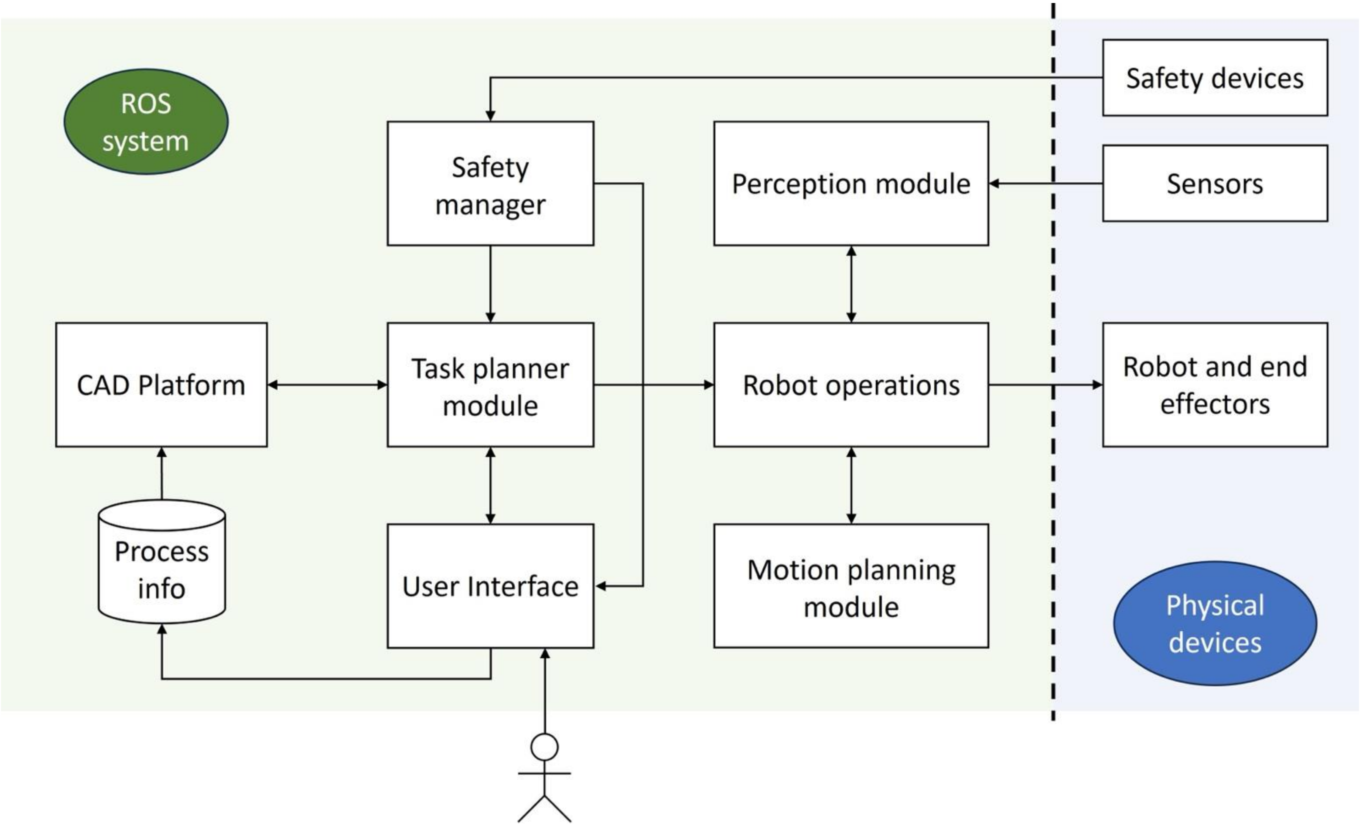

Proposed Task-level programming system

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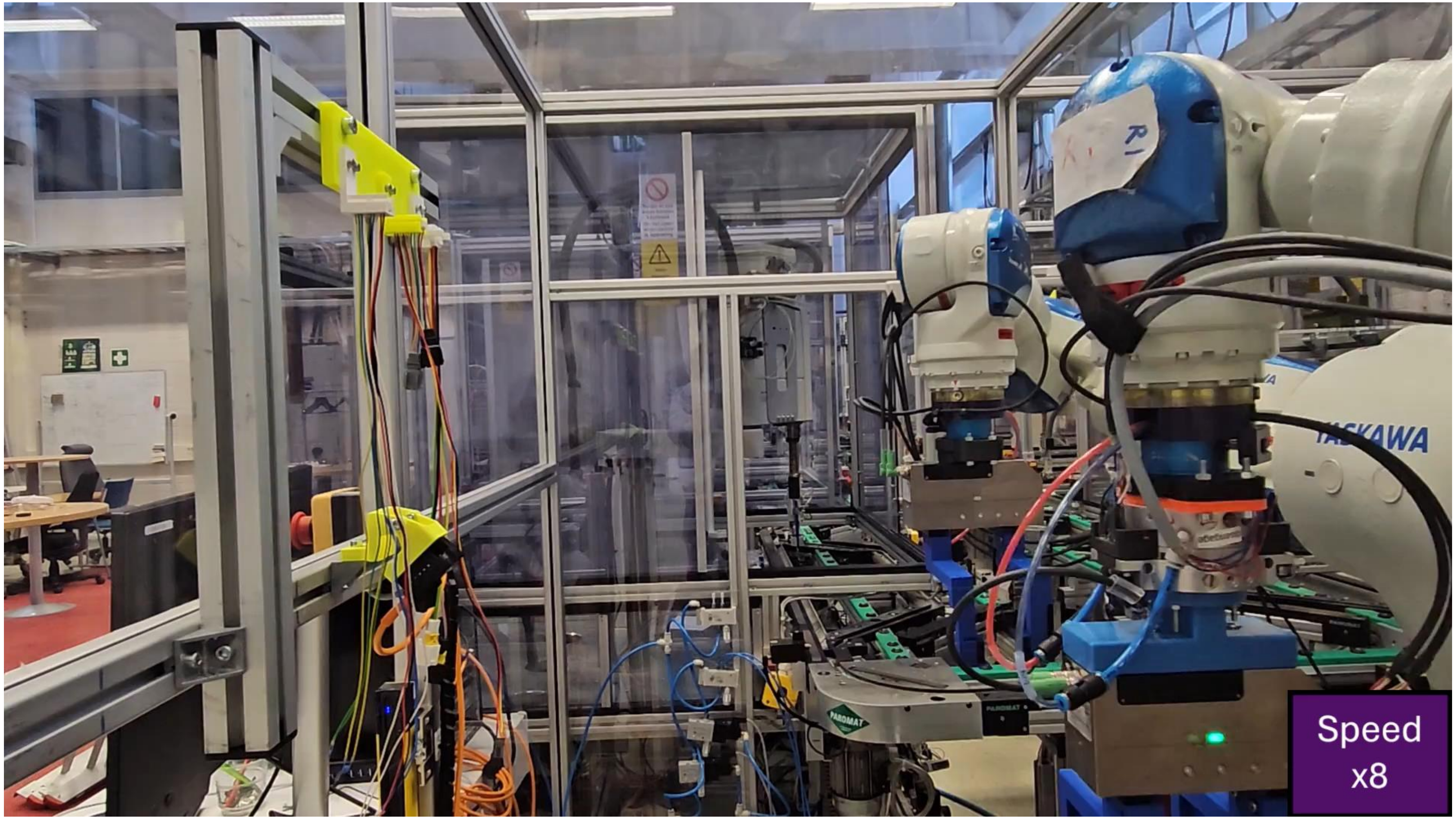


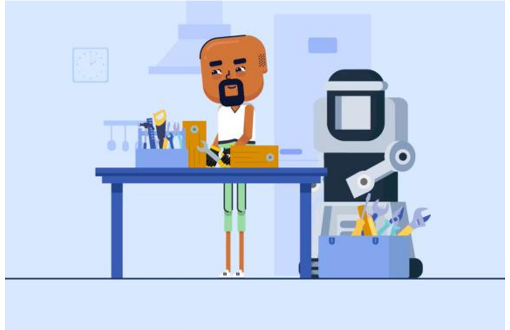
RQ4. How can robotic systems be intuitively programmed and reconfigured to adapt to rapidly changing industry demands?

Programming by demonstration

Motion-level PbD

Task-level PbD

- Inspired by how humans learn
- Requires experience in the task, not in robotics



RQ4. How can robotic systems be intuitively programmed and reconfigured to adapt to rapidly changing industry demands?

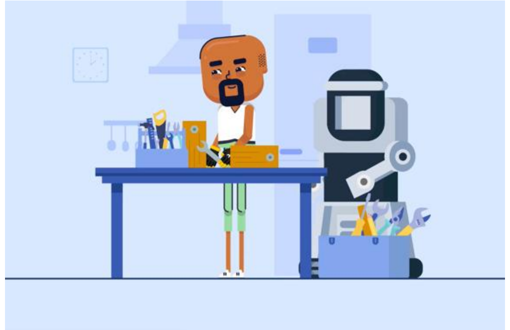
Programming by demonstration

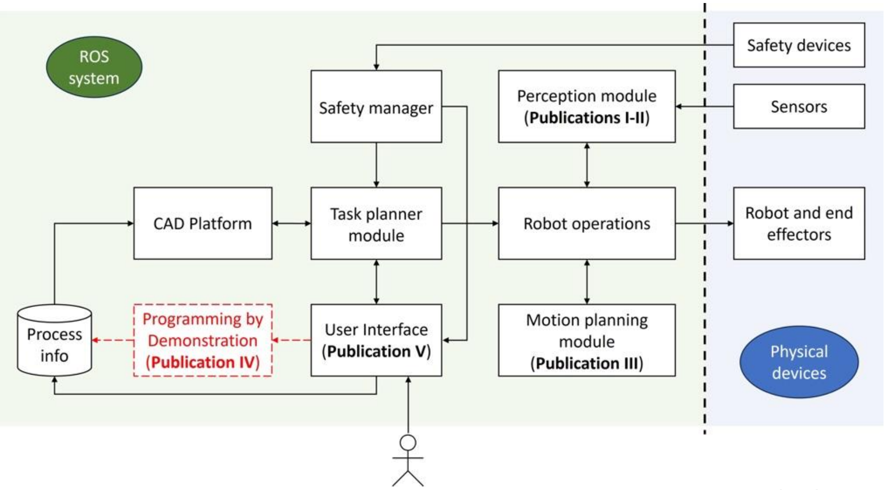
- Motion-level PbD
- **Task-level PbD**

Task-level PbD:

- Robust against task variations
- Compatible with previous framework

- Inspired by how humans learn
- Requires experience in the task, not in robotics

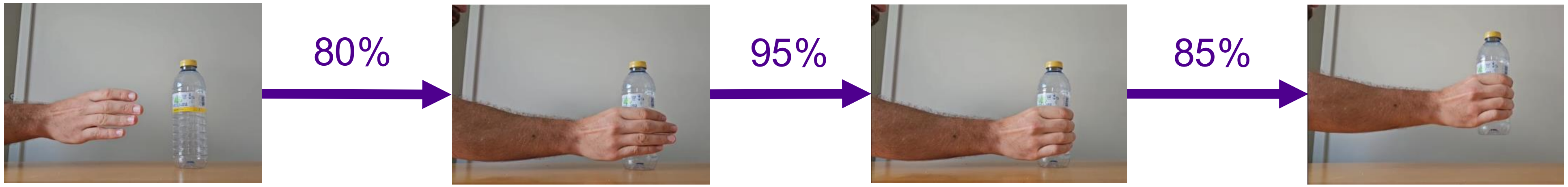




RQ4. How can robotic systems be intuitively programmed and reconfigured to adapt to rapidly changing industry demands?

- Variation of **Markov Models** for multimodal data

Example: Grasp bottle operation transition probabilities

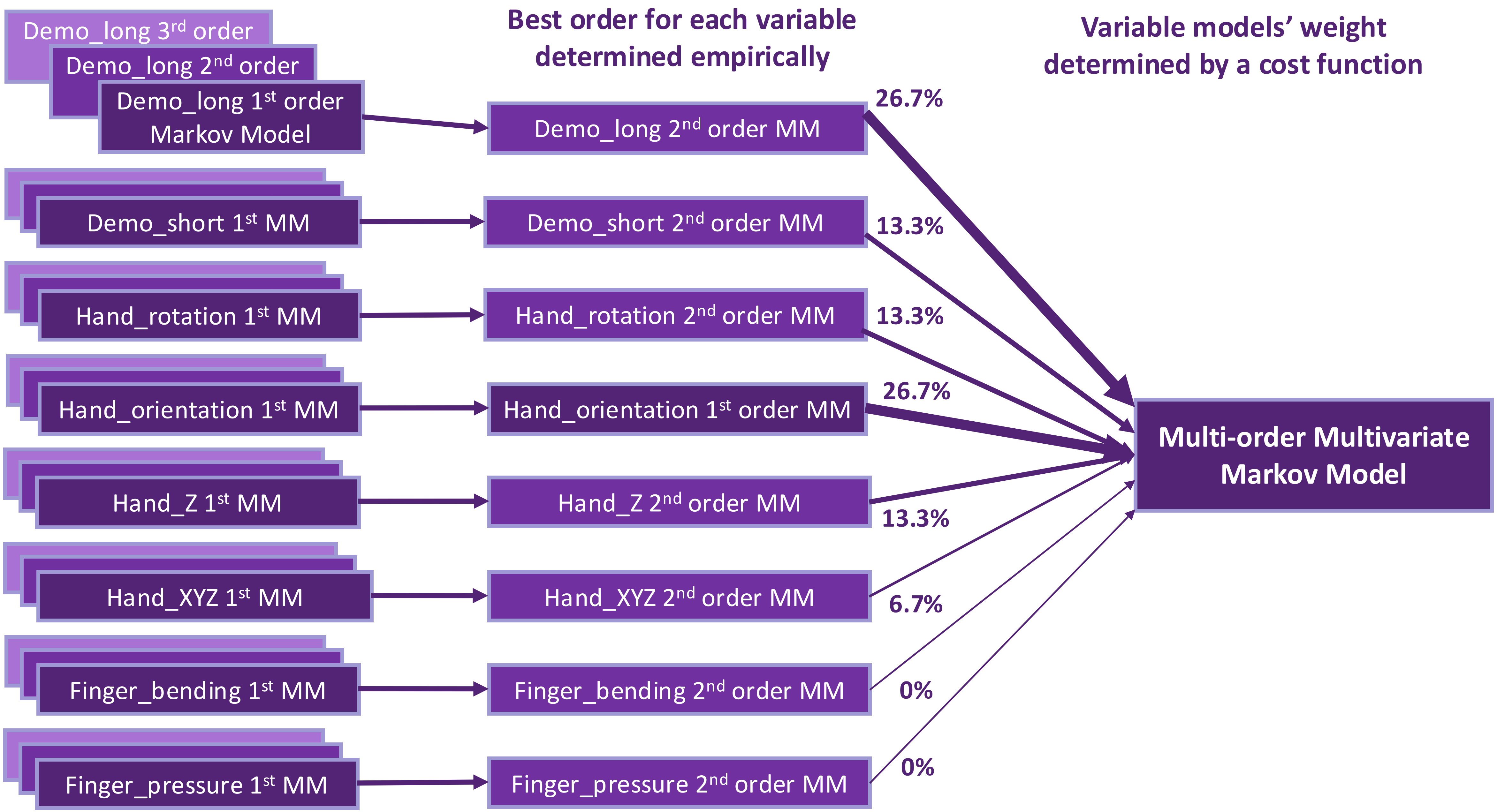


Move hand +X | Close hand | Pressure fingers | Move hand +Z

Two phases

- **Training:** Learn the operation probabilities
- **Prediction:** Compare demonstration with the transition probabilities of each operation model

Grasp Bottle Model



Tampereen yliopisto
Tampere University

RQ4. How can robotic systems be intuitively programmed and reconfigured to adapt to rapidly changing industry demands?

Operation sequence recognition

Training phase

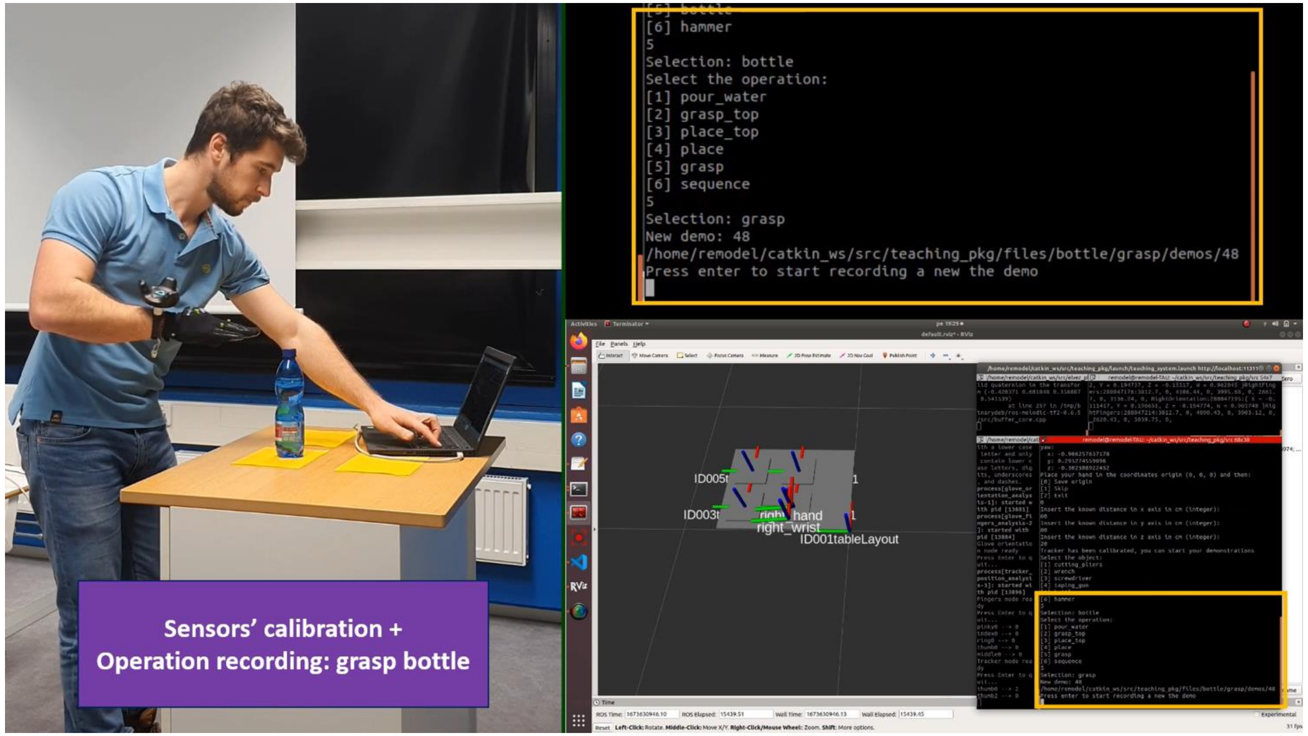
Sensor's data → Primitives (Markov states) → Operations Markov models

Recorded data:

> **Hand tracker:** Hand's position and orientation

> **Dataglove:** Fingers' angles and pressure applied

Grasp bottle operation demonstration recording



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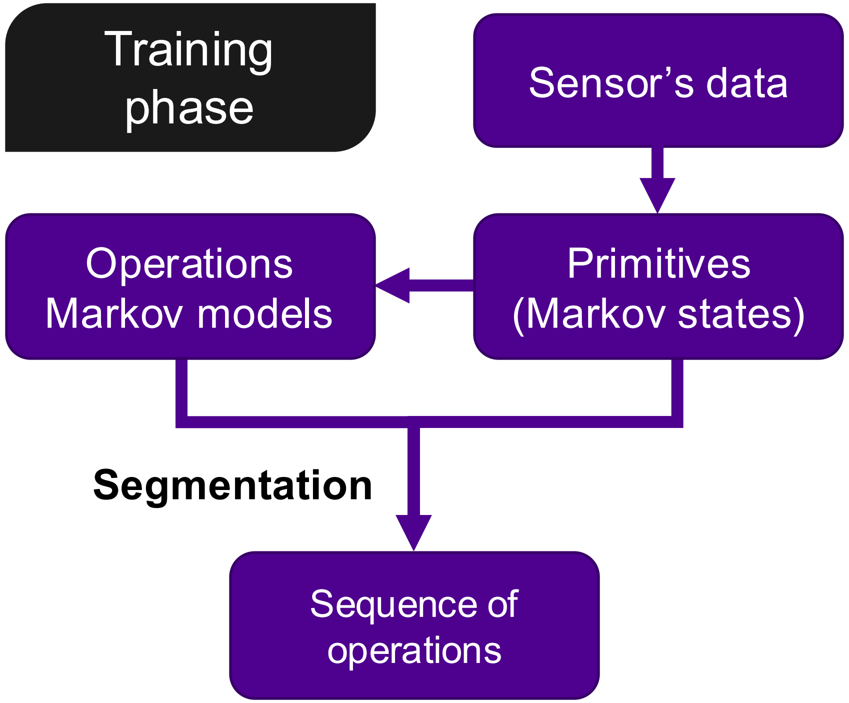
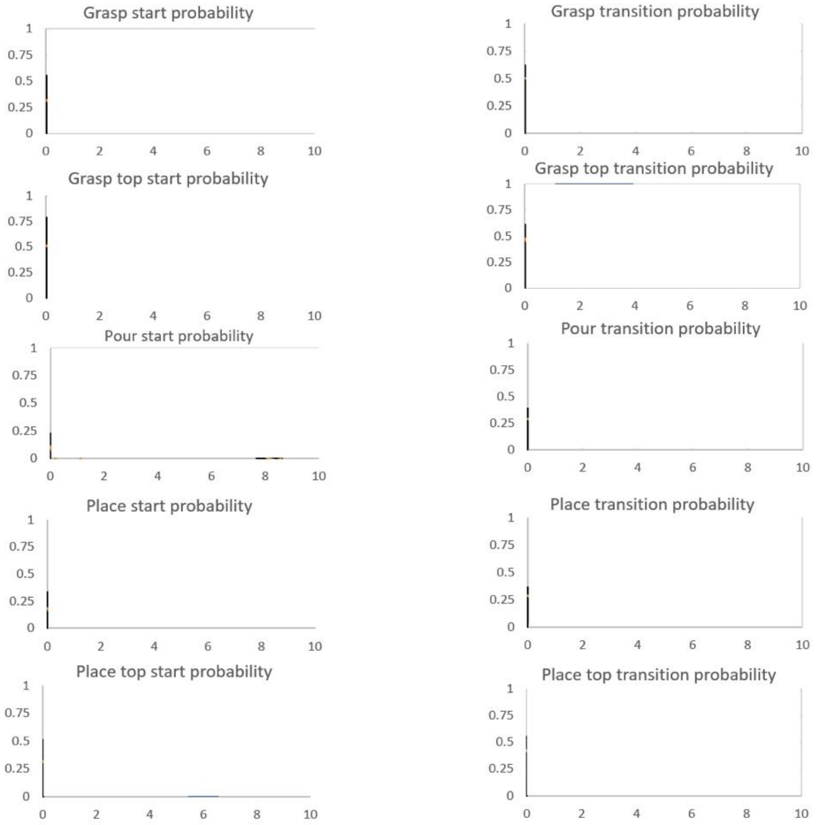
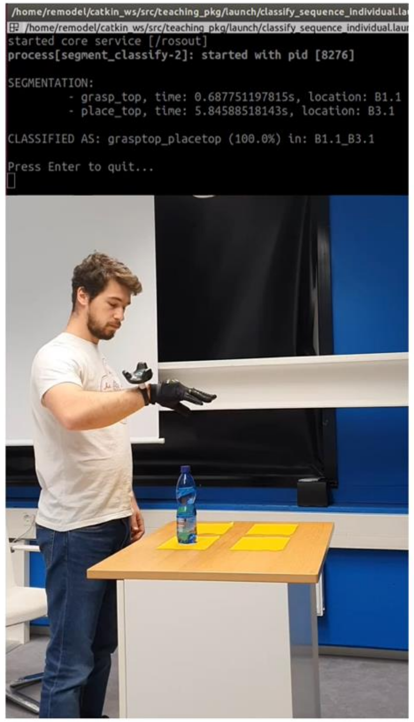
Operation sequence recognition





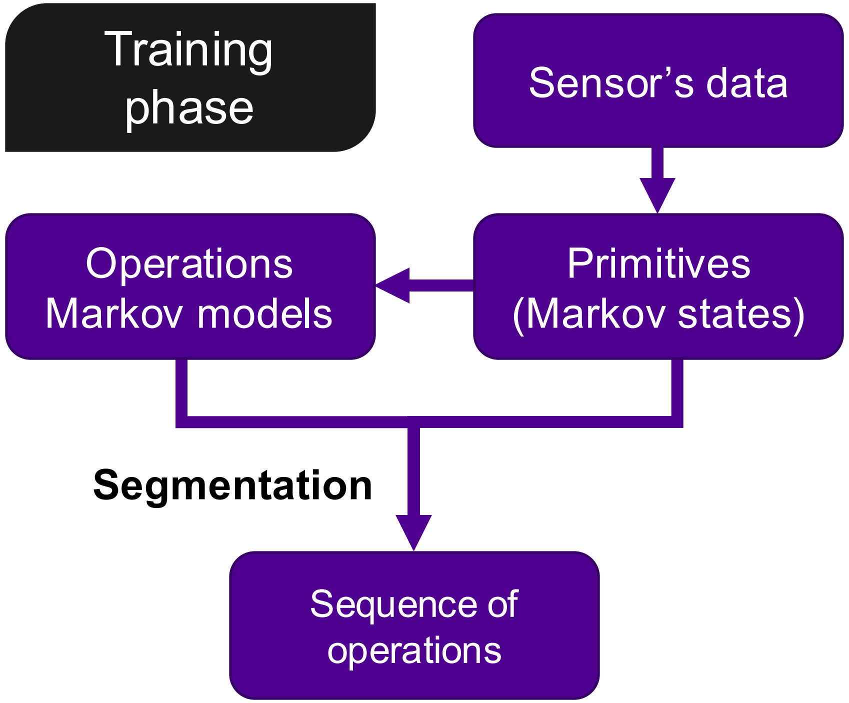
Process segmentation. Bottle: Grasp top (L1) - Place top (L3)

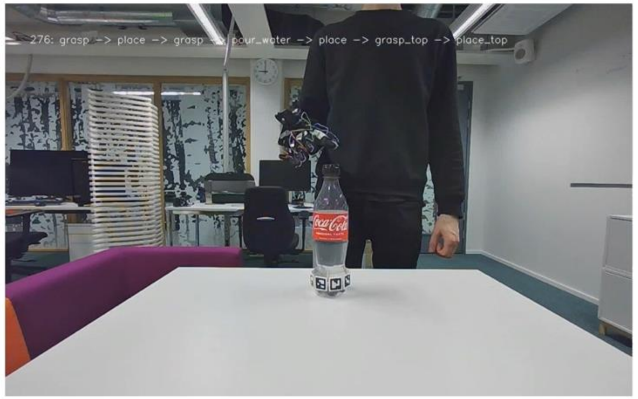


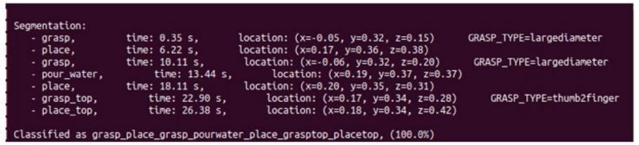
› **Not tested yet for MDLO processes**

RQ4. How can robotic systems be intuitively programmed and reconfigured to adapt to rapidly changing industry demands?

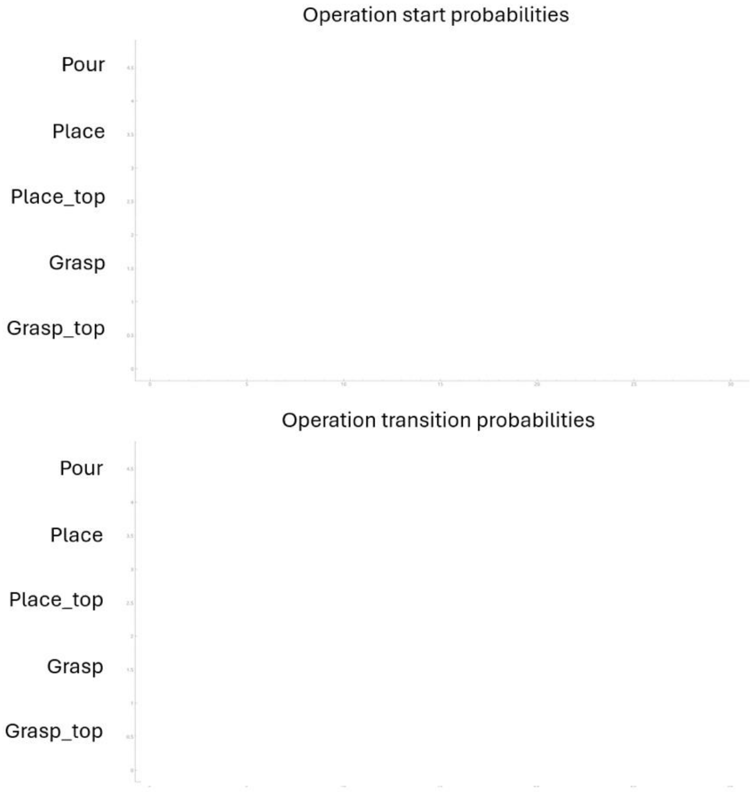
Operation sequence recognition





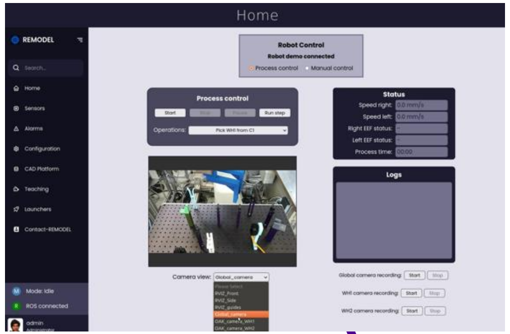


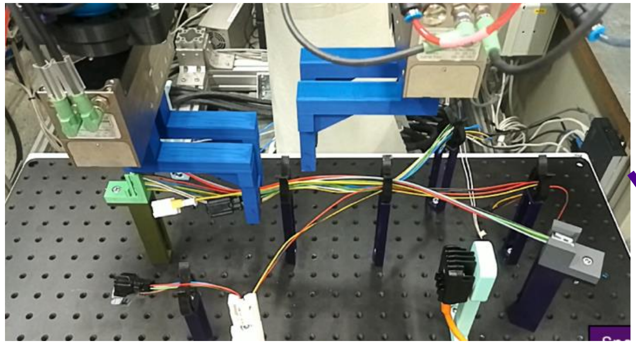
```
Segmentation:
  - grasp,        time: 0.35 s,      location: (x=-0.05, y=0.32, z=0.15)     GRASP_TYPE=largediameter
  - place,        time: 6.22 s,      location: (x=0.17, y=0.36, z=0.38)
  - grasp,        time: 10.11 s,      location: (x=-0.06, y=0.32, z=0.20)     GRASP_TYPE=largediameter
  - pour_water,        time: 13.44 s,      location: (x=0.19, y=0.37, z=0.37)
  - place,        time: 18.11 s,      location: (x=0.20, y=0.35, z=0.31)
  - grasp_top,        time: 22.90 s,      location: (x=0.17, y=0.34, z=0.28)     GRASP_TYPE=thumb2finger
  - place_top,        time: 26.38 s,      location: (x=0.18, y=0.34, z=0.42)

Classified as grasp_place_grasp_pourwater_place_grasptop_placetop, (100.0%)
```



- **Not tested yet for MDLO processes**

Summary





RQ3

Publication V
Graphical user interface for ROS-based systems

RQ1

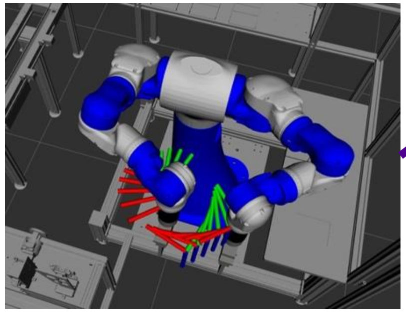
Publication II
Synthetic MDLO segmentation dataset generation

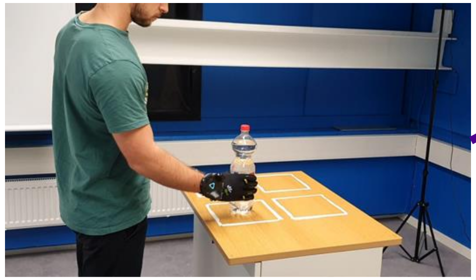
RQ2

Publication III
Advanced motion planning capabilities

Publication VI
Task-planner and integration for wire harness assembly

Publication I
Vision-based MDLO shape estimation





Publication IV
Task-level Programming by Demonstration framework

RQ4

Perception and planning for dual-arm robotic manipulation of multi-deformable linear objects in wire harness assembly

ELLIIT Focus period Lund 2025

Pablo Malvido Fresnillo – Tampere University

Thank you