MSc.
Robotics and Computer Vision

Comparative Analysis for a Peg-In-Hole Assembly Task with 4 different Control Approaches

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Thesis Defense

Table of Content

1.

Introduction

- The Era of Robotics
- Automation in Robotics
- Serial manipulators
- Human Robot Interaction (HRI)
- Autonomy Level

Serial Manipulators challenges

- Performance
- Measurement
- Manufacturers & Users

Accuracy

Reaching the commanded position with minimum error

Repeatability

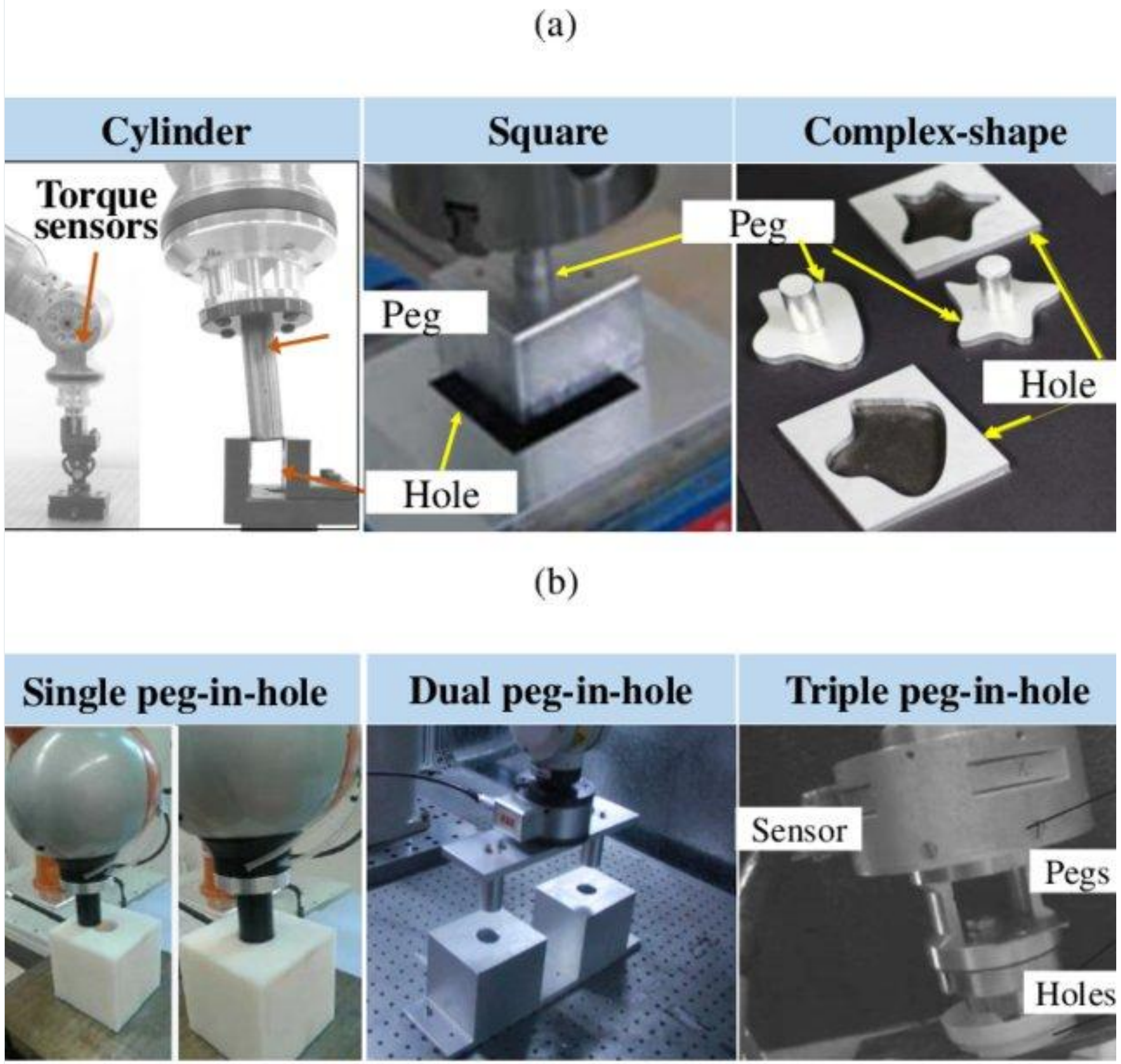
How likely can the system perform accurately given the same task

Resolution

The smallest increment value the system can read/write in control

Serial Manipulators challenges

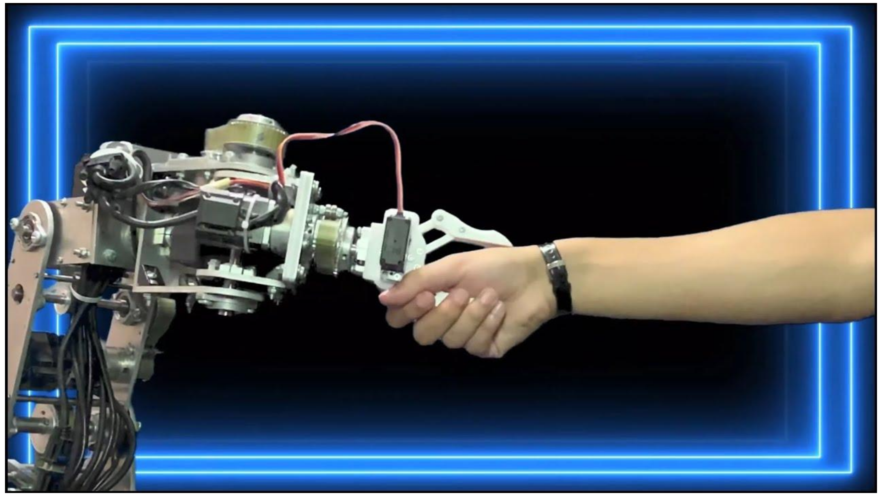
- Assembly Tasks with small clearances
- The positional errors can be > the clearance of the task



source: Xu, Jing & Hou, Zhimin & Liu, Zhi & Qiao, Hong. (2019). Compare Contact Model-based Control and Contact Model-free Learning: A Survey of Robotic Peg-in-hole Assembly Strategies.

Human-Robot Interaction

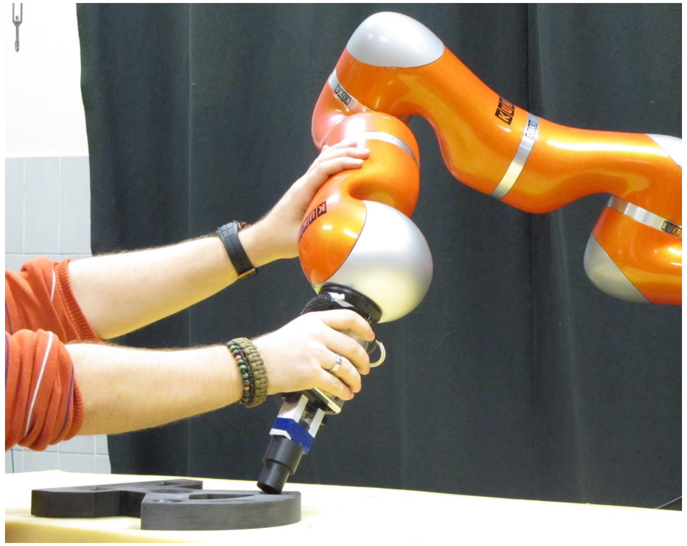
> "Human–Robot Interaction (HRI) is a relatively young discipline that has attracted a lot of attention over the past few years due to the increasing availability of complex robots and people's exposure to such robots in their daily lives"



M. Soegaard and R. F. Dam, "38," in *Encyclopedia of Human-Computer Interaction*, Interaction Design Foundation, 2013.

Human-Robot Interaction

Physical operation



Acquired from: trinityrobotics.ru

Tele-operation

Co-operation

Acquired from: blog.pal-robotics.com

Thesis Scope and Approach

Problem Statement

1. Autonomous systems:
   - accuracy & repeatability
   - Intolerant to dynamic environments
   - hard to program
2. Human:
   - experience dependent
   - adaptable to dynamic changes
   - easy to program

Objectives

1. Evaluate Autonomous control
2. Development of a Tele-operation system to assist in tasks
3. Developing a LfD framework
4. Conduct experiments and give comparative analysis between the different approaches

Thesis Problem Statement

Autonomous Systems

- accuracy & repeatability
- Intolerant to dynamic environments
- hard to program

Human

- experience dependent
- adaptable to dynamic changes
- easy to program

Thesis Objectives

1. Autonomous

- Develop a control framework with force & camera feedback

2. Tele-operation

- Develop a Bi-lateral system with haptic feedback

3. Learning from Demonstration

- LfD framework
- Offline & Online LfD

4. Experiments

- Give comparative analysis between the different approaches

2.

Hardware Description

- Touch Haptic Device
- Kuka Iiwa LWR 14

Touch Haptic Device

- Kinematic Structure
- OpenHaptics
  - HDAPI
  - HLAPI

Nominal position resolution	~0.055 mm
Maximum exertable force/torque	3.3 N
Operating frequency	~1 kHz

Kuka LBR iiwa 14

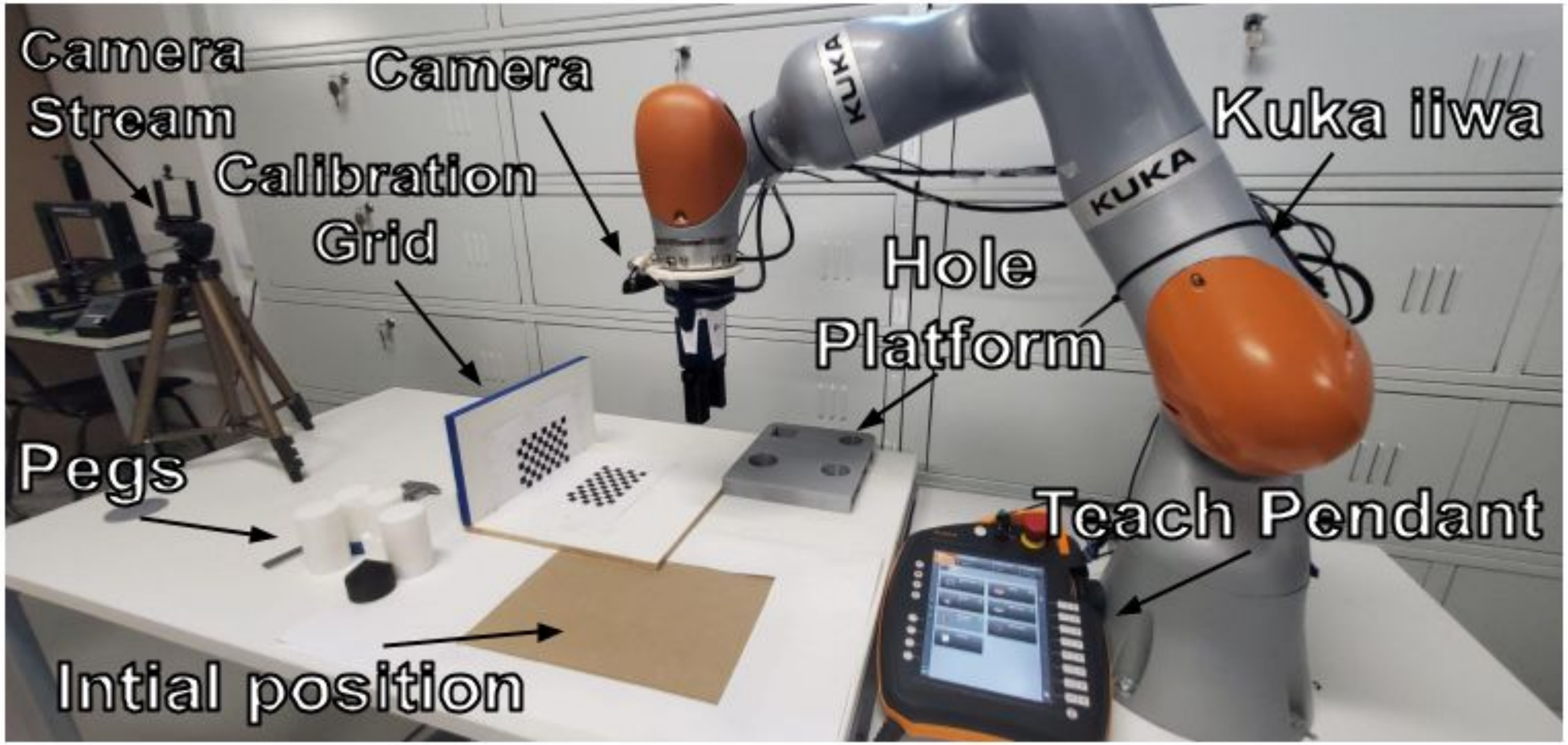
- Kinematic Structure
- Sunrise.Os
  - Sensitive and flexible
  - Safe and precise

Workspace Reach	820 mm
Load Capacity	14 Kg
axis-specific torque accuracy	±2% max torque

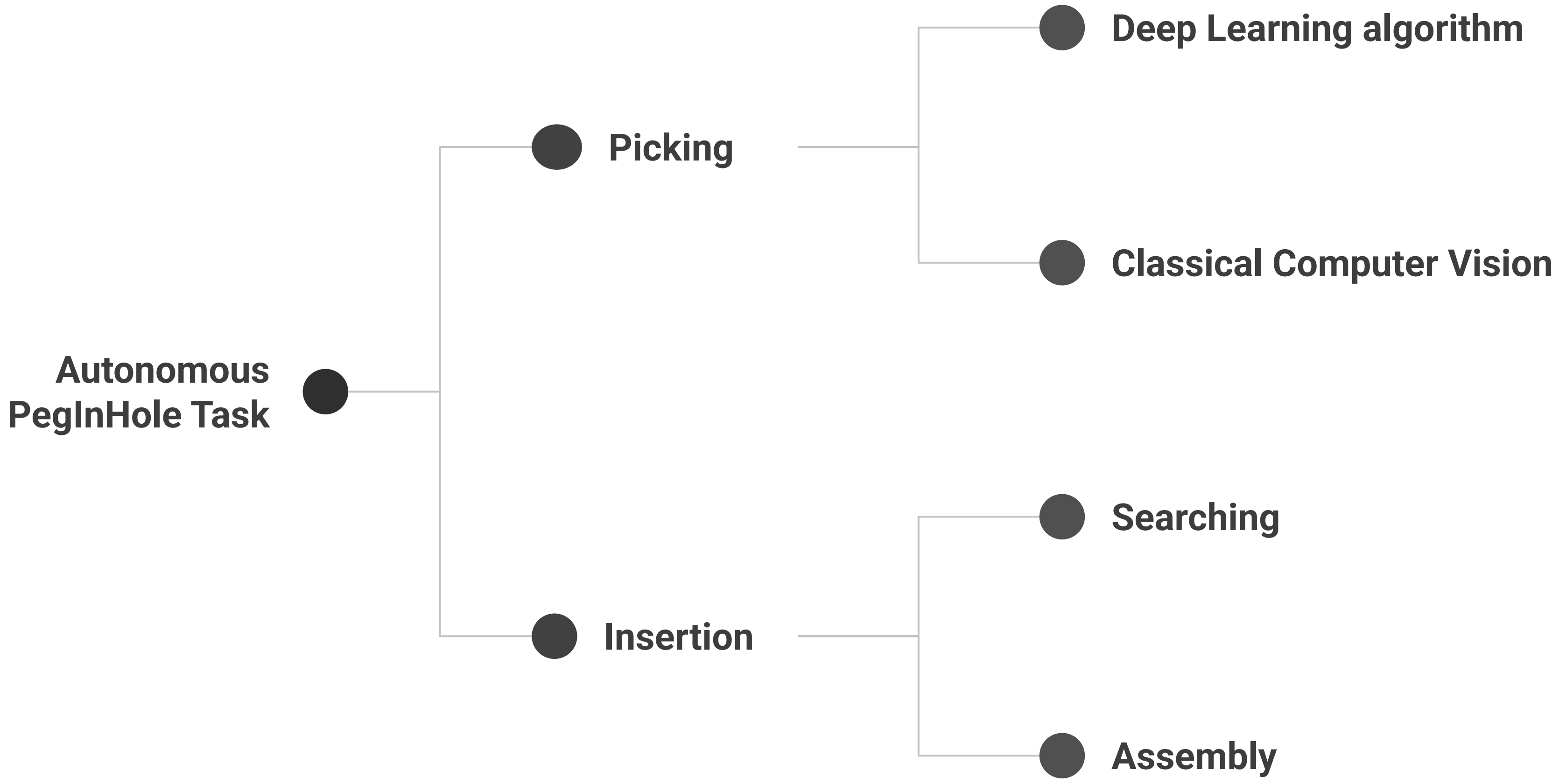
3. Methodology

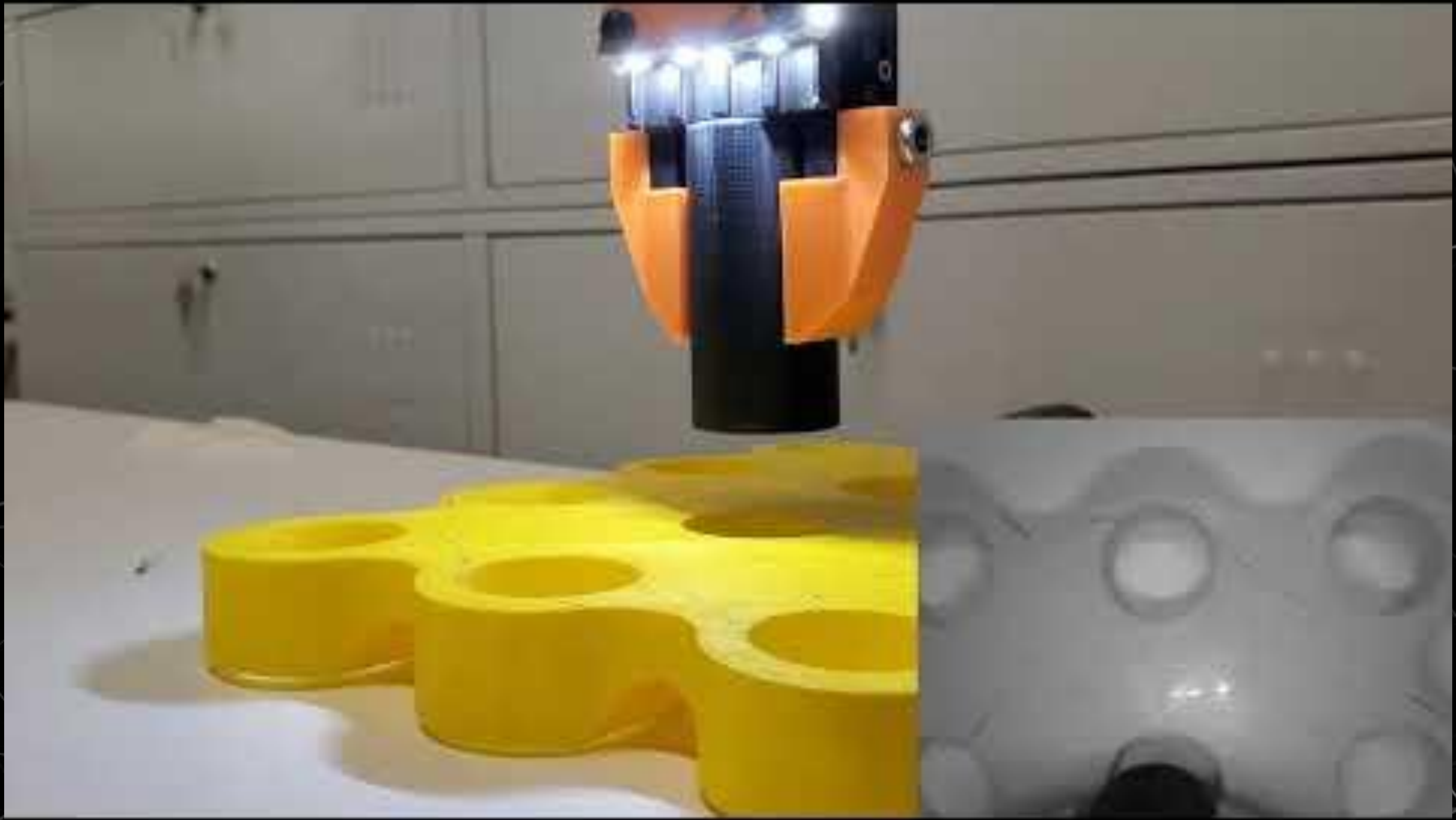
- Autonomous Control
- Bi-lateral Tele-Operation System
- Learning from Demonstration

Environment Setup



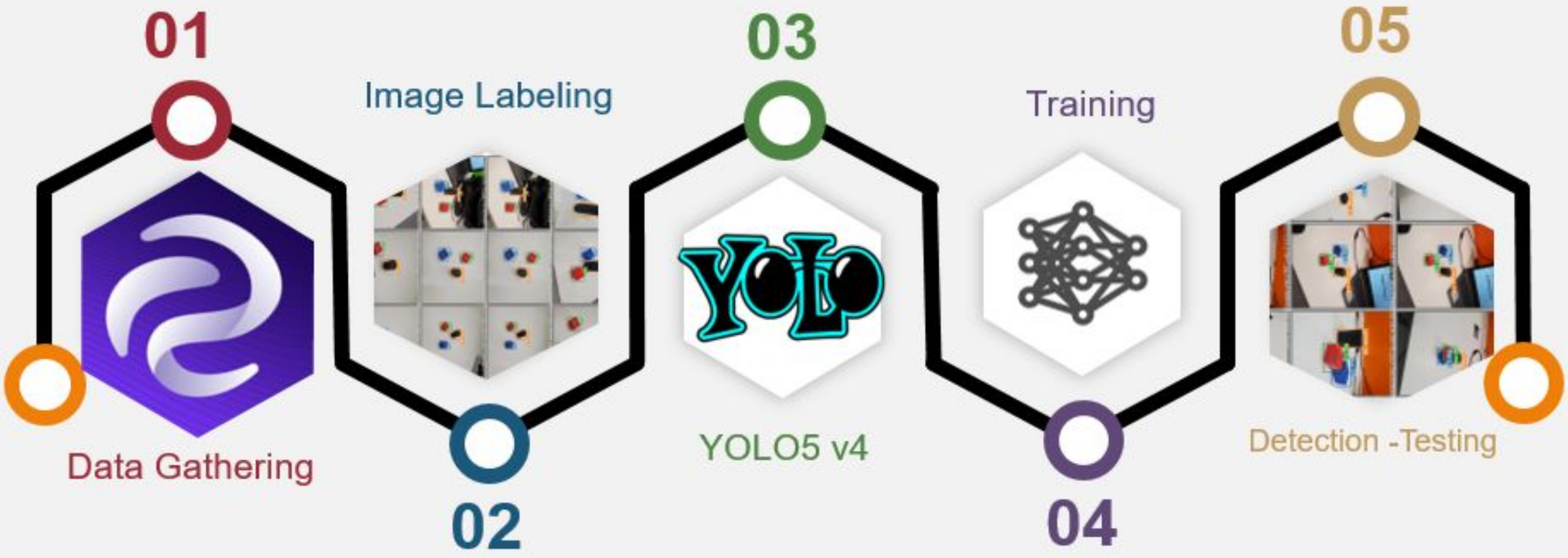
Task Outline

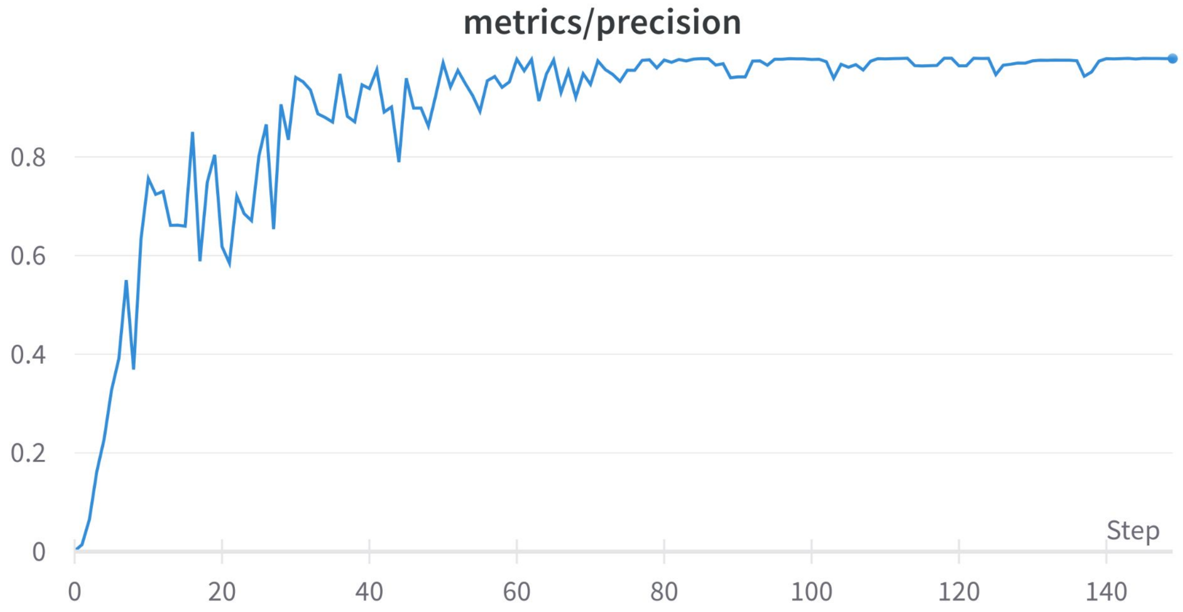


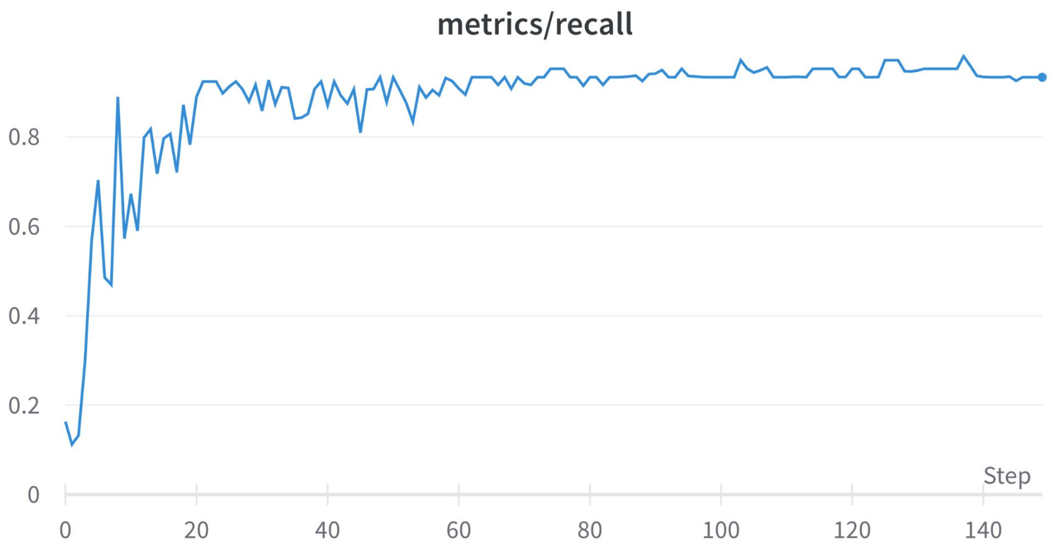


Object Classification and Detection

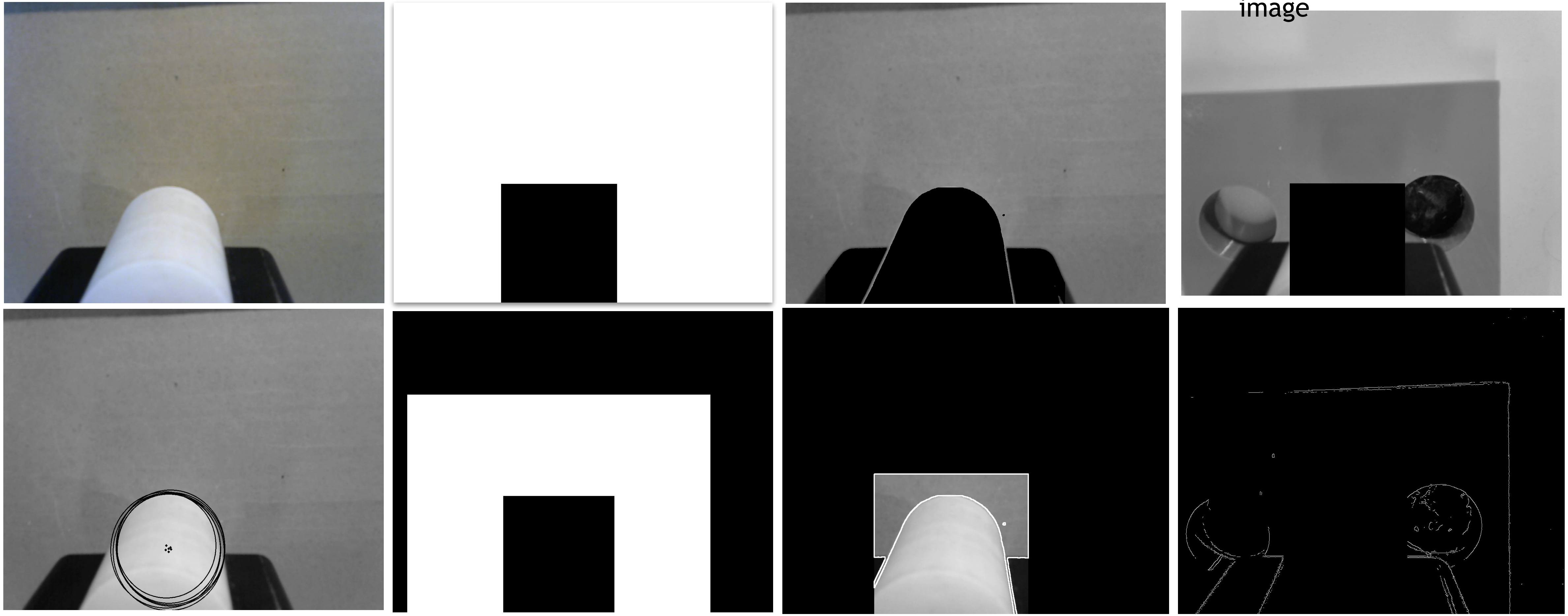
Using Deep Learning Method




metrics/precision
0.8
0.6
0.4
0.2
0
Step
0
20
40
60
80
100
120
140


metrics/recall
0.8
0.6
0.4
0.2
0
Step
0
20
40
60
80
100
120
140

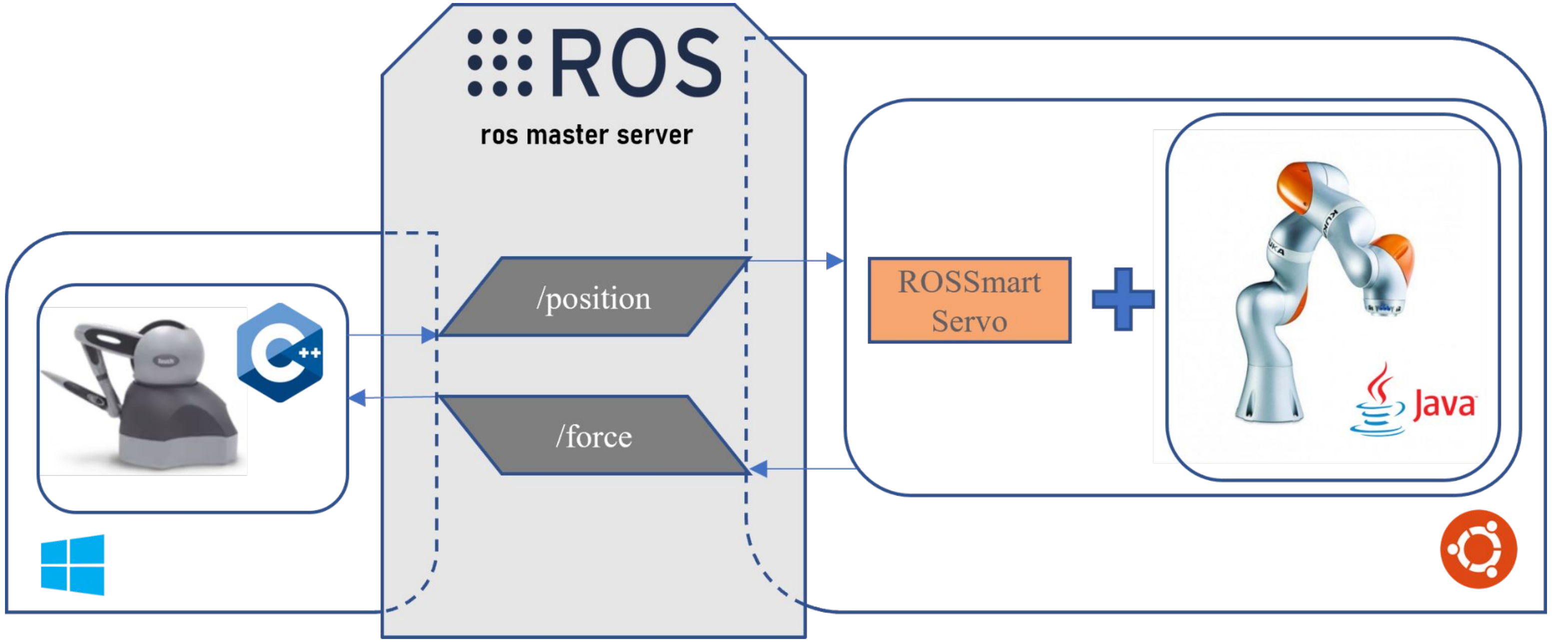
Captured image | Rough detection | Mask for Peg and Jaws | Rough detection image

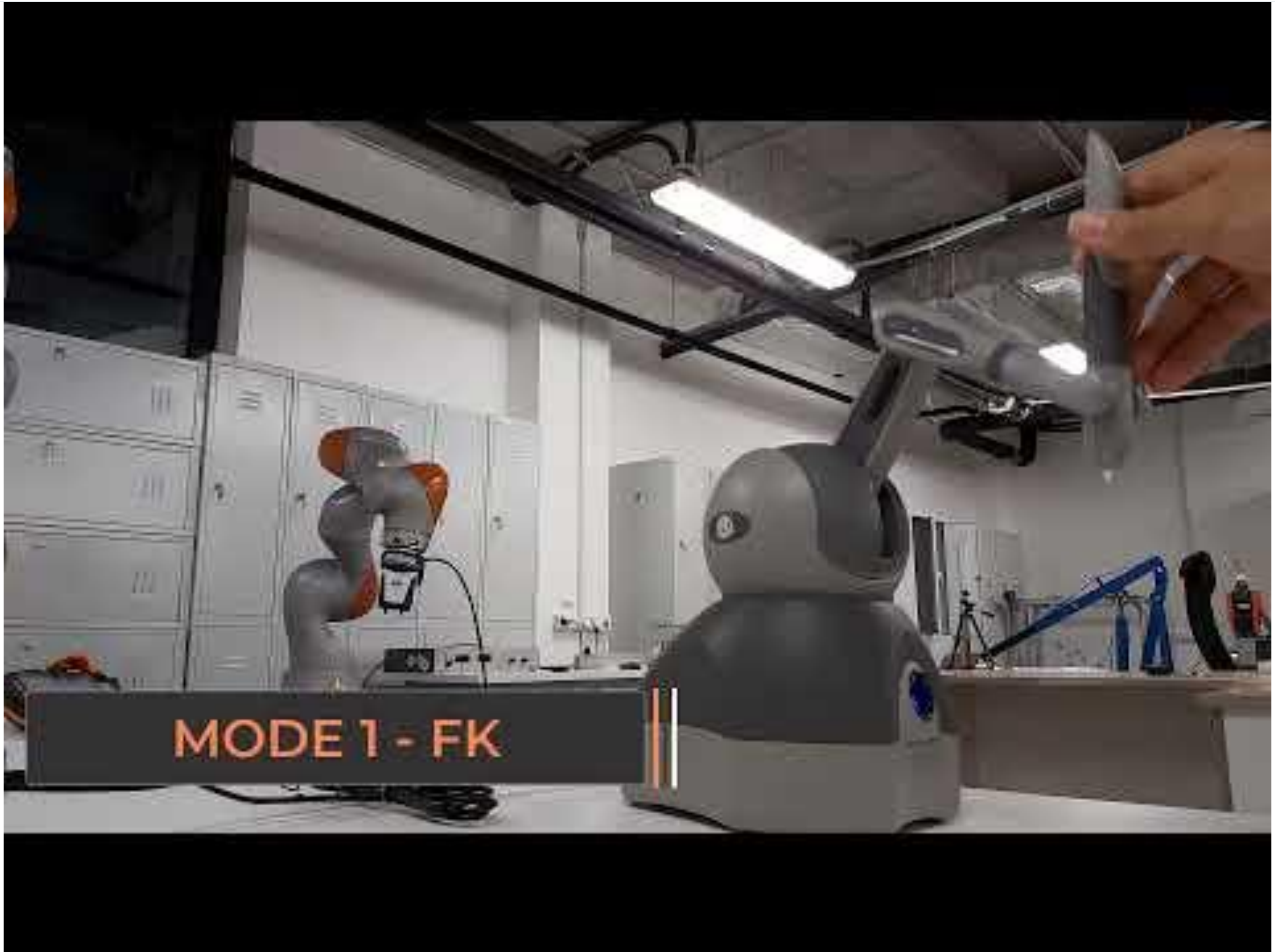


Circle detection | Fine detection | Contour for searching | Dilated Canny filter

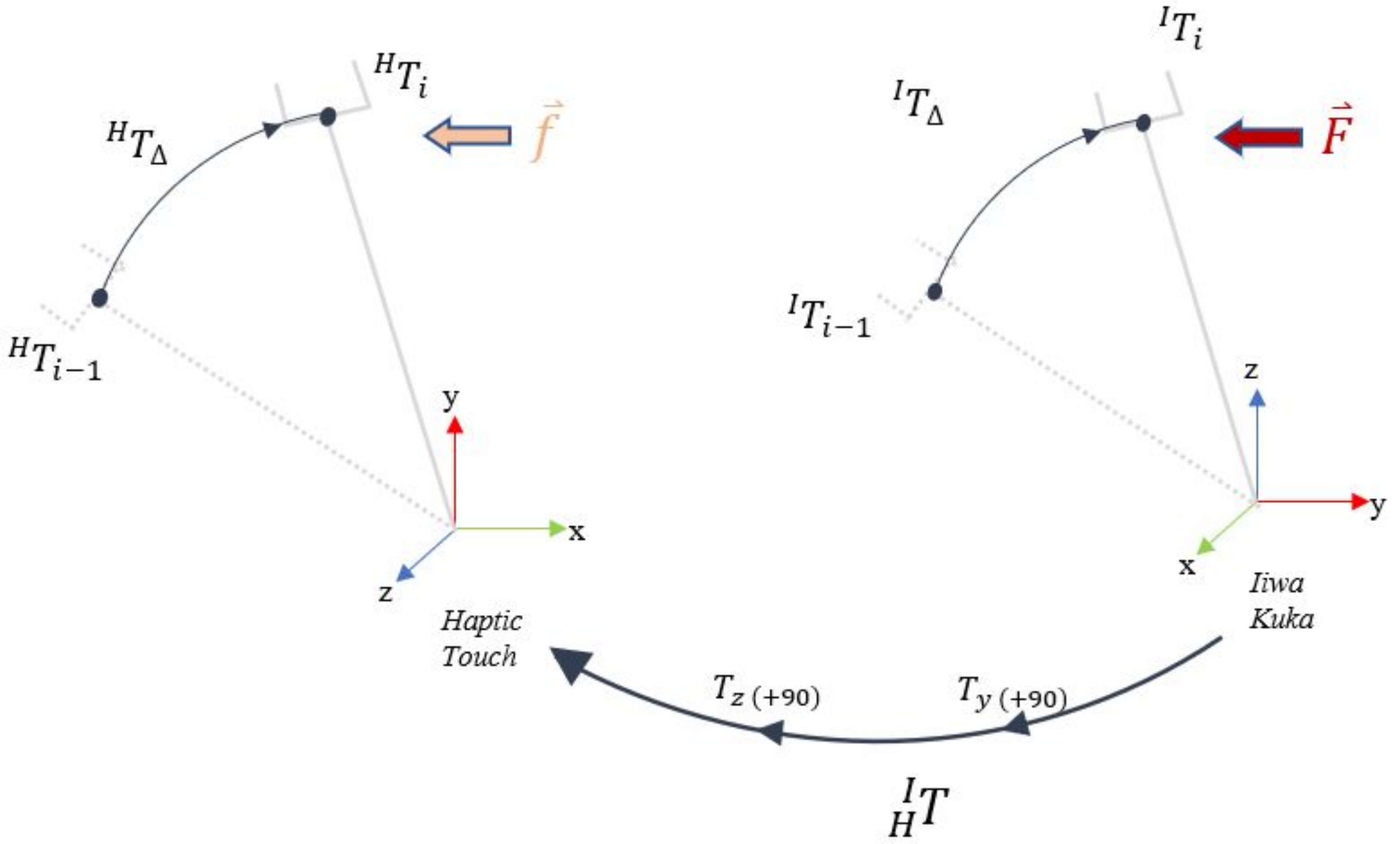
Bi-lateral Tele-Operation System

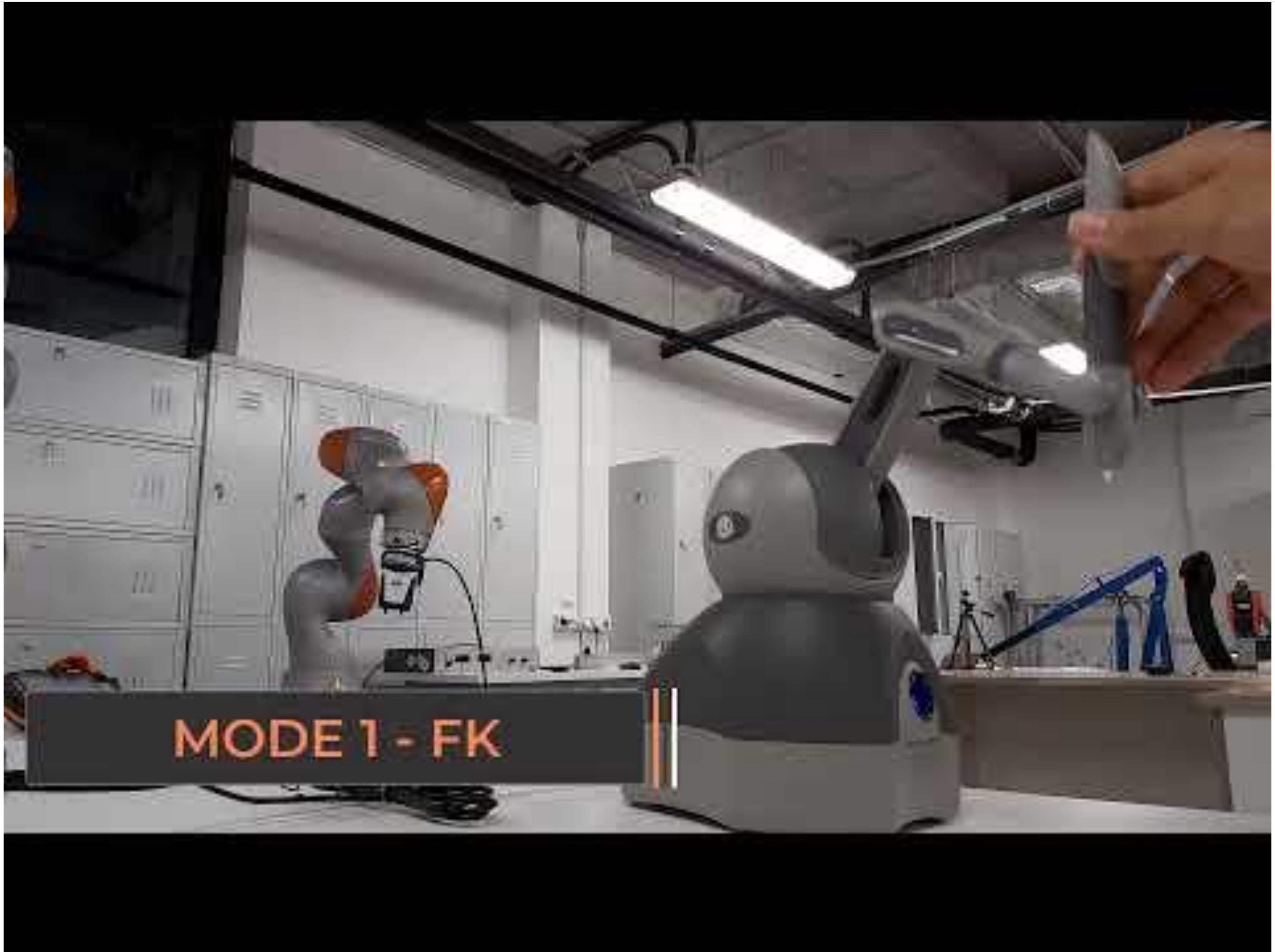
- Joint Space
  - one-to-one mapping
  - Safety checks
- Cartesian Space
  - Δ pose
  - mapping
- Force Feedback




MODE 1 - FK

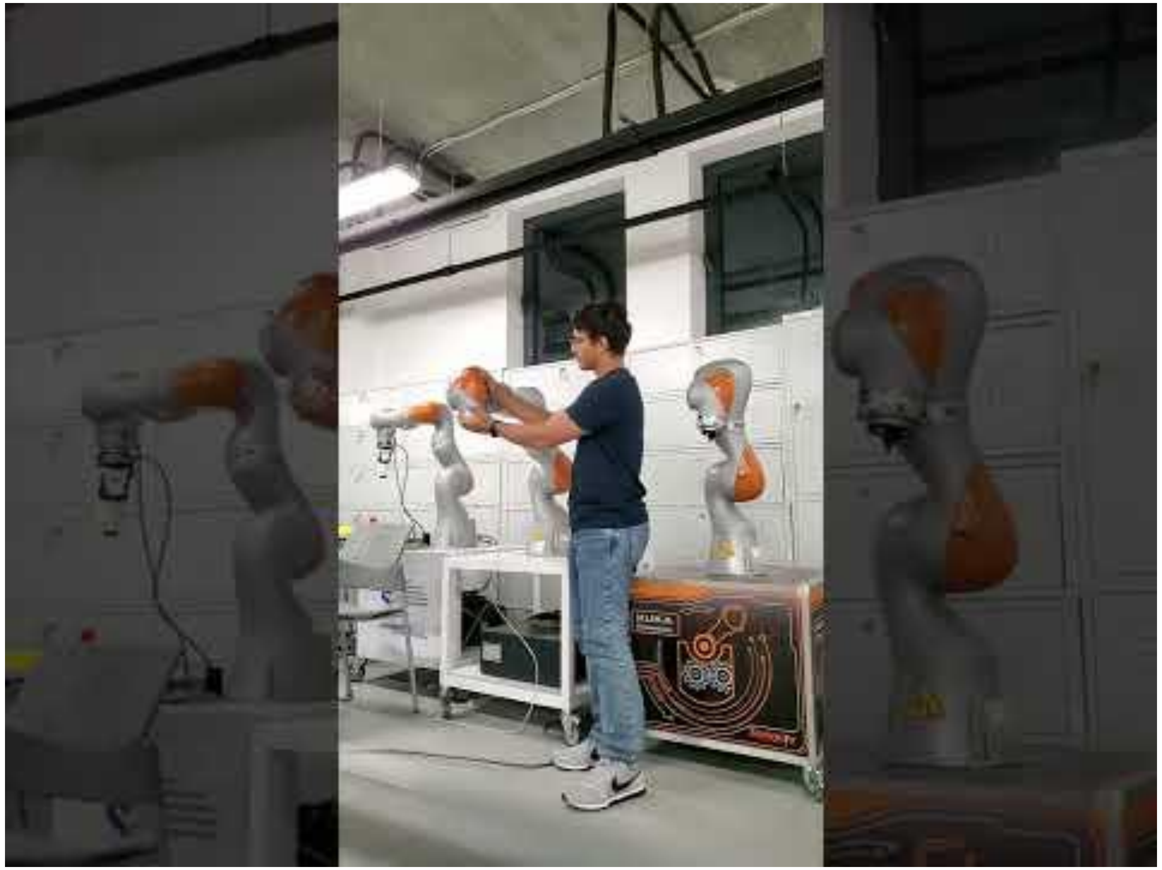
→ Mapping of cartesian pose



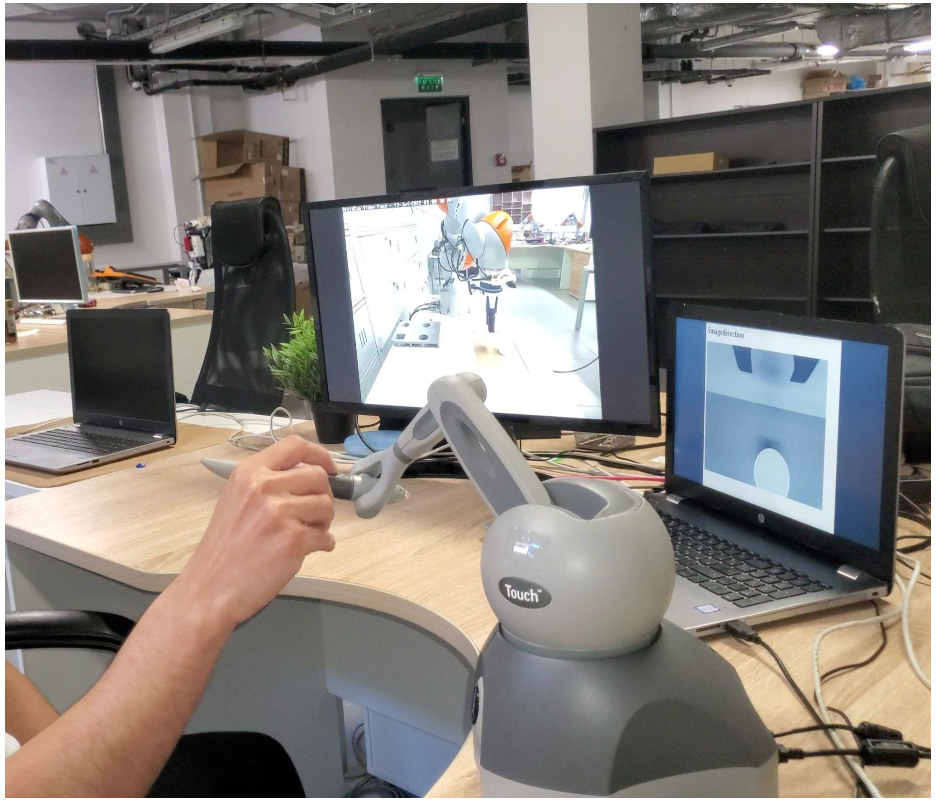

MODE 1 - FK

Learning from Demonstration

Kinesthetic Demonstrations



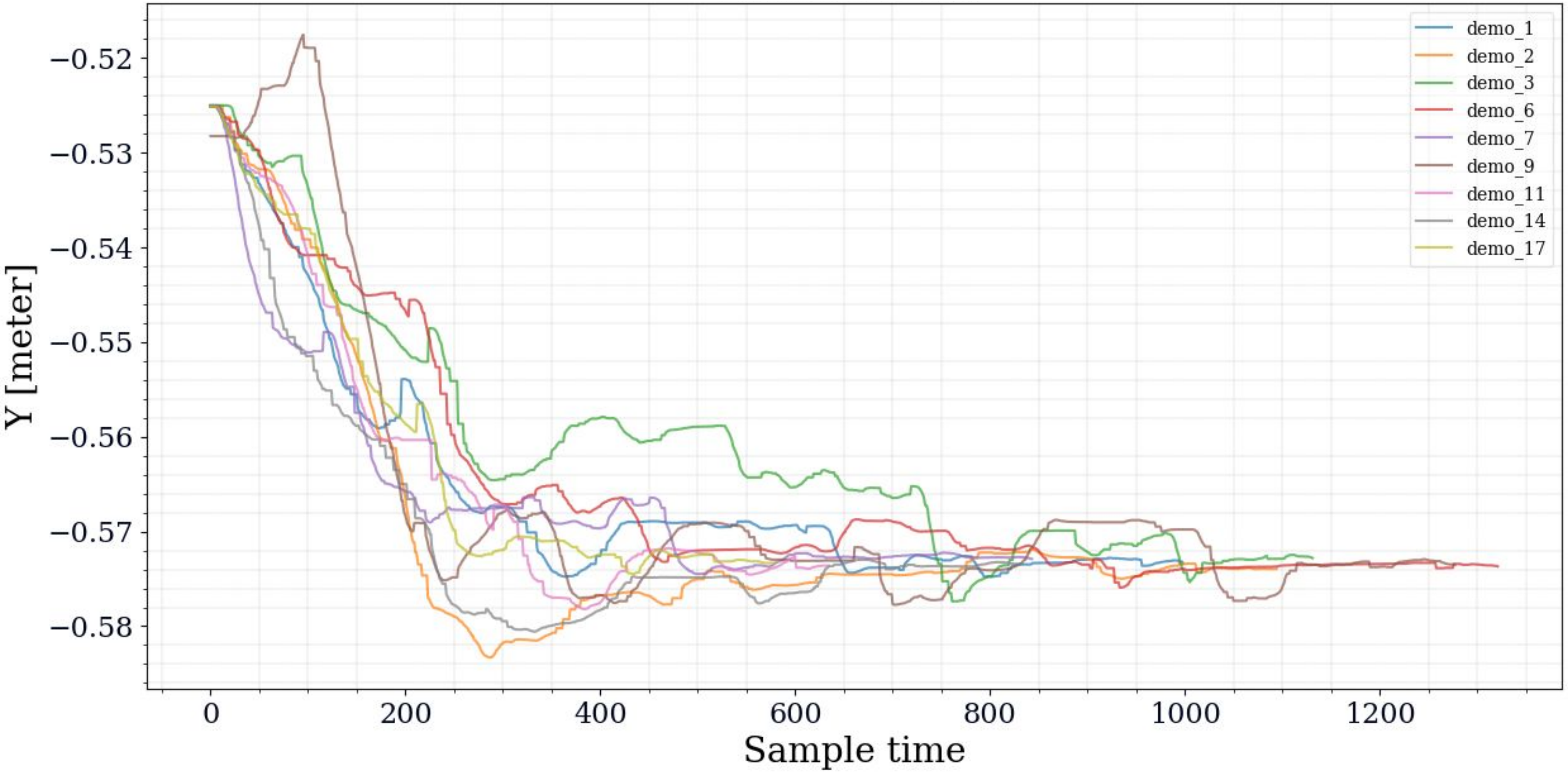
Tele-operated Demonstrations



Learning from Demonstration

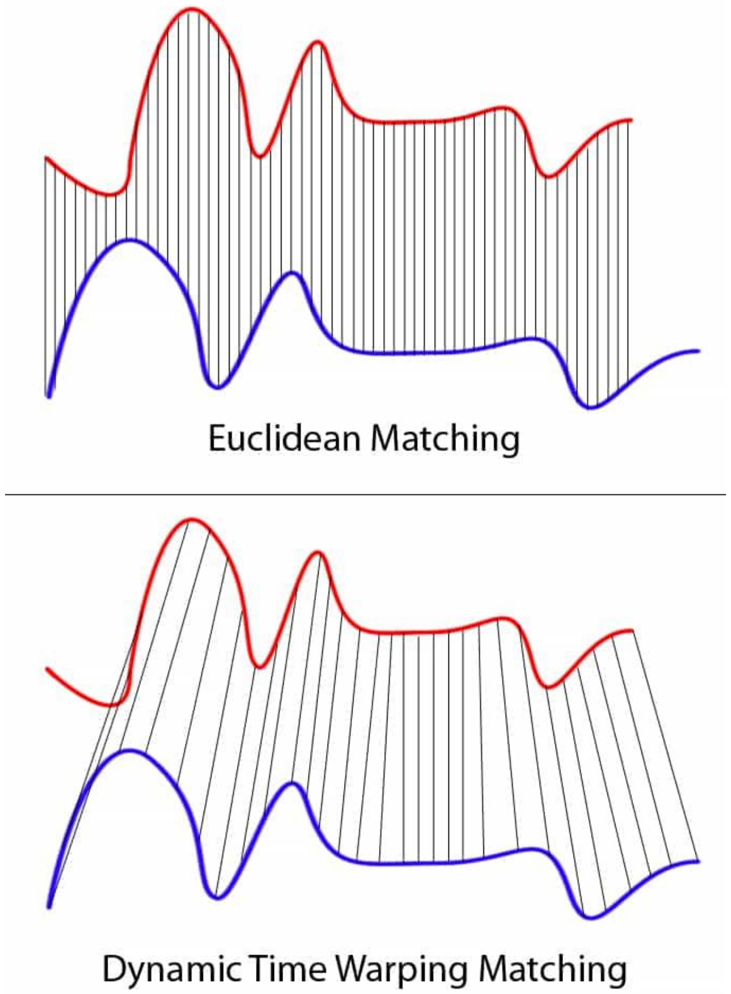
$$
\begin{cases}
\vec{p} & = [x, y, z] \rightarrow \vec{p} : \text{position vector of Kuka's Iiwa EE,} \\
X_n & = \{\vec{p}, t\}, \quad t : \text{temporal variable which is time sequence,} \\
X_n & \in Demon \rightarrow n : \text{Demonstration index from Demonstrations library}(Demon), \\
\therefore & X_n \in R^4 \rightarrow X : \text{Demonstration data of dimension 4.}
\end{cases}
$$

Learning from Demonstration



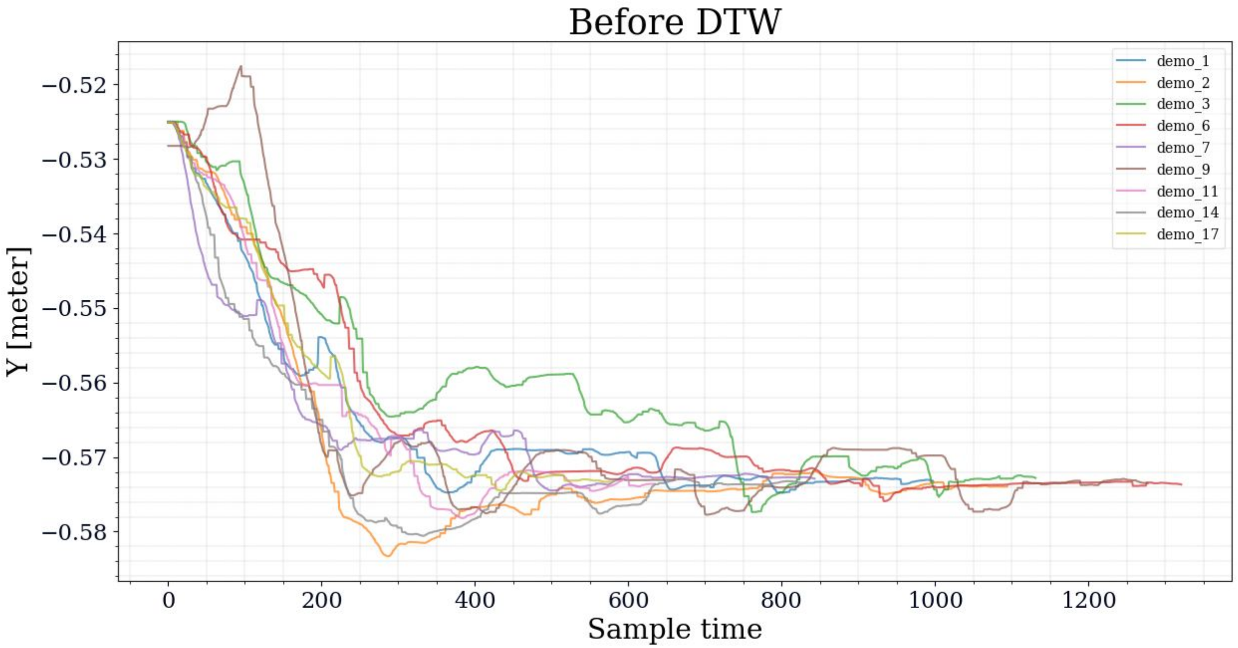
Dynamic Time Warping (DTW)

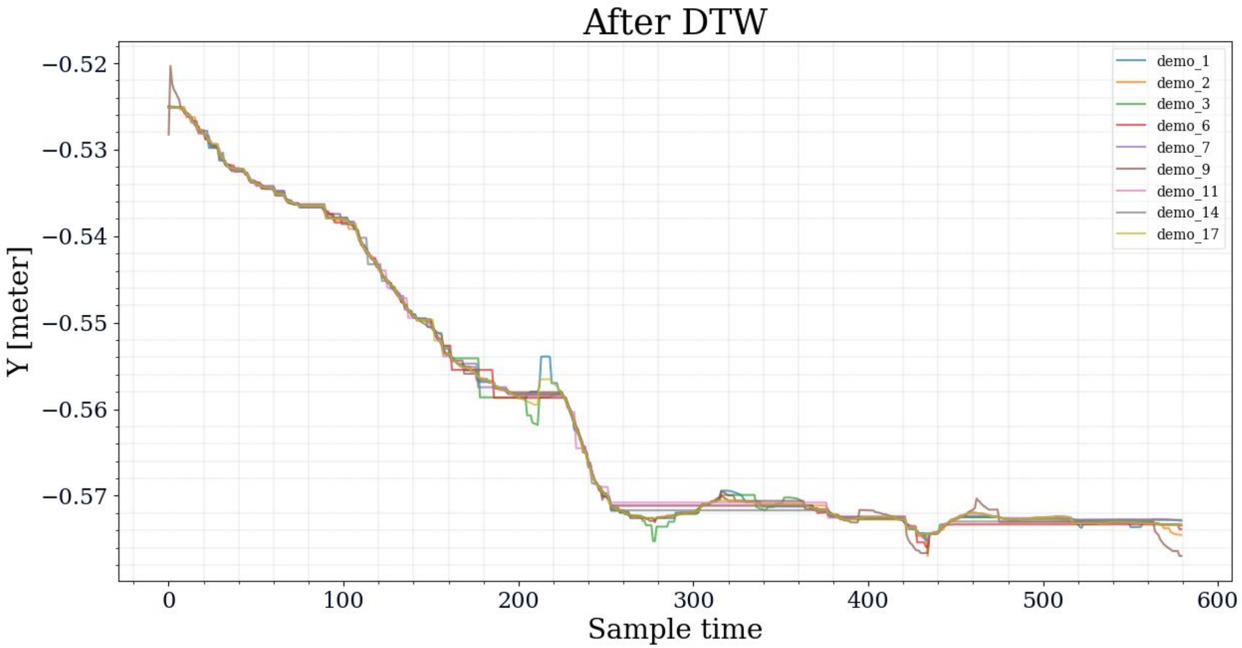
- ➔ Is an algorithm that matches any 2 time series signals.
- ➔ It computes the Distance matrix between the two signals, matching each point to one or more points from the other signal.
- ➔ Used in:
  - ◆ Speech recognition
  - ◆ Financial Stocks
  - ◆ Recording motion patterns
- ➔ We use it here to find the best Demonstration and match the others to it.



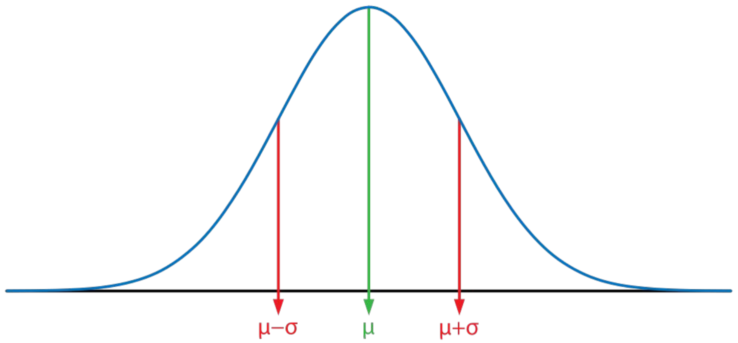
Acquired from: databricks.com

Dynamic Time Warping (DTW)



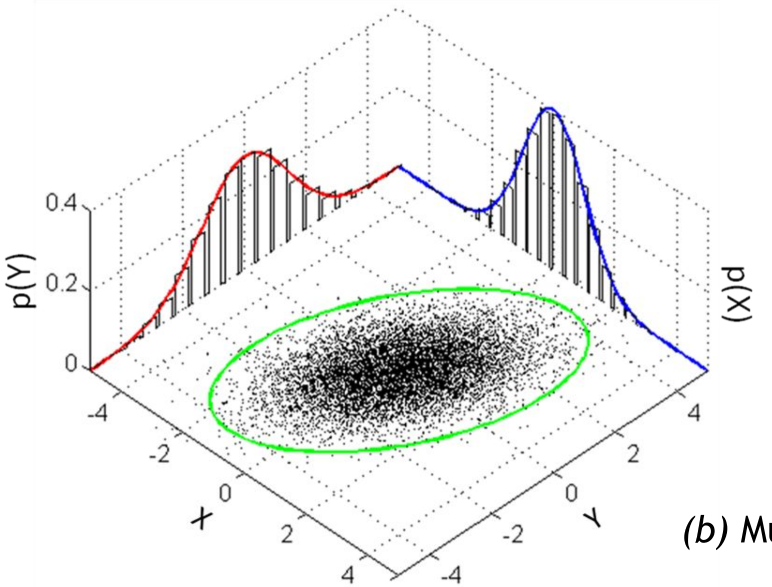


Gaussian Mixture Model (GMM)



$$P(x|\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp - \frac{(x-\mu)^2}{2\sigma^2} \quad \equiv \quad \mathcal{N}(\mu, \sigma)$$

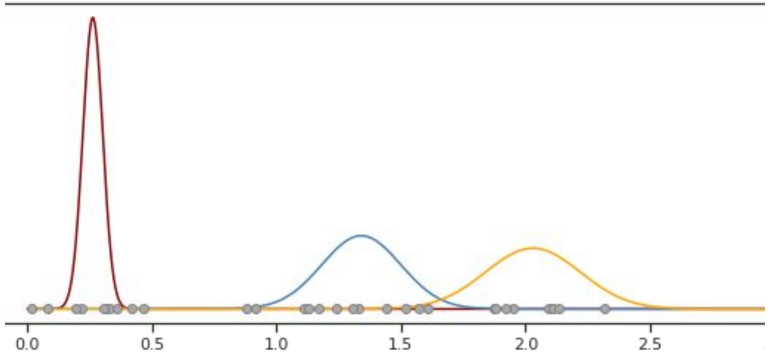
(a) Univariate Gaussian Model



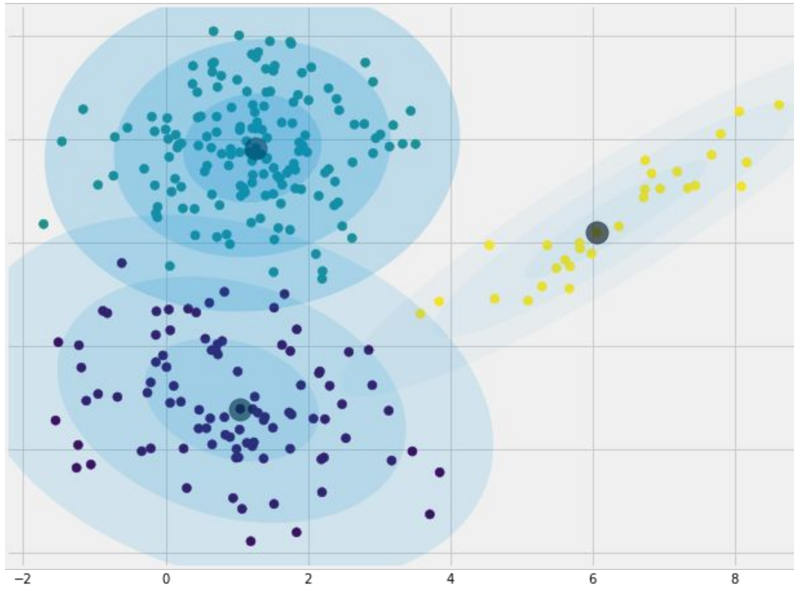
$$P(X|\theta) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{\frac{1}{2}}} \exp - \frac{(X-\mu)^T\Sigma^{-1}(X-\mu)}{2} \quad \equiv \quad \mathcal{N}(\mu, \Sigma)$$

(b) Multivariate Gaussian Model

Gaussian Mixture Model (GMM)



(c) Univariate Gaussian Mixture Model



(d) Multivariate Gaussian Mixture Model

$$P(X) = \sum_{k=1}^{K} \pi_k \mathcal{N}_k(X|\mu_k, \Sigma_k)$$

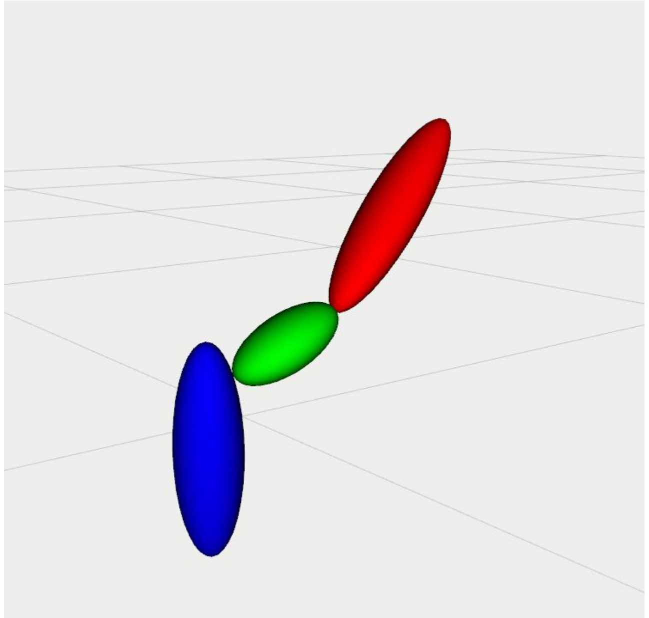
$$0 \leq \pi_k \leq 1 \quad , \quad \sum_{k=1}^{K} \pi_k = 1$$

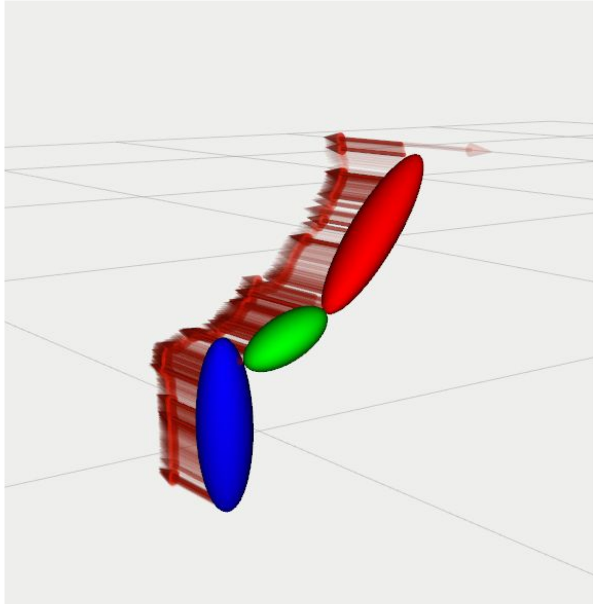
$$\mu_k \in R^4 \quad , \quad \Sigma \in R^{4\times 4}$$

Gaussian Mixture Model (GMM)

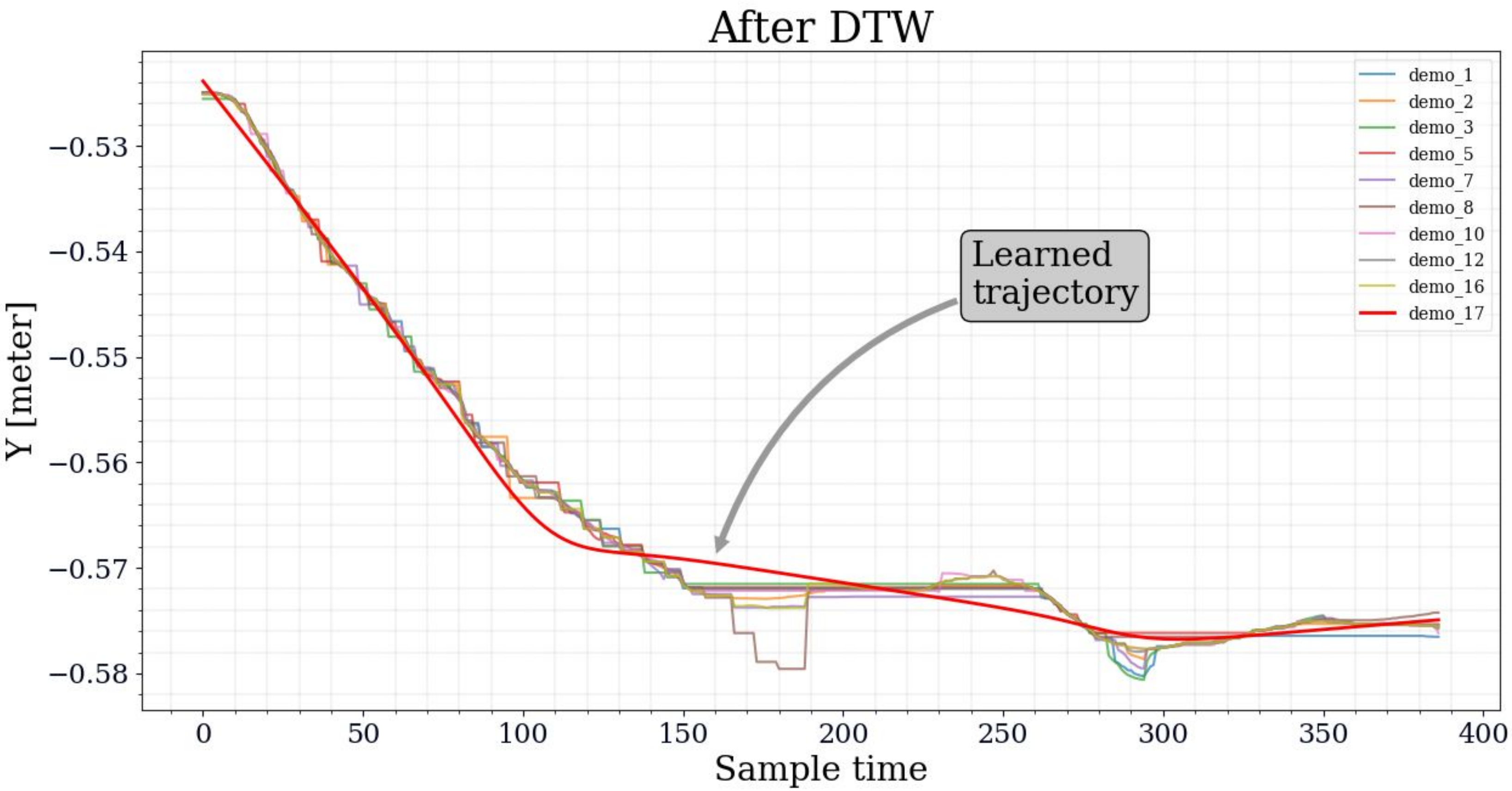
Using Expectation Maximization (EM) algorithm to maximize the likelihood to get the GMM parameters.

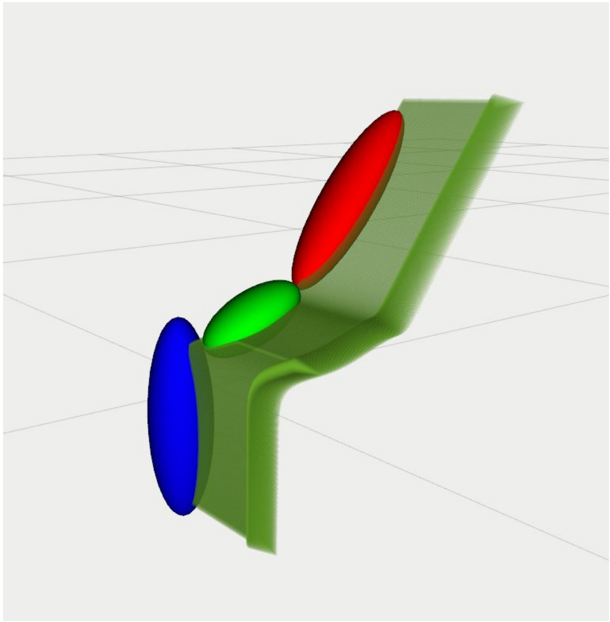
$$\log p(X|\{\mu, \Sigma, \pi\}_k) = \sum_{i=1}^{N} \log(\sum_{k=1}^{K} \pi_k \mathcal{N}_k(X_i|\mu_k, \Sigma_k))$$



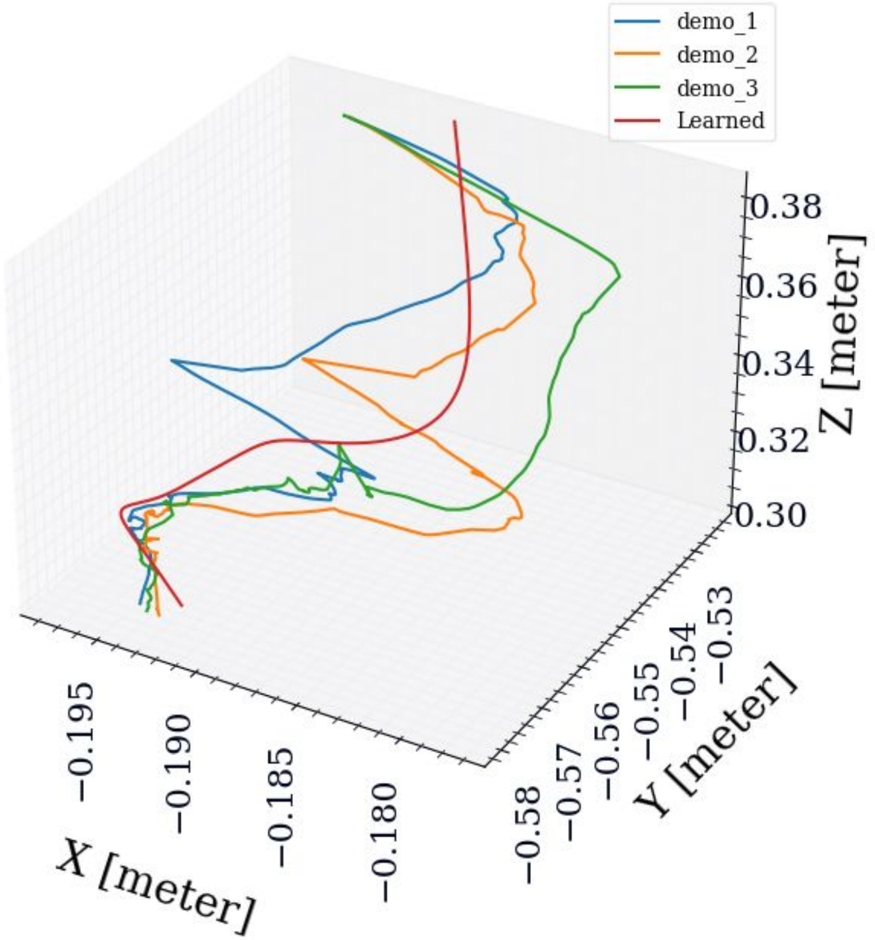


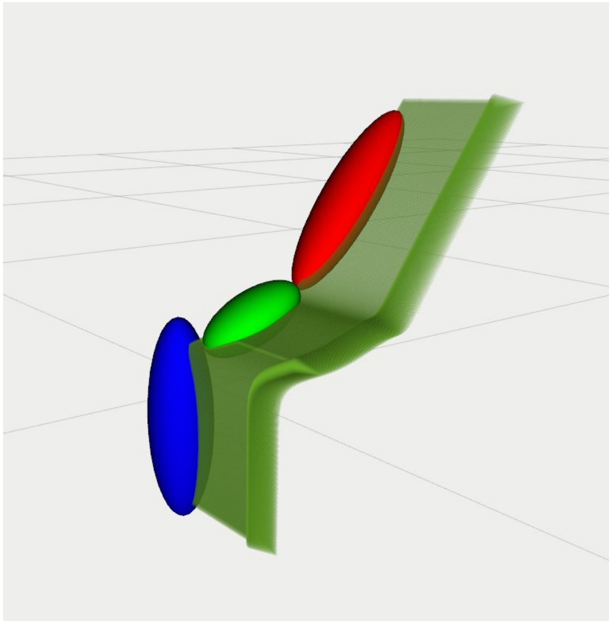
Gaussian Mixture Regression (GMR)



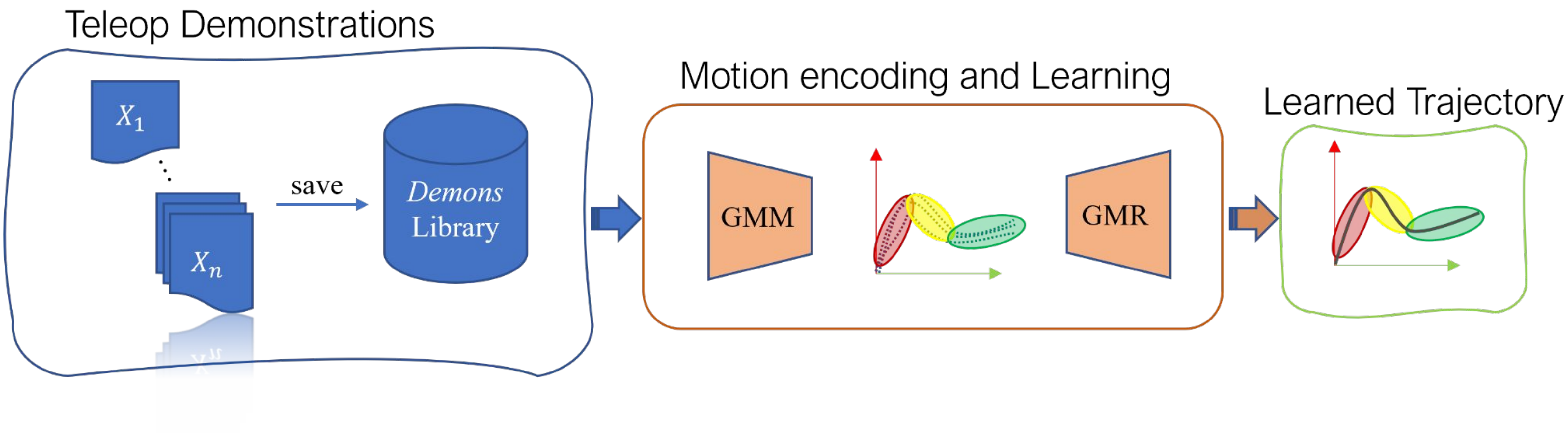


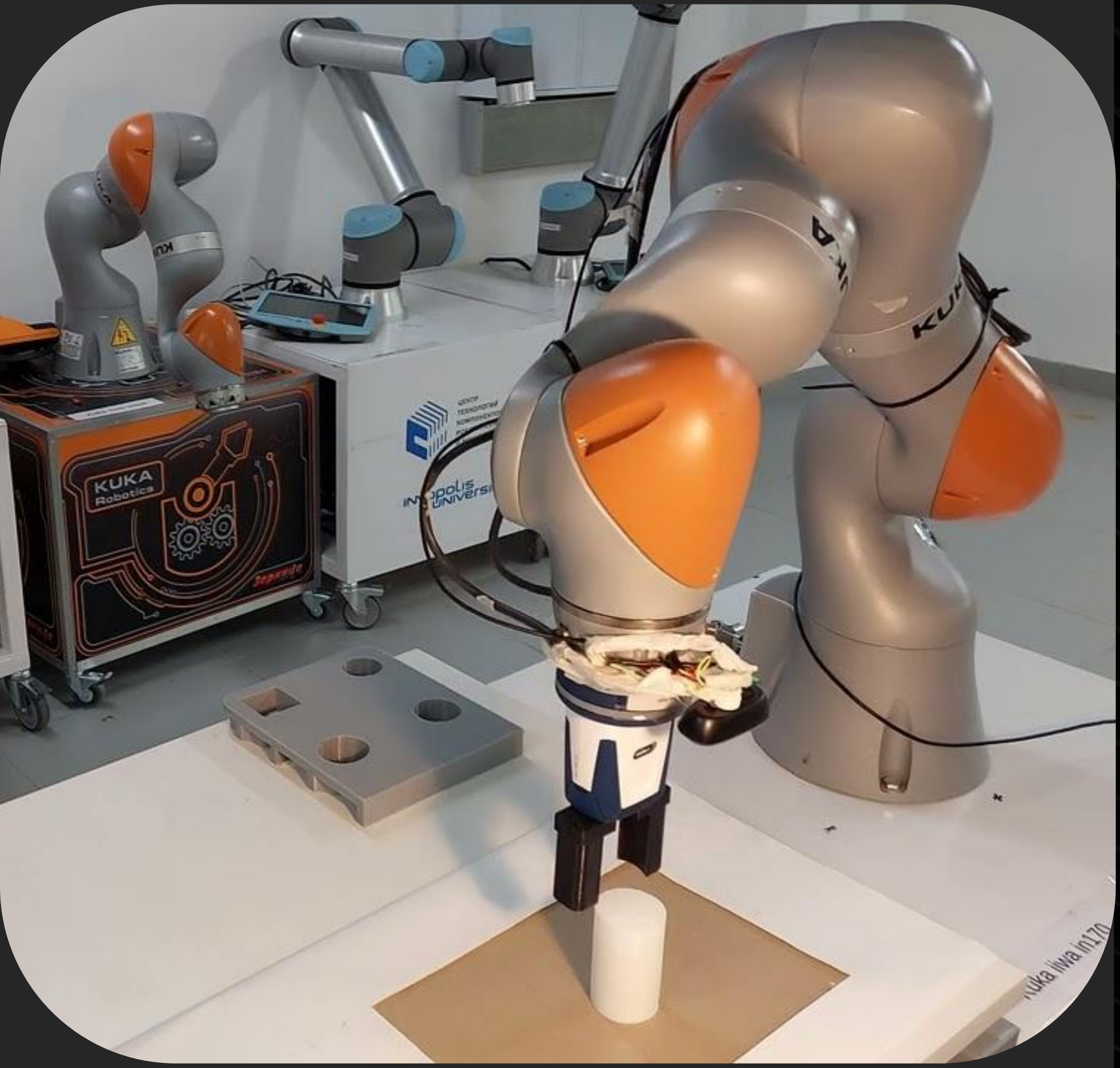
Gaussian Mixture Regression (GMR)





Gaussian Mixture Regression (GMR)

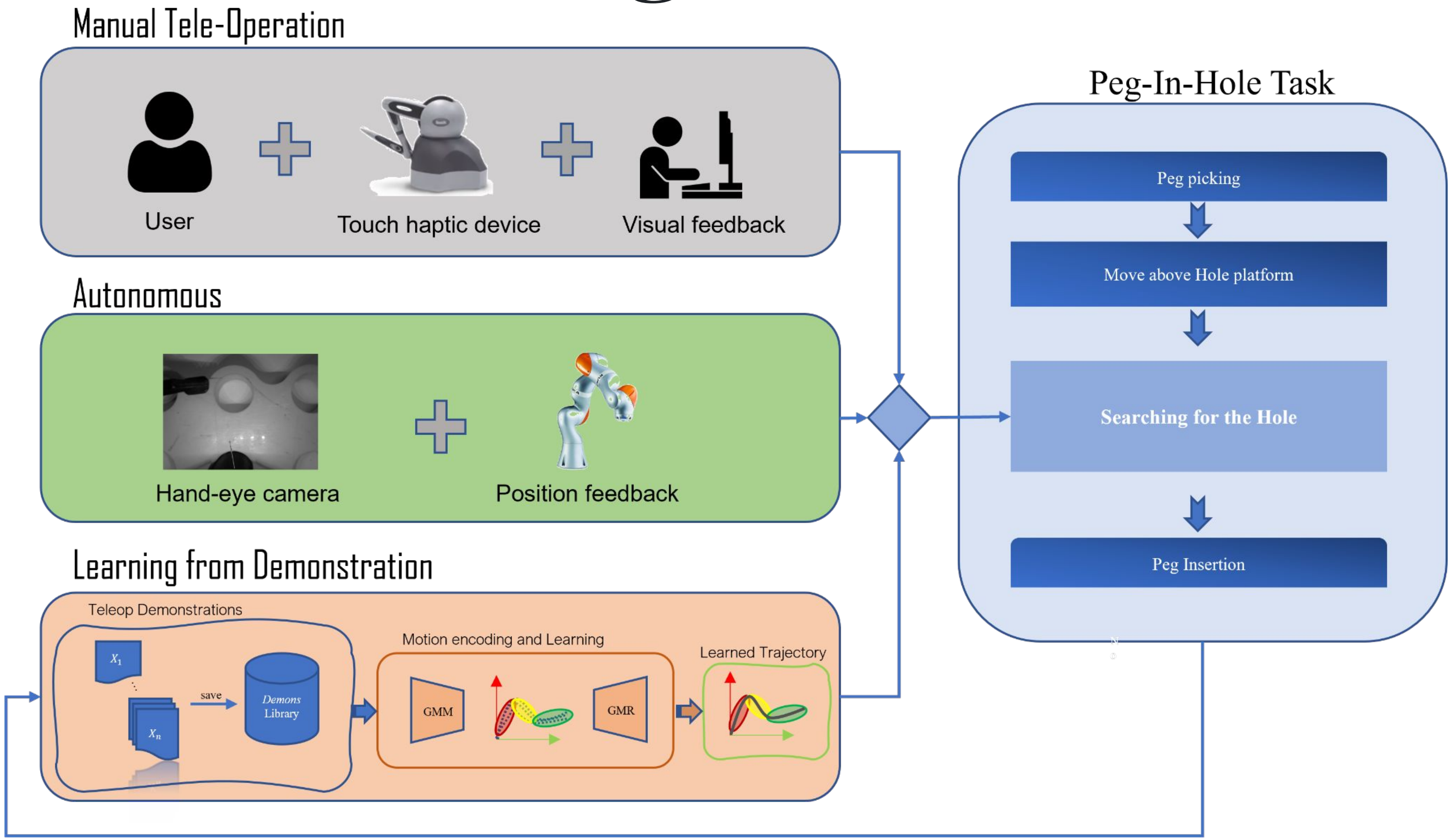




5. Experimentation

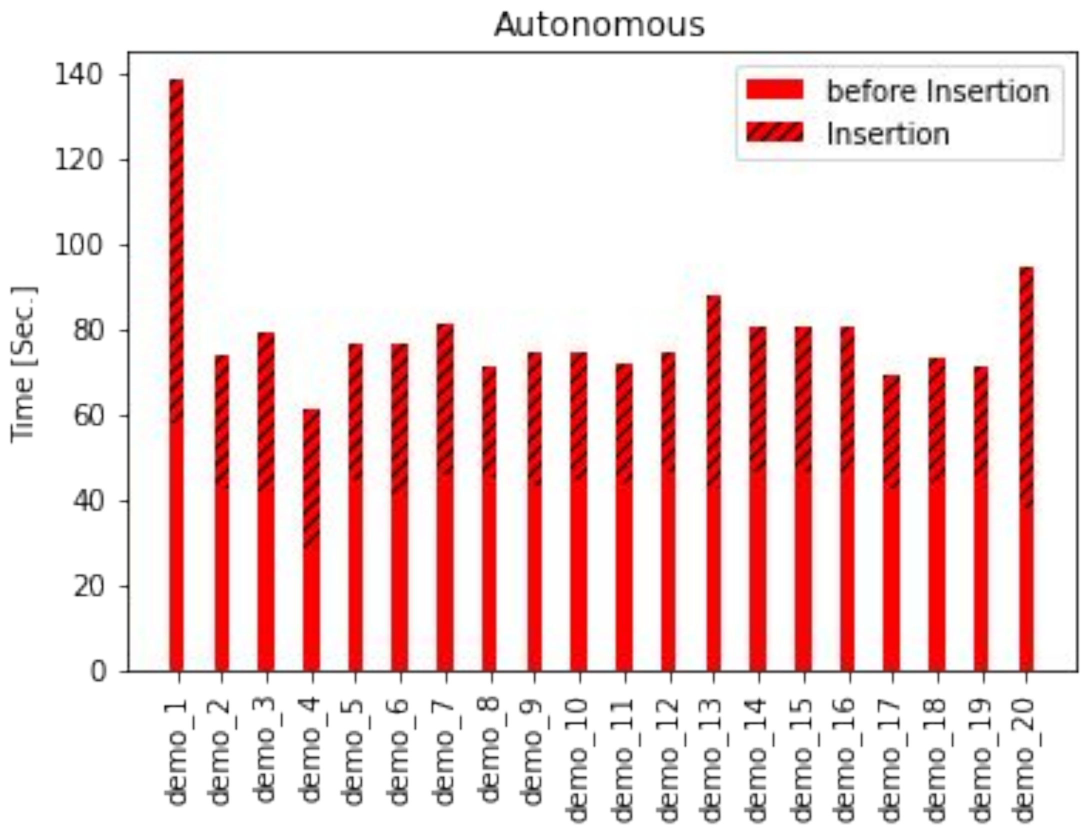
- Environment setup and task description
- 20 Experiments for each control approach:
  - Autonomous
  - Shared
  - Offline LfD
  - Offline LfD

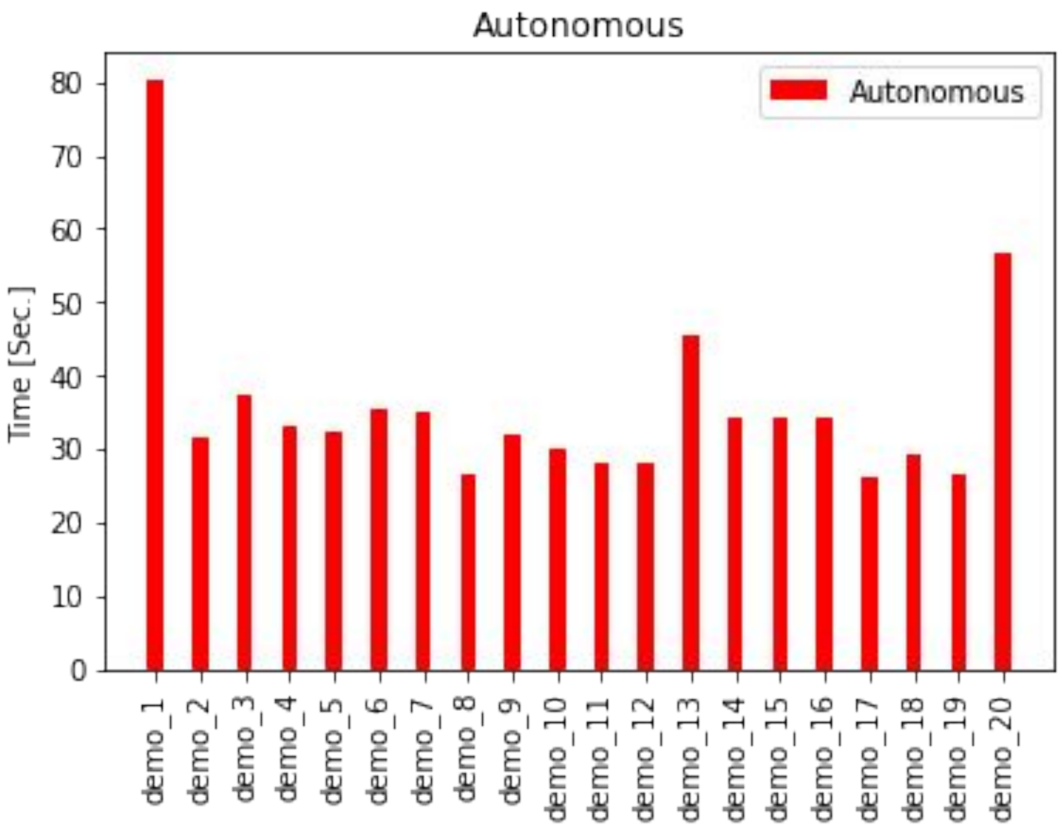
Experiment diagram



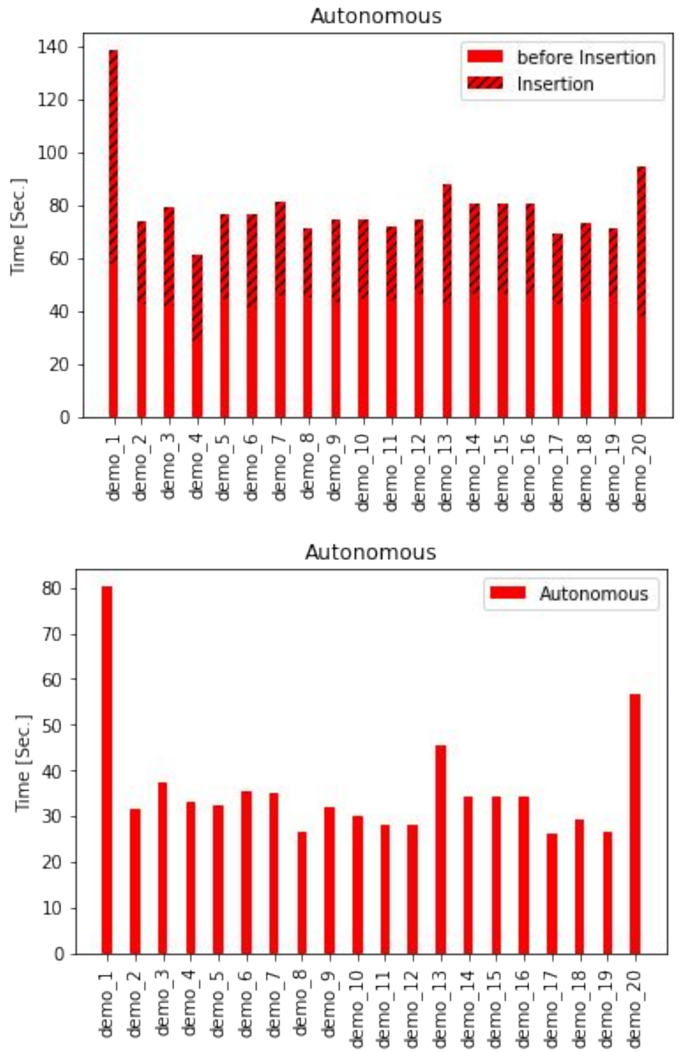

x2

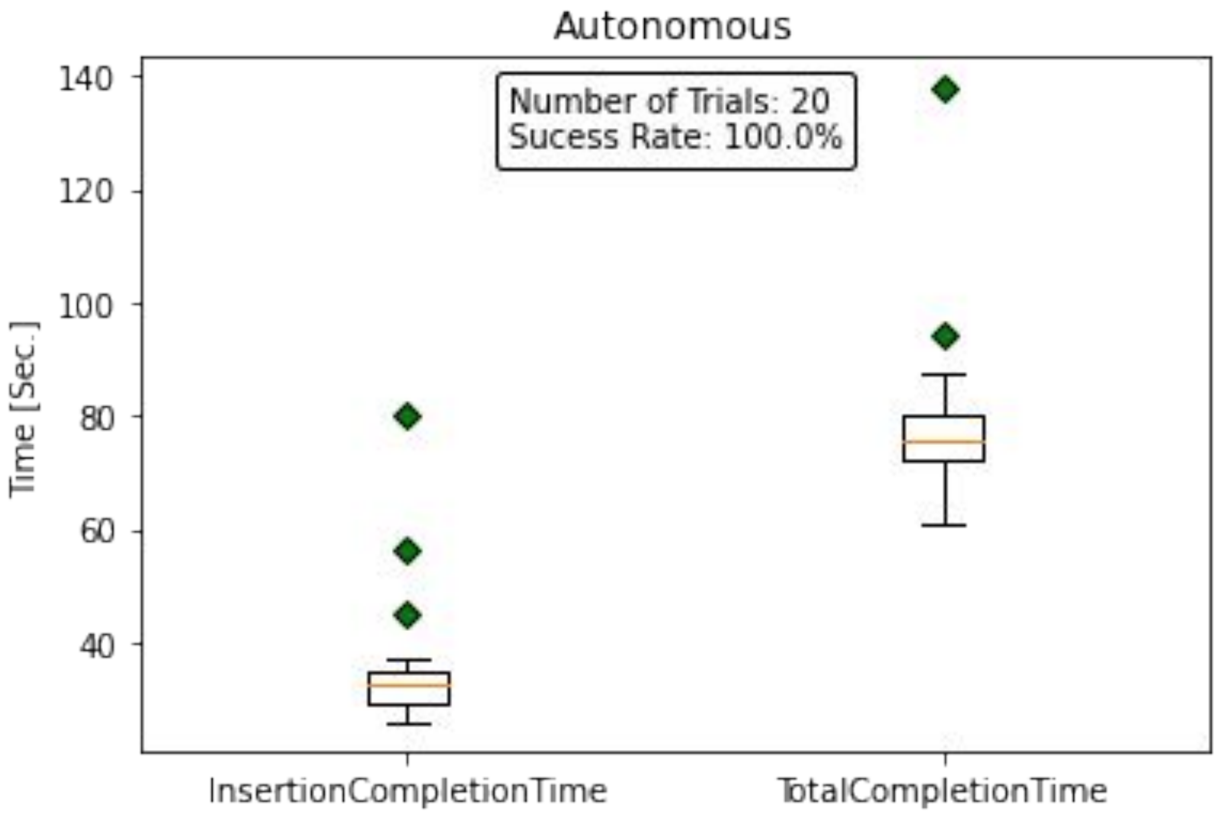
Autonomous Results of 20 trials





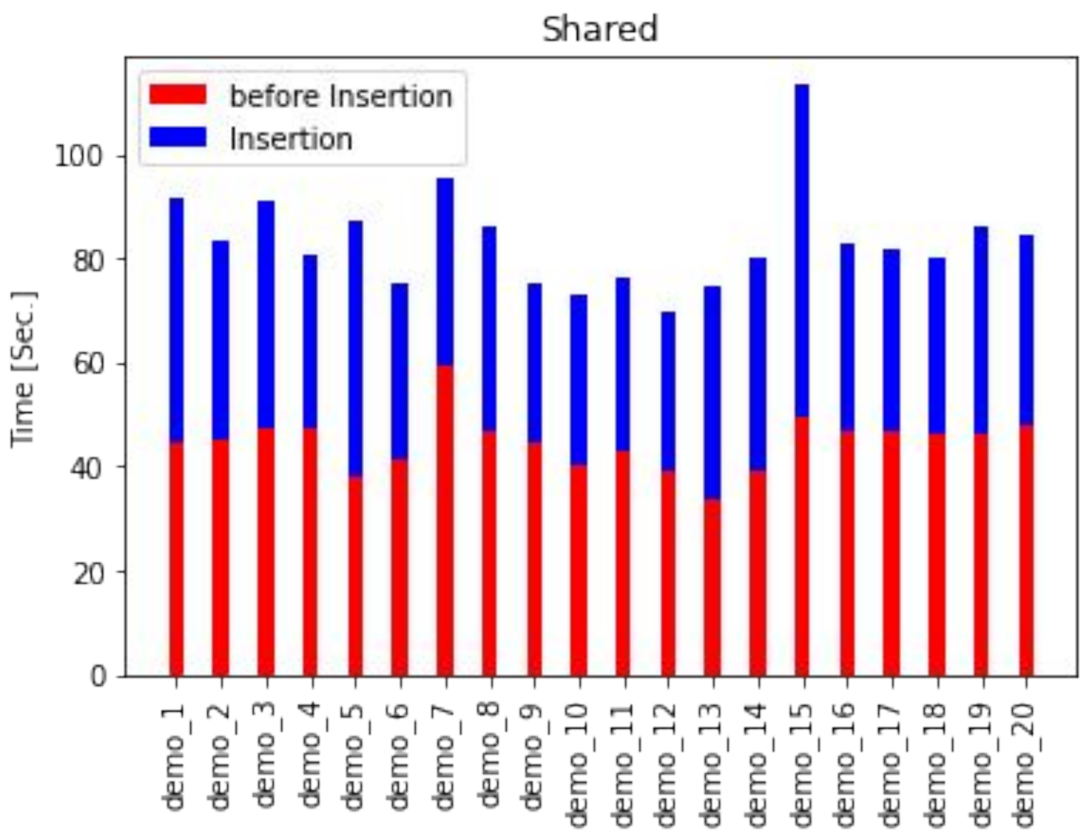
Autonomous Results of 20 trials

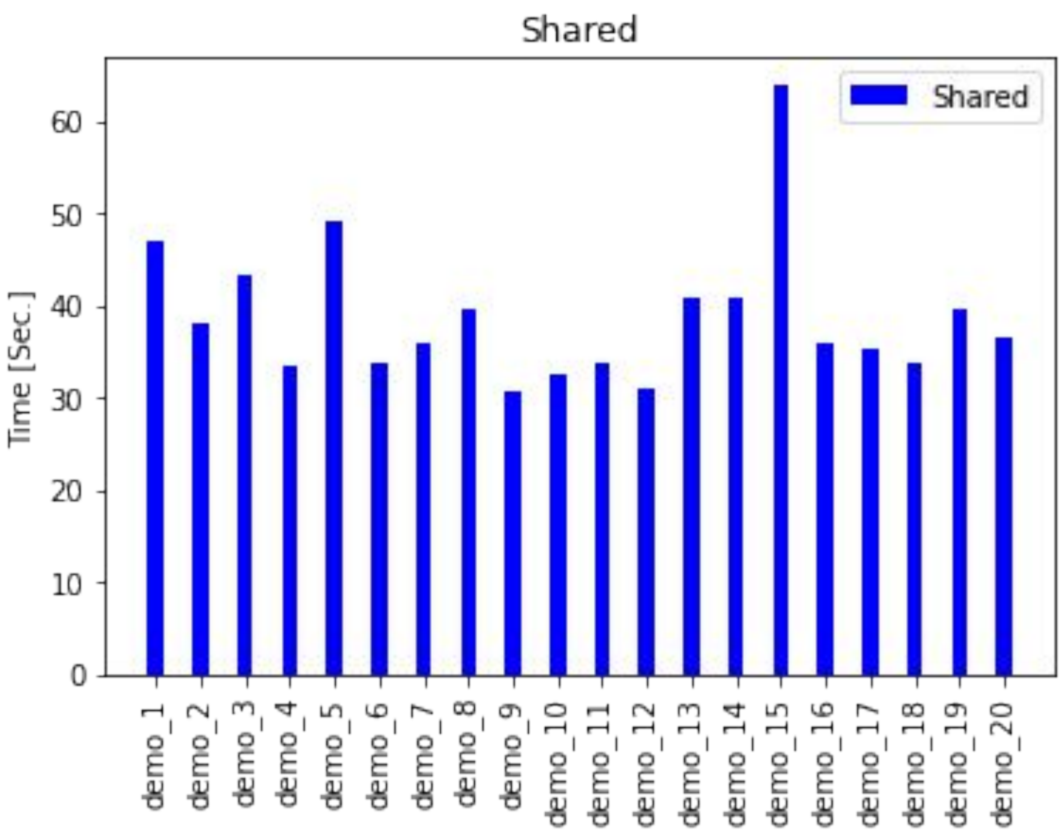




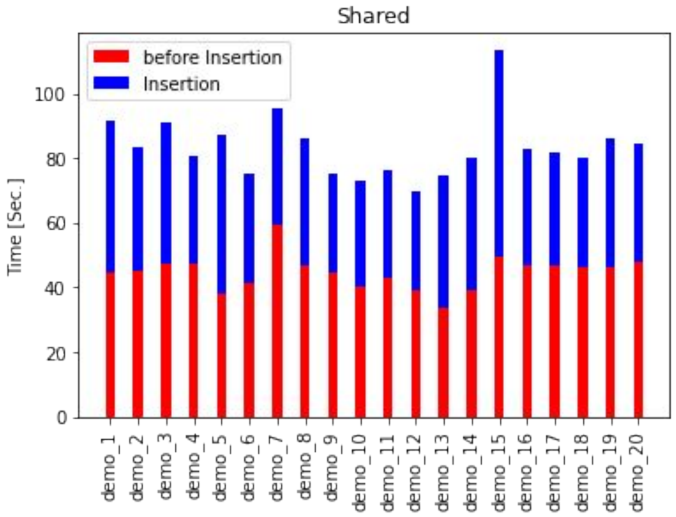

x2

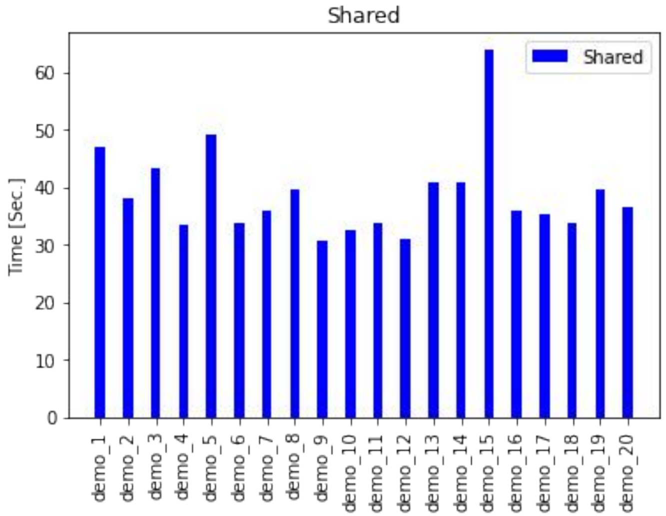
Shared Control Mode Results of 20 trials

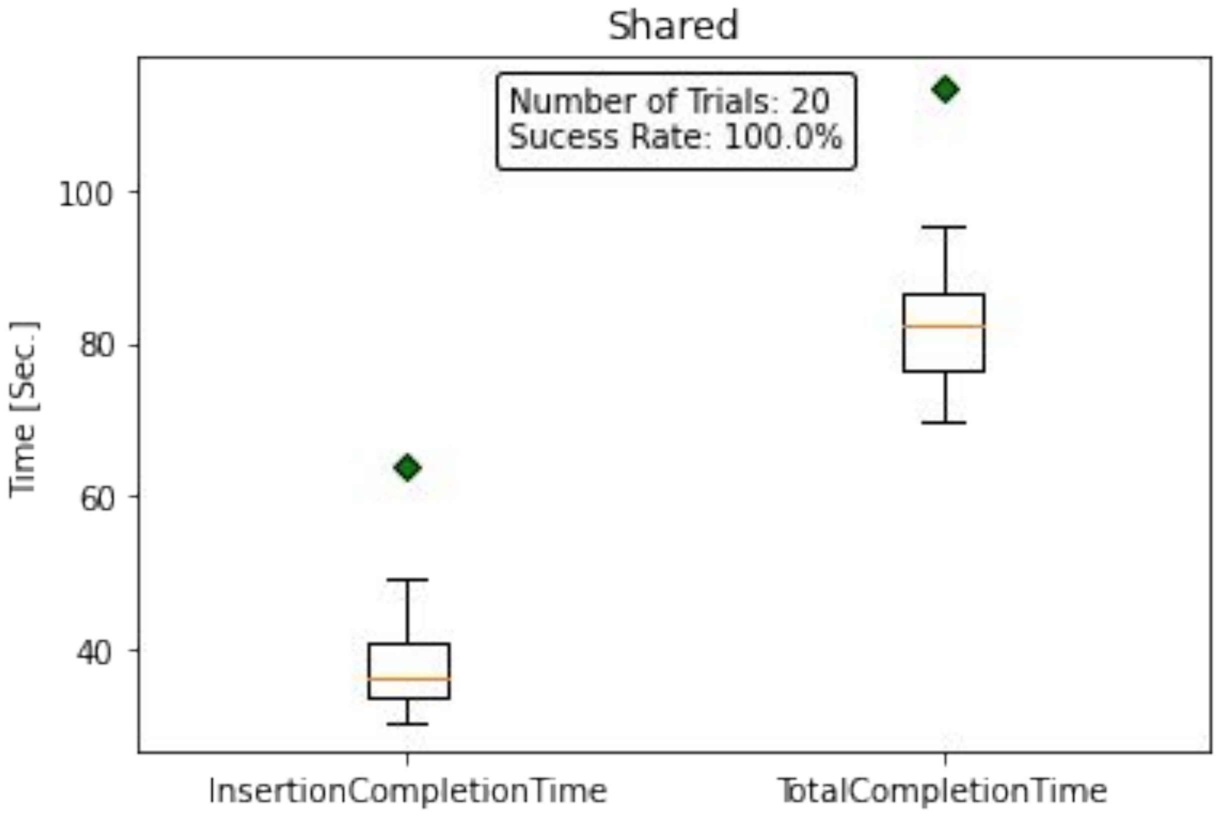


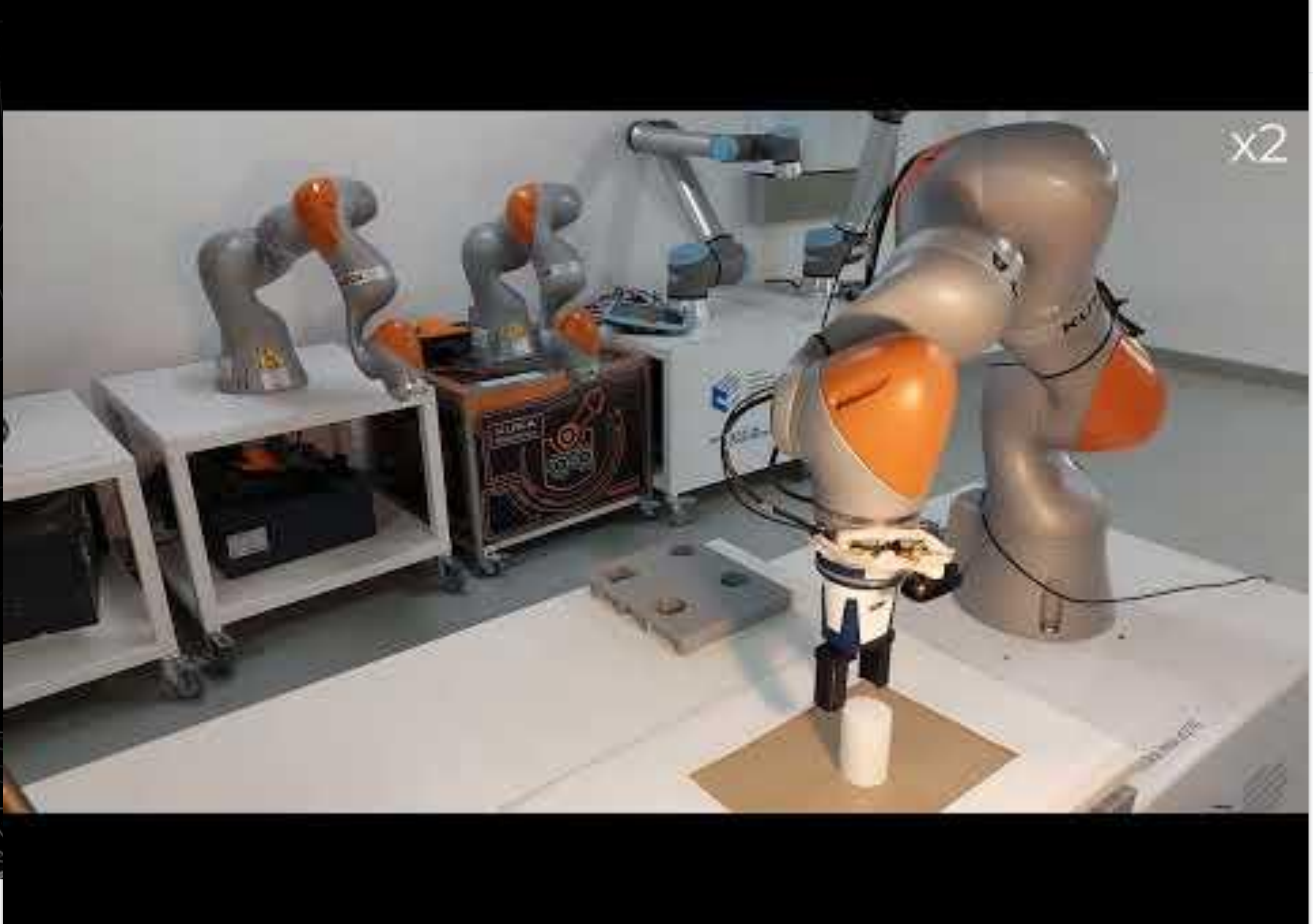


Shared Control Results of 20 trials

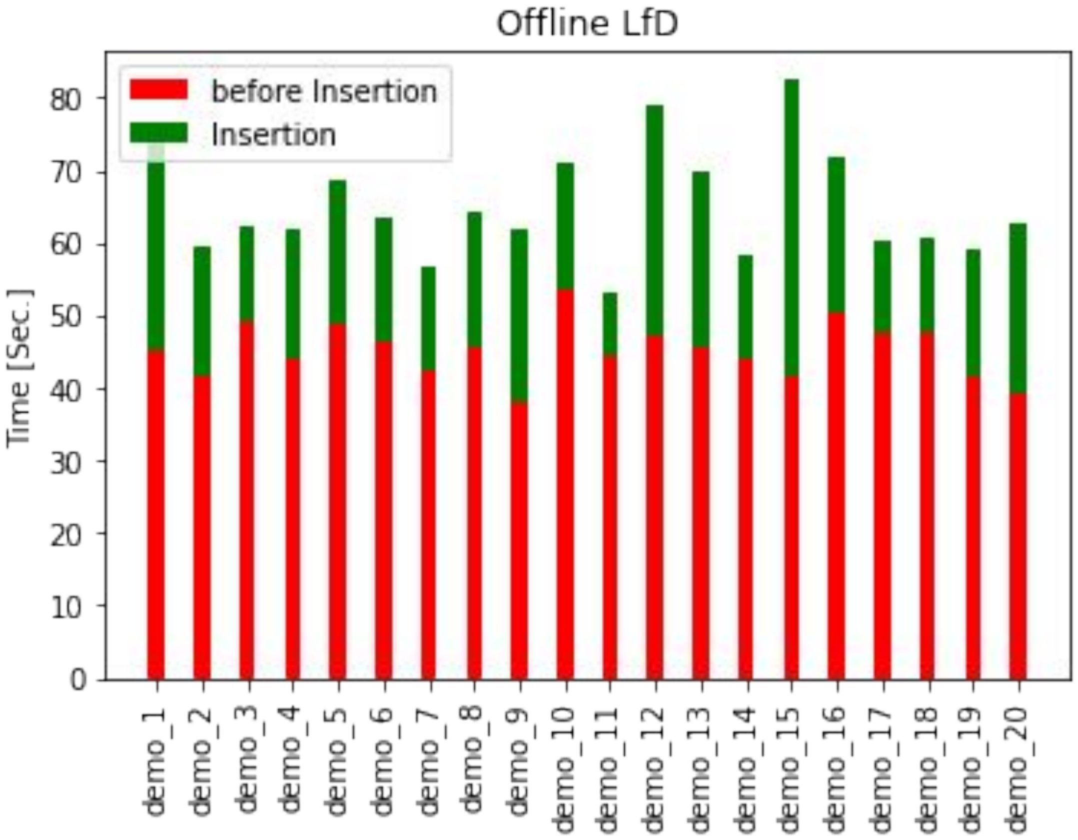


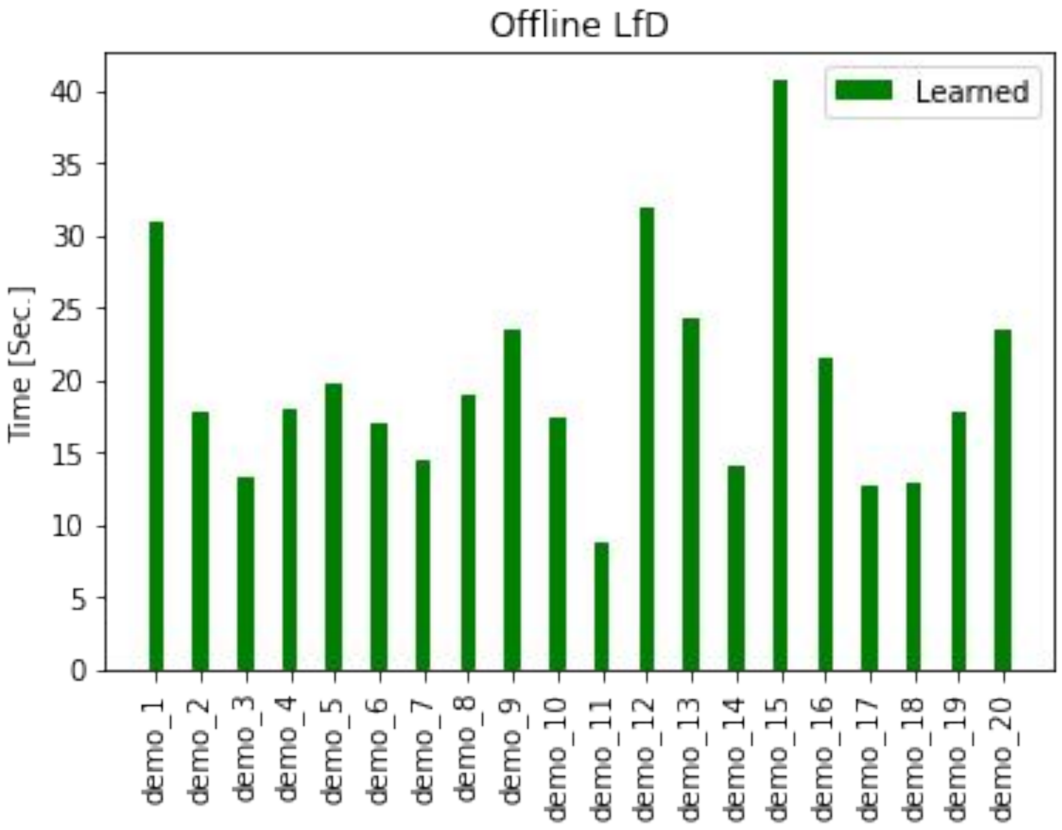




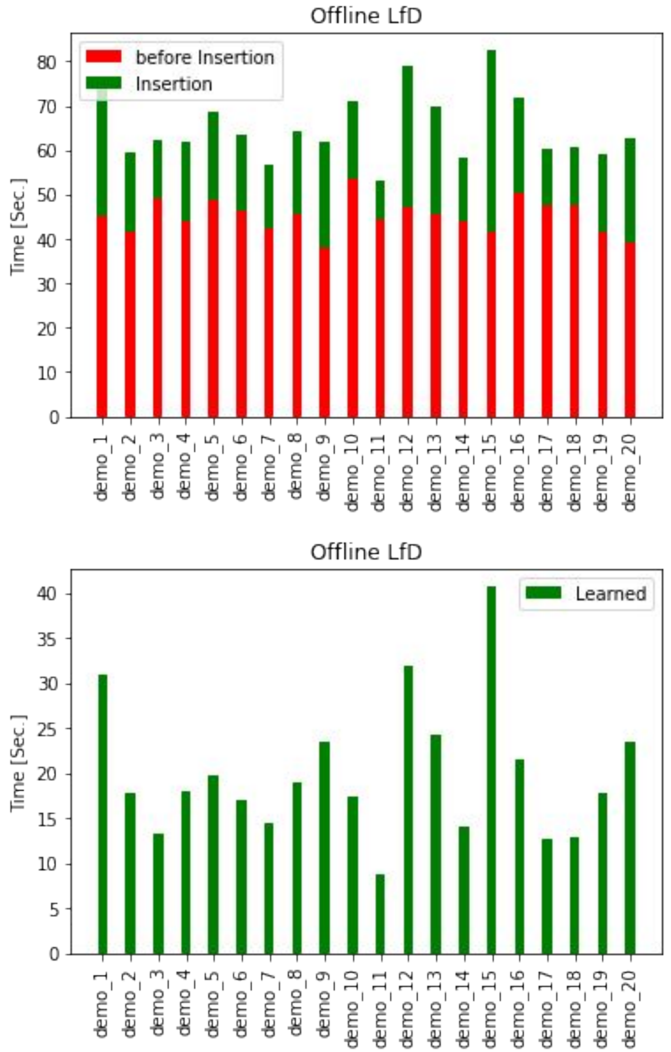

x2

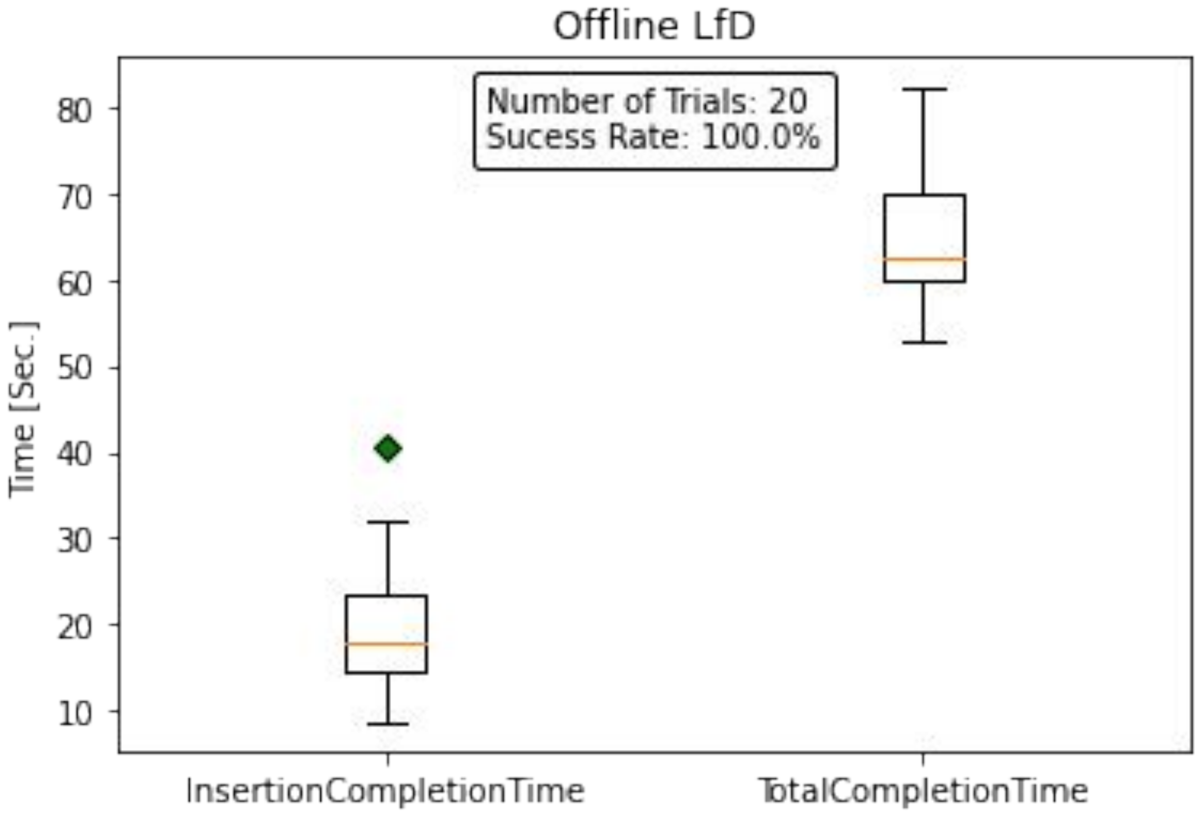
Offline LfD Results of 20 trials



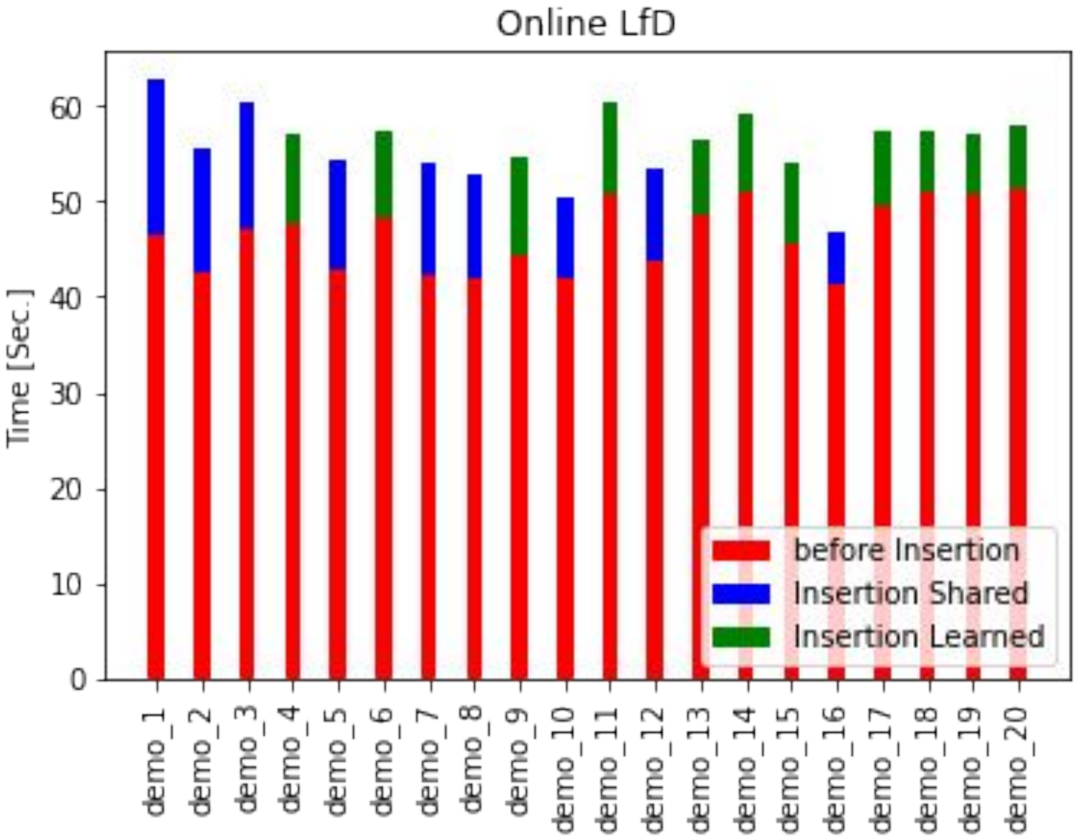


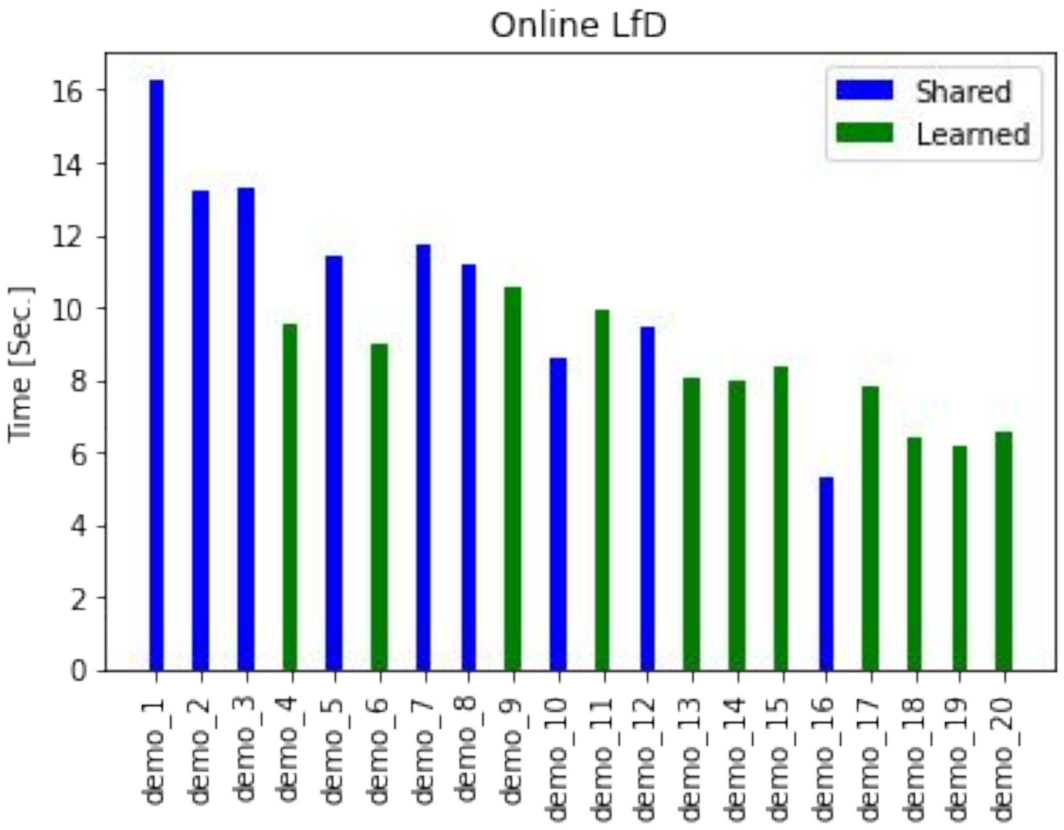
Offline LfD Results of 20 trials



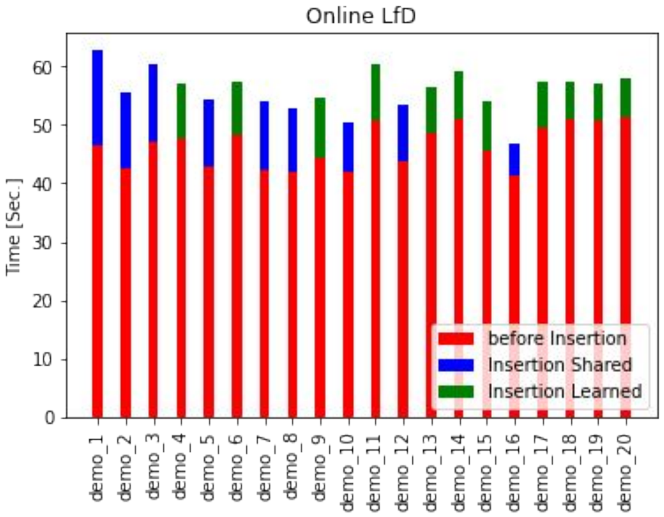


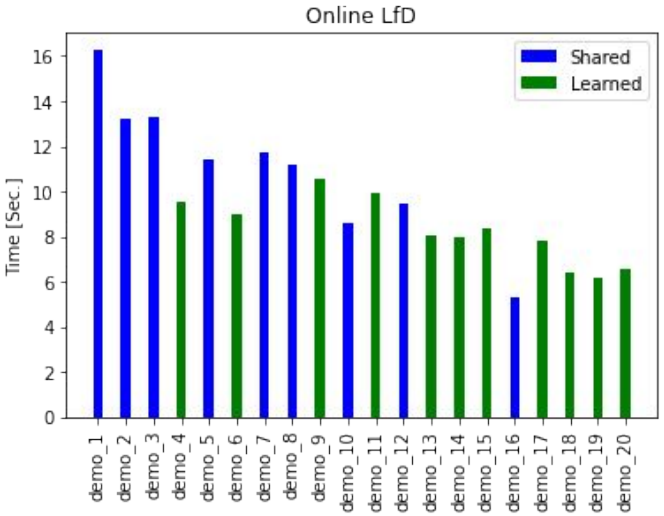
Online LfD Results of 20 trials

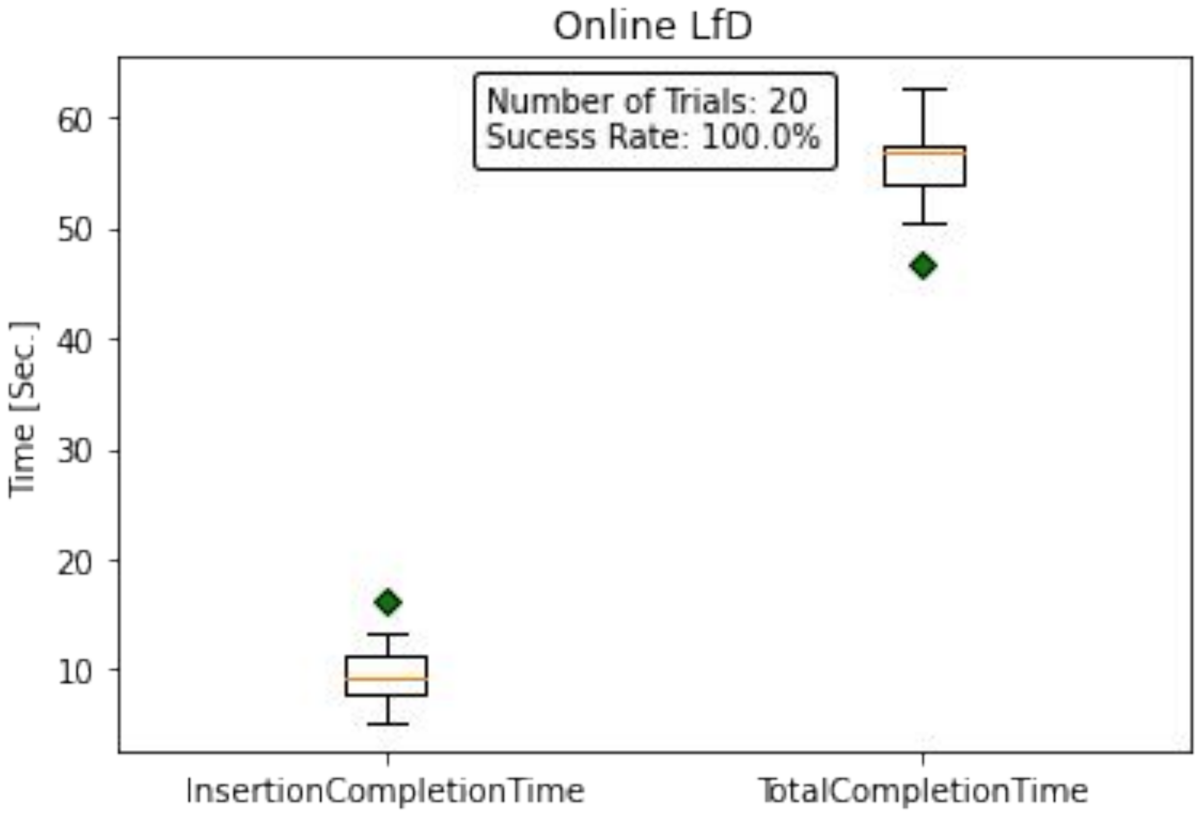


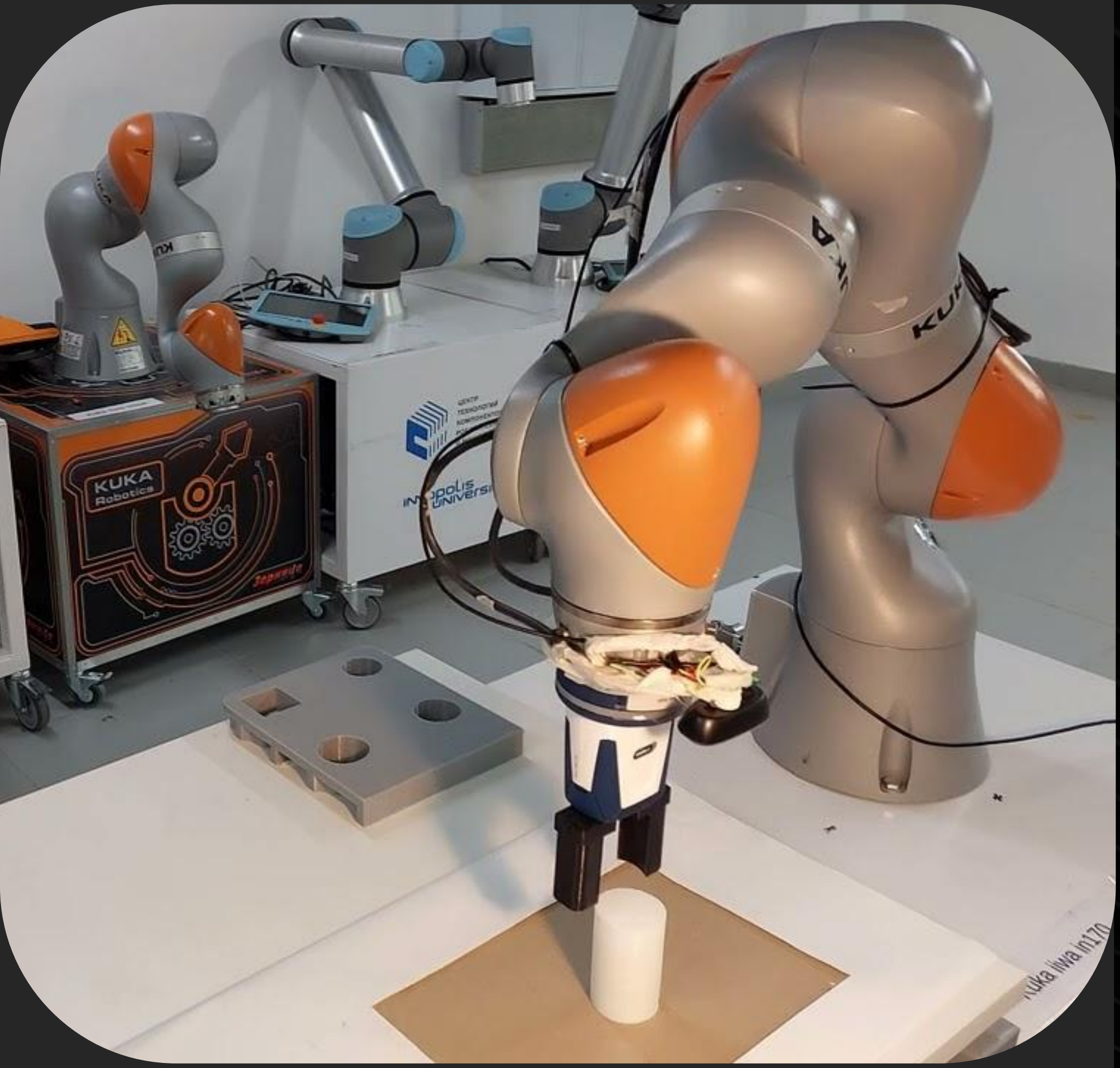


Online LfD Results of 20 trials









6.

Results & Conclusion

ANOVA

Test Results

P-value is smaller than 0.01

1. Null hypothesis can be rejected.
2. Relationship between different modes
is significant in statistical and practical sense.

>

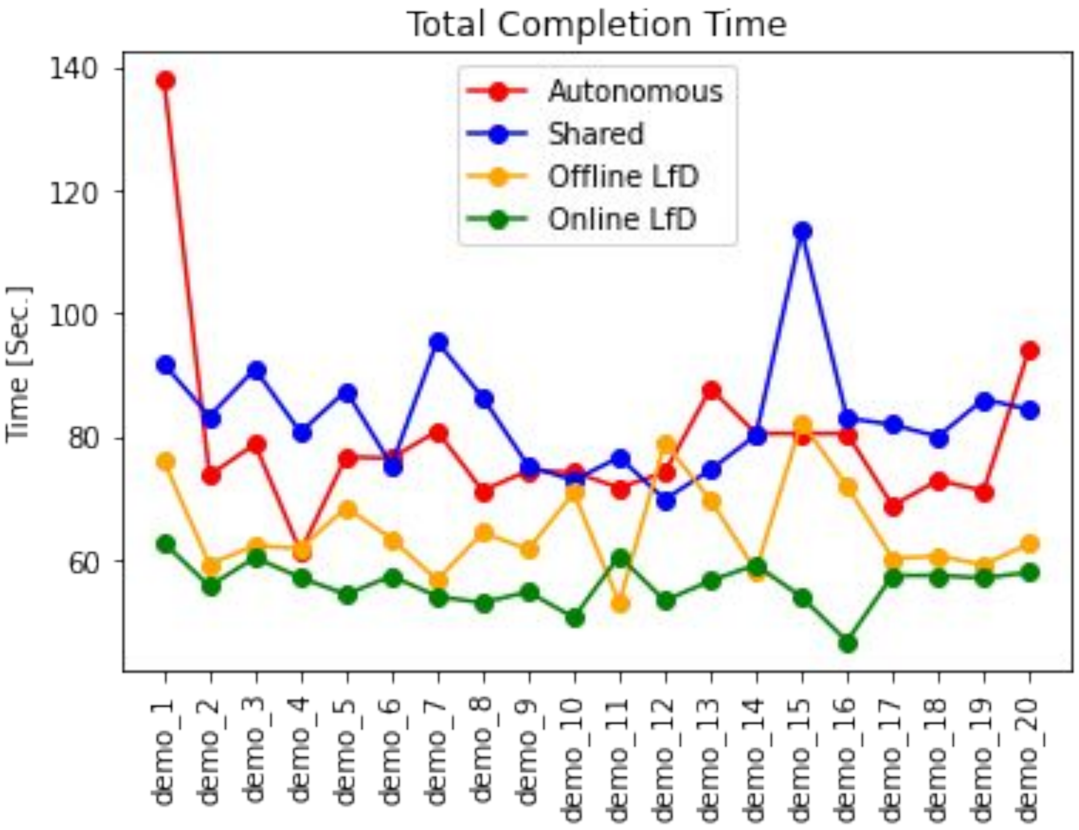
0.01

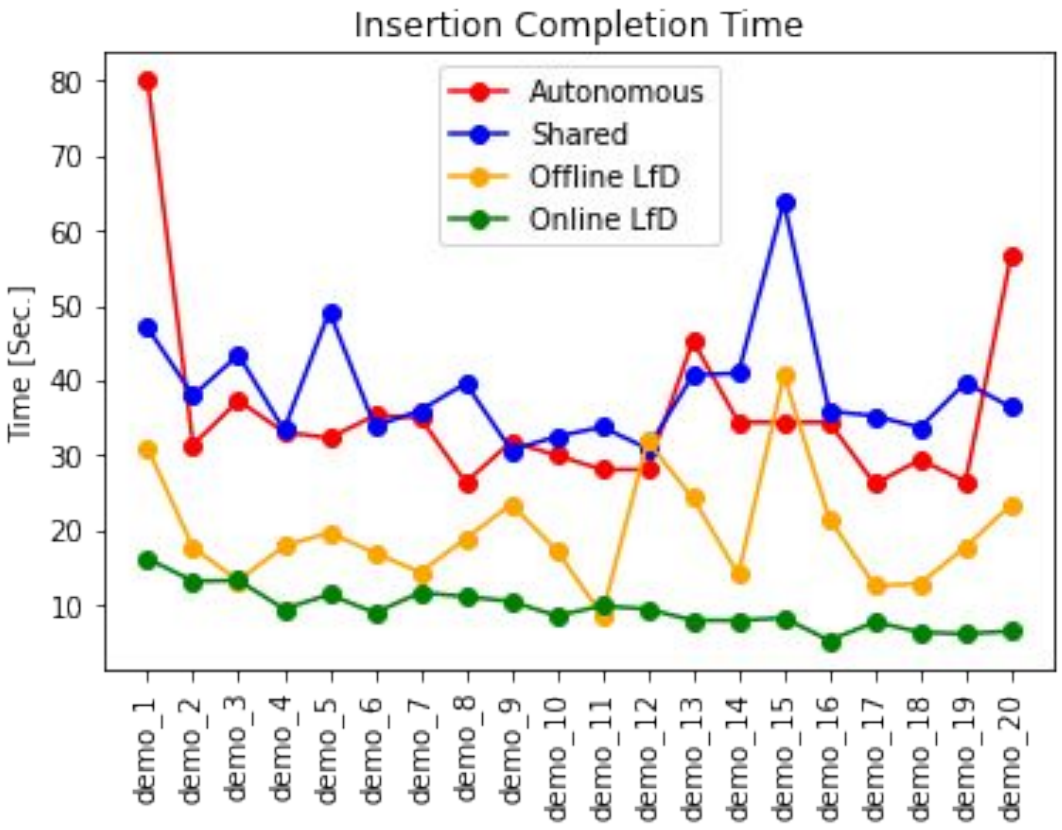
Groups	*Count*	*Sum*	*Average*	*Variance*
Automatic	20	716.1	35.805	158.3941842
Online LfD	20	190.6967	9.534835	7.522363292
Offline LfD	20	398.71	19.9355	58.44585763
Shared	20	774.69	38.7345	59.94036289

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	11323.7062	3	3774.568732	53.10632405	**0.001**	2.724943949
Within Groups	5401.752593	76	71.07569201			
Total	16725.45879	79				

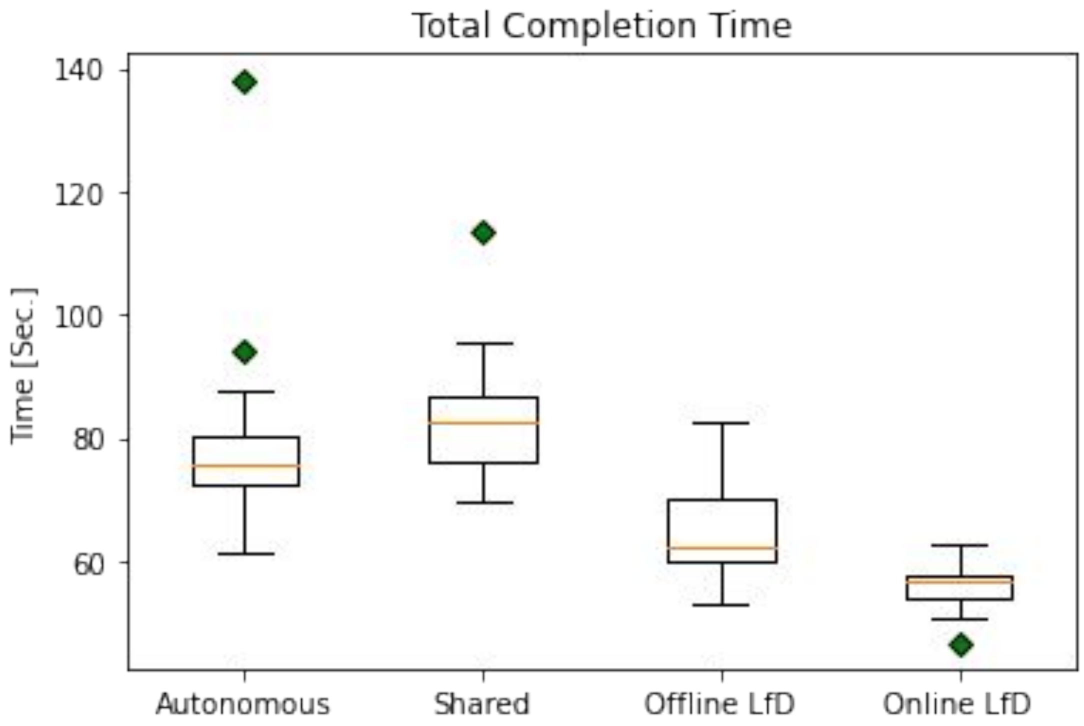
Anova: Single Factor statistical analysis for comparing different control modes Insertion completion time

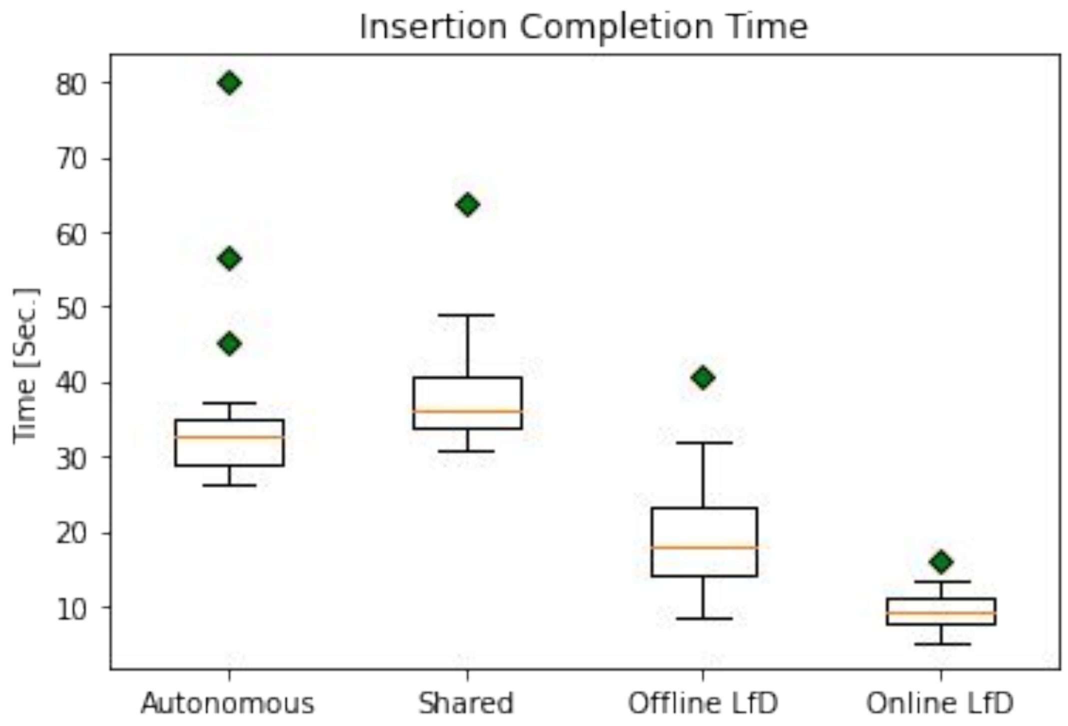
Comparison between different Control Modes





Comparison between different Control Modes





Conclusion

Autonomous

Pros:

- Adapting to the environment properties and move accordingly.
- Searching process is effective and good .

Cons:

- Calibration error affects the process extensively.
- Takes more time to adapt to the environment and interact with it .

Shared Control

Pros:

- The Operator can interact anytime and take control with dynamic environment.
- The task success is guaranteed within a reasonable time.

Cons:

- Time consuming and expensive to keep an operator.
- Depends on the operator experience and quality of force and visual feedback.

Offline LfD

Pros:

- Depends mainly on the operator experience
- Trained on various demos without limitation in their number.

Cons:

- Static and hard to adapt to new changes in task or environment.
- Static and hard to adapt to new changes in task or environment.

Online LfD

Pros:

- Improve the Operator Performance with time.
- Adapt to dynamic changes in the scene and task.

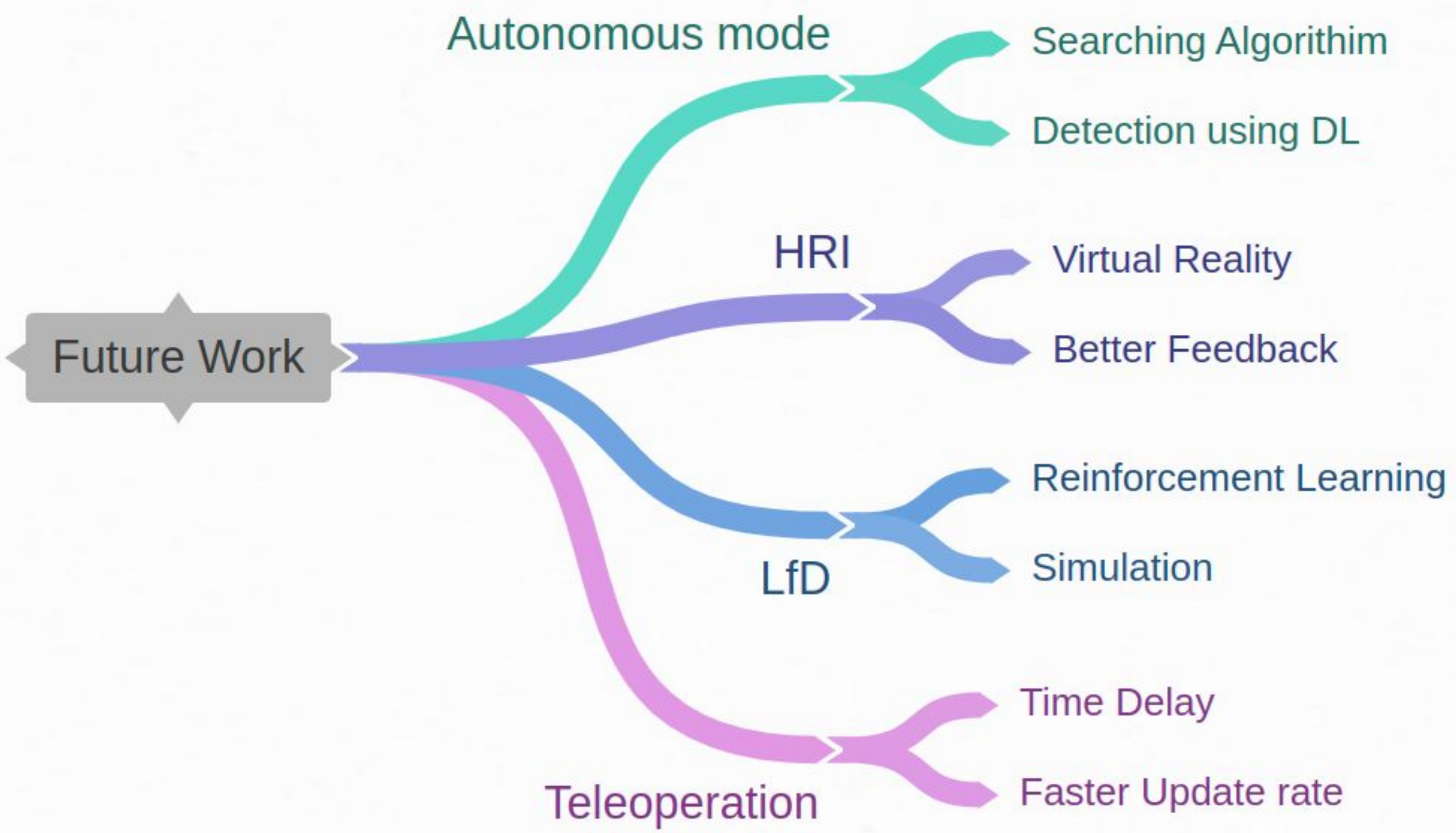
Cons:

- Online computation and adaptation are done every trial.
- Limitation on number of trials computed Each trial.

Future work

Improvements:

- Complete User Study on operators with different experience level.
- Different Peg shape (Square, irregular shapes).



Thank You

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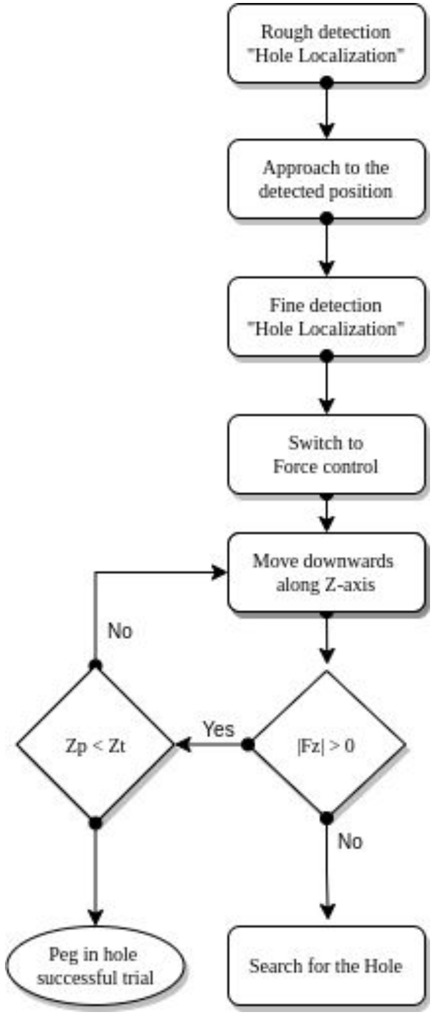
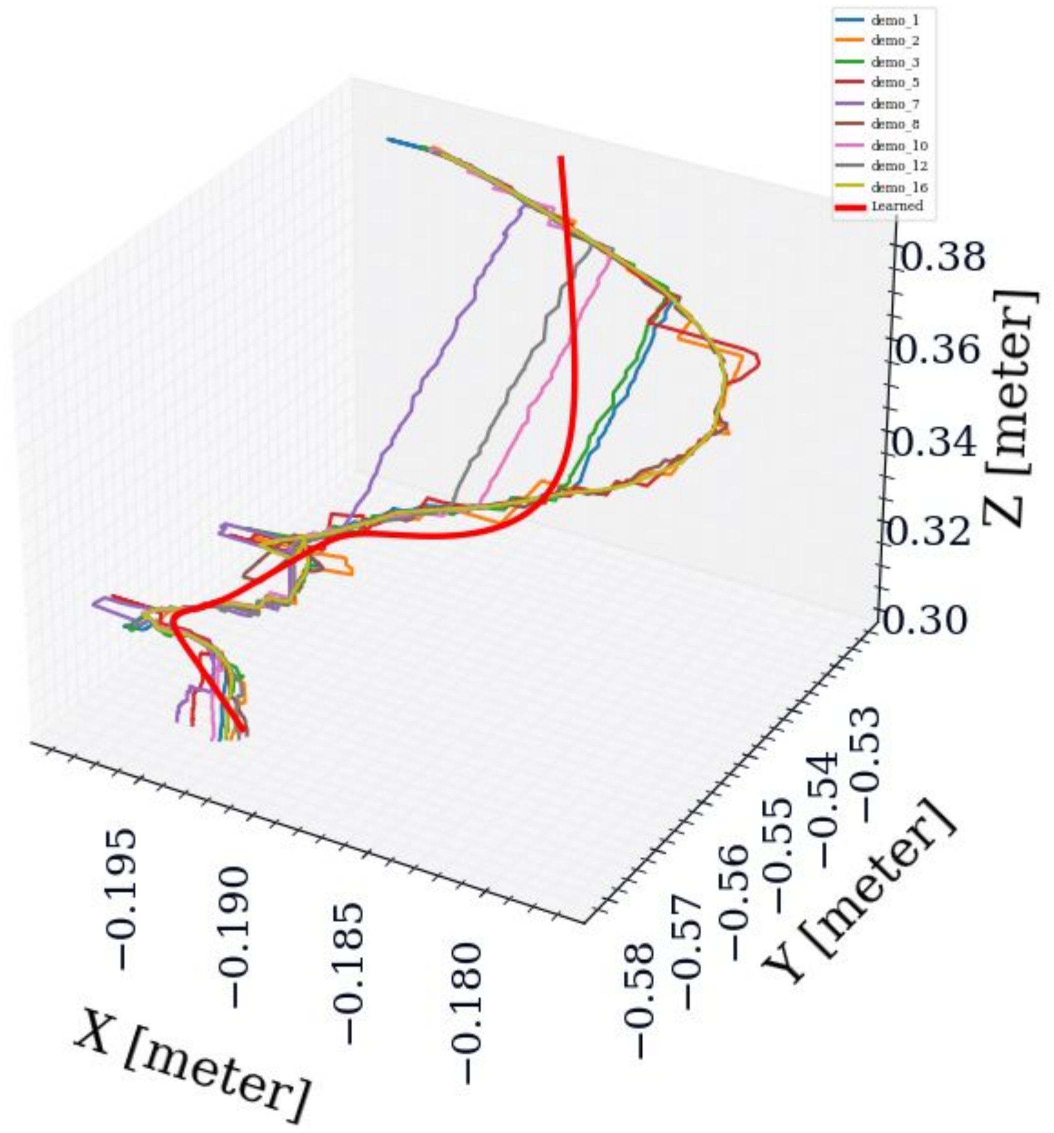
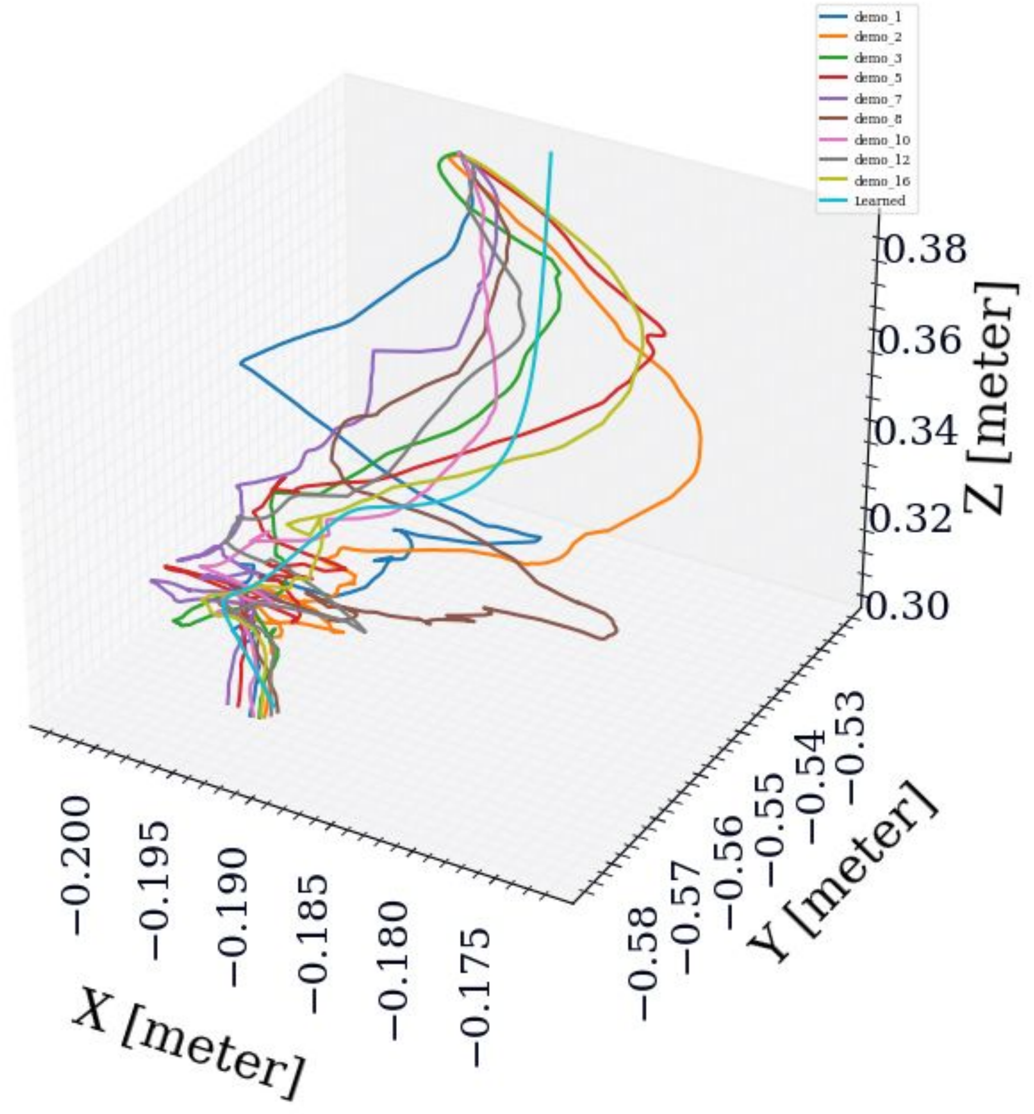
Autonomous Control

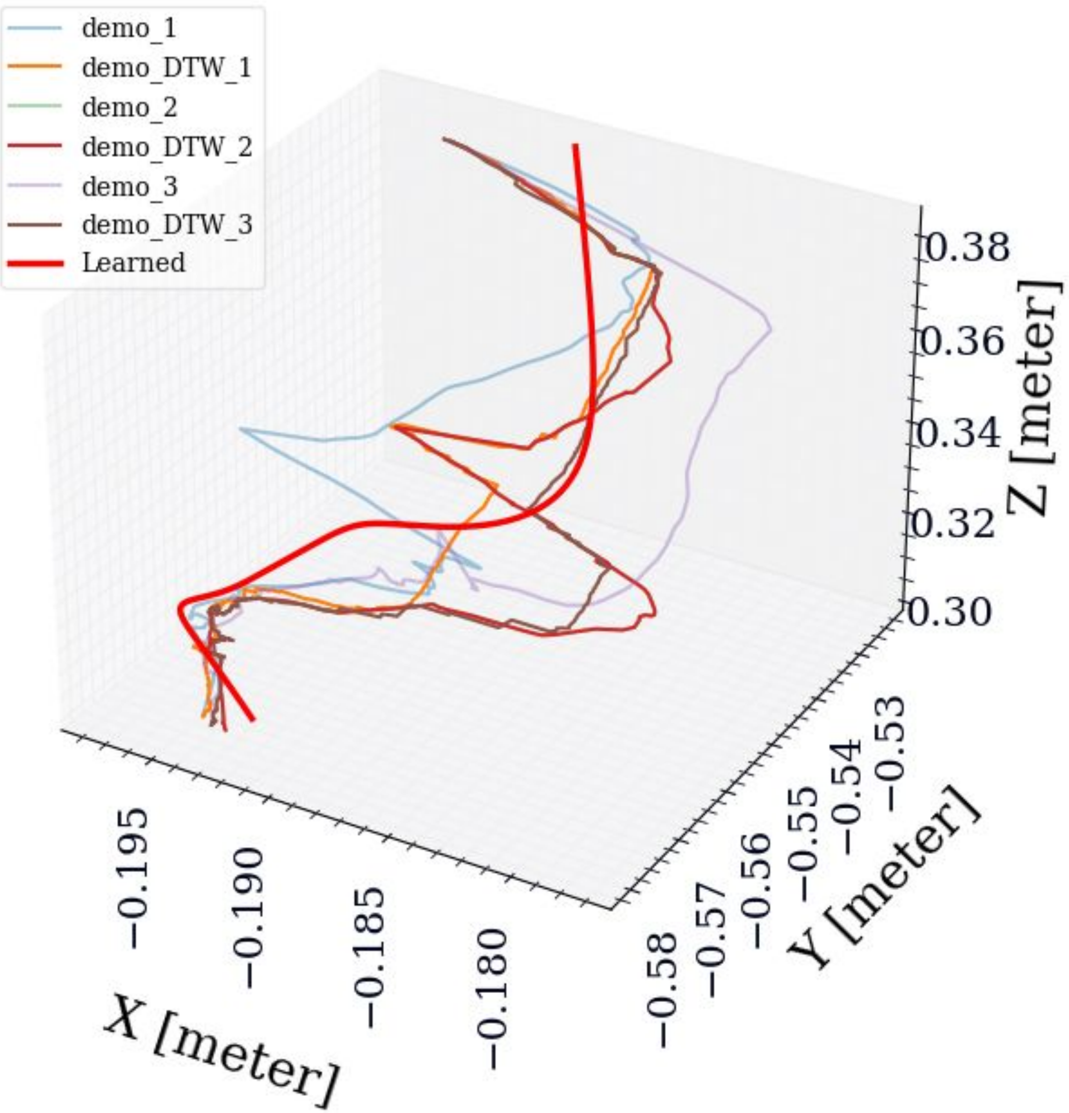


Data: Intrinsic Matrix and Hand-eye calibration data.
Zg: Z coordinate of the gripper.
Zt: Z coordinate of assembly plane.
Fz: external force acting on the end-effector along Z axis.
Ft: the allowable engagement force.
$pos1$: position over object for detecting the pose.
$pos2$: position over hole for detecting hole position.

begin
  Initialization;
  Move to $pos1$;
  Start a timer for the total task completion
  Localize the Peg using detection algorithm;
  Move to the detected XY positionS;
  while $|Fz| > Ft$ **do**
    Move downwards along Z;
  end
  Pick up the Peg;
  Move to $pos2$;
  Start a timer for hole searching
  Do *Rough localization* for the hole position;
  Move Closer and approach the detected XY position;
  Capture image and do *Fine localization*;
  Align in XY plane with estimated position;
  while $|Fz| < Ft$ **do**
    Reduce Z_g;
  end
  Measure Zt;
  while $|Fz| \geq Ft$ **do**
    while *Hole is not detected in the image* **do**
      Measure moments mx and my;
      Rotate the camera around Z according to $\tan^{-1}\frac{-m_x}{m_y}$;
    end
    Detect the hole edge and measure the furthest point of the center of the Peg;
    Move, by steps, towards the direction of the furthest point of the hole edge;
    while $|Fz| < Ft$ **do**
      Move downwards by dz;
      if $Zg < Zt$ **then**
        break;
      end
    end
    Assemble the peg;
    Retreat upwards
    move to a random x,y within placing position
  end
end


demo_1
demo_2
demo_3
demo_5
demo_7
demo_8
demo_10
demo_12
demo_16
Learned
X [meter]
Y [meter]
Z [meter]


demo_1
demo_2
demo_3
demo_5
demo_7
demo_8
demo_10
demo_12
demo_16
Learned
X [meter]
Y [meter]
Z [meter]


demo_1
demo_DTW_1
demo_2
demo_DTW_2
demo_3
demo_DTW_3
Learned
0.38
0.36
0.34
0.32
0.30
Z [meter]
−0.195
−0.190
−0.185
−0.180
X [meter]
−0.58
−0.57
−0.56
−0.55
−0.54
−0.53
Y [meter]