HRI for assisted tele-manipulation:
combining autonomous grasp planning with haptic cues

Maxime Adjigble

Extreme Robotics Lab, University of Birmingham, UK

About ERL

Rustam Stolkin

Professor of Robotics
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Maxime Adjigble

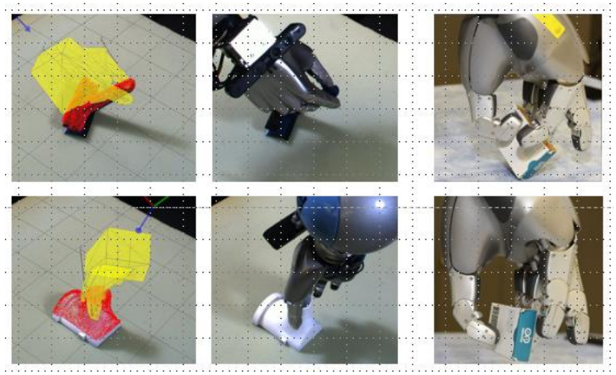
Senior Robotic Engineer
PhD Student

Extreme Robotics Laboratory

- Leading a £42 million fund for the National Centre for Nuclear Robotics (NCNR)
- Opened new 1000 sq ft Laboratory in the Birmingham, UK
- 10 PhD Students, 10 Postdocs

NCNR website: https://www.ncnr.org.uk/
ERL Website: https://www.birmingham.ac.uk/research/activity/metallurgy-materials/robotics

About ERL



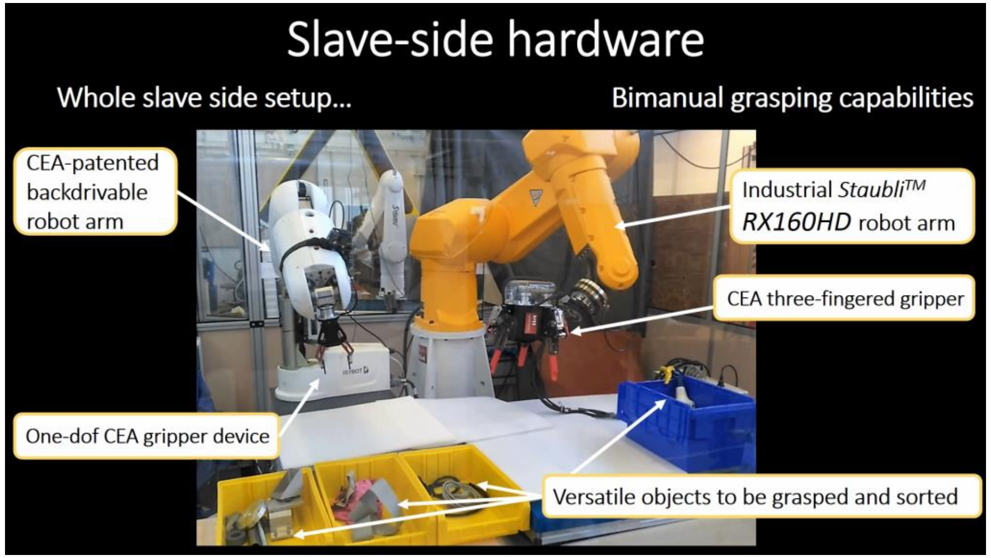
Expertise

- Mobile Robotics
- Robot Control
- Robotic Grasping
- Human Robot Collaboration
- Machine Vision

KUKA JAGUAR LAND ROVER NASA KAERI Korea Atomic Energy Research Institute NISSAN

NATIONAL NUCLEAR LABORATORY Sellafield Ltd Inria inventors for the digital world iDS AUSTRALIAN CENTRE FOR ROBOTIC VISION

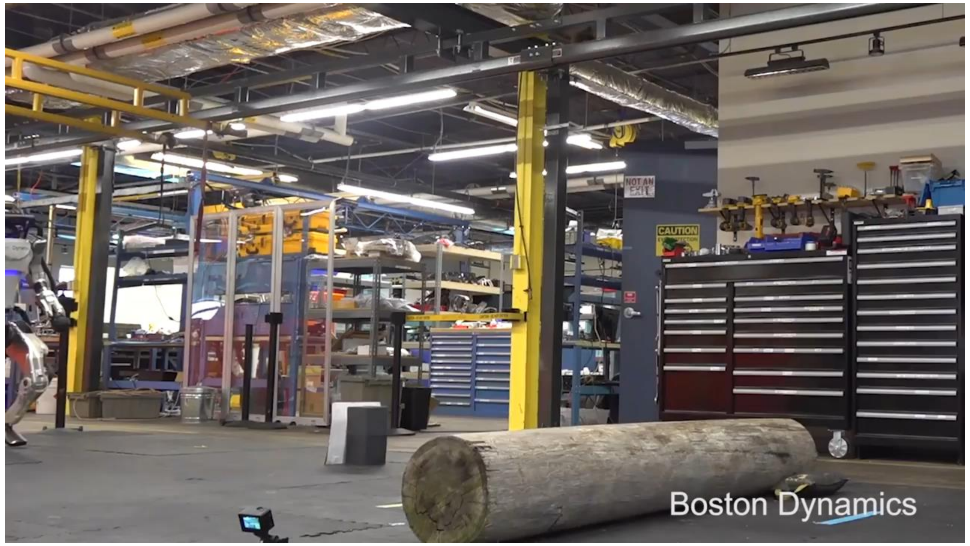
About ERL

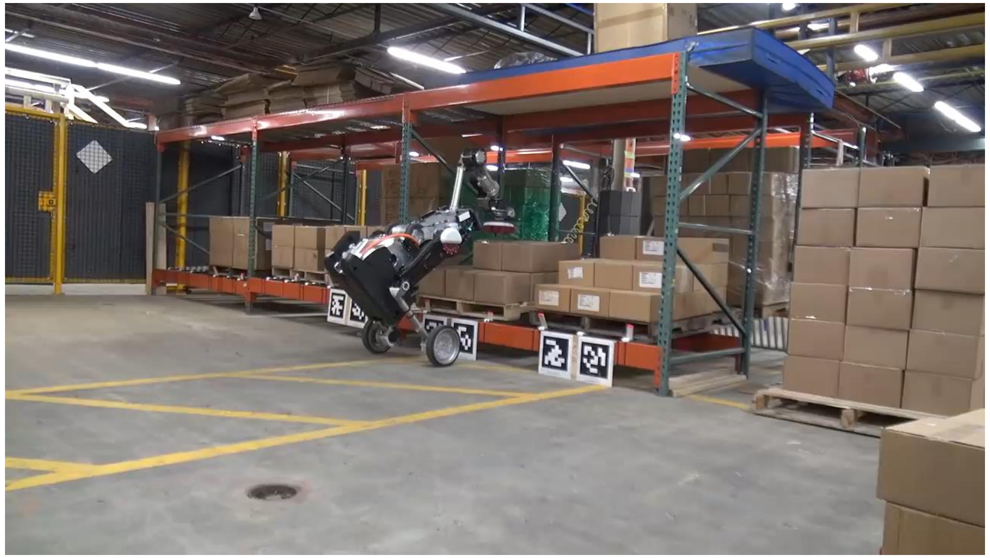


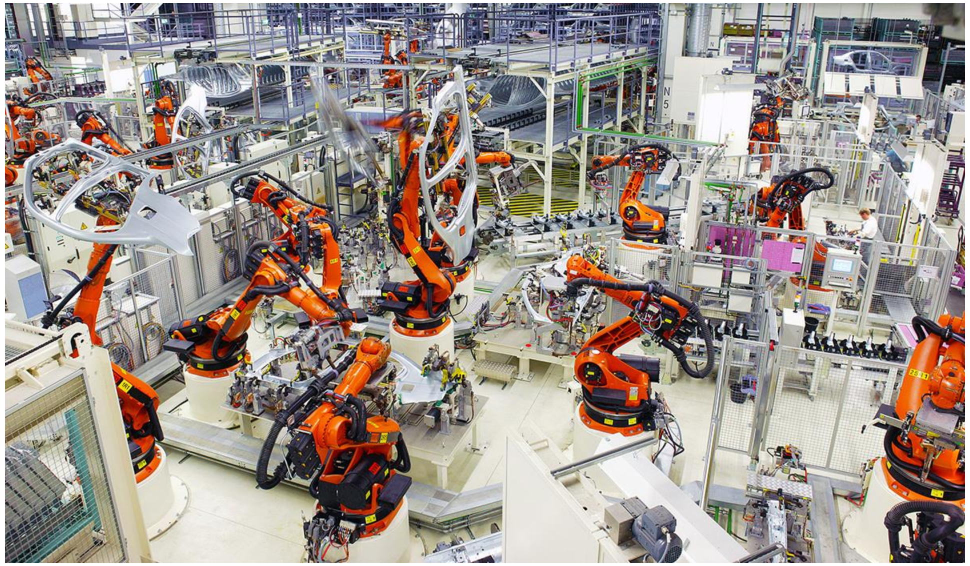
Recent Projects

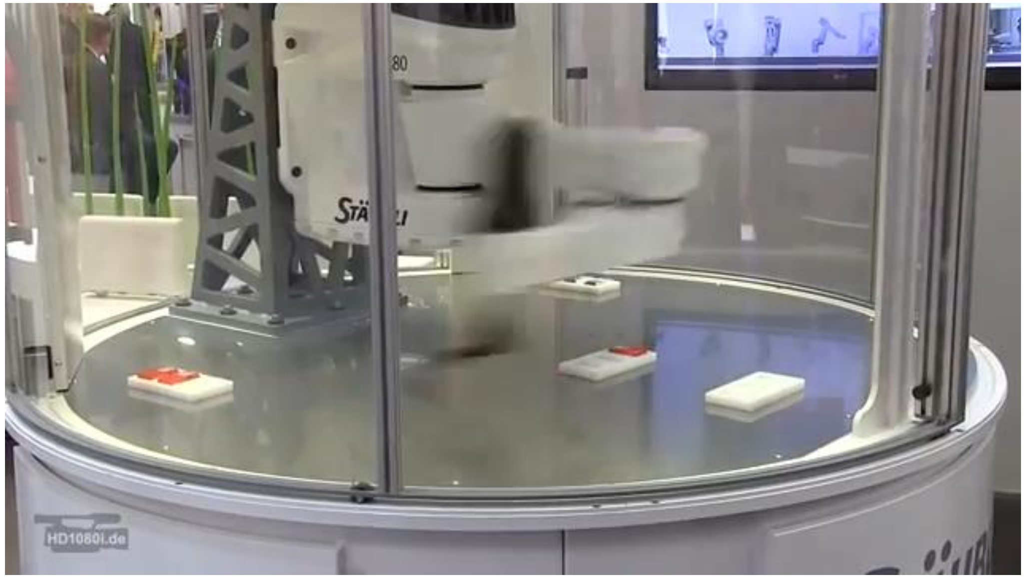
- Bimanual Teleoperation with novel Grippers (ROMANS – CEA)
- HRI Assisted Tele-manipulation (ROMANS – ERL/NNL)
- Autonomous Laser Cutting (5KW) in Active Nuclear Cell

Motivations









Motivations

Human robot Interaction (Goal)

- Intuitive interaction
- Mutual assistance
- Collaboration
- Use the strength of one to compensate the weaknesses of the other
- Solve difficult problems that can’t be solved either by the robot or the human alone

Motivations

Human robot Interaction (Reality)

- Steep Learning curve for operators
- Prior knowledge of robotics
- Initial training required
- Deep 3D understanding
- Requires medium to high mental effort
- Not intuitive
- Human has to adapt to an imperfect system

Motivations

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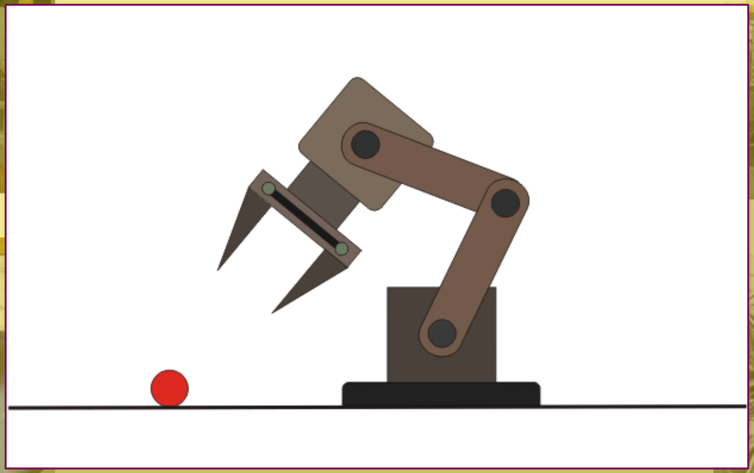
Key differences:

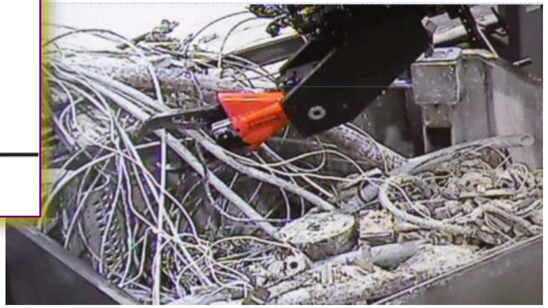
Human	Robot
Flexible	Rigid/stiff
Slow	Fast
Light	Heavy
Dexterous	Clumsy
Slow thinking	Fast computation
High level Reasoning	Low level reasoning

How to exploit the differences to make an overall better system?

Case Study: Tele-manipulation

Motivations

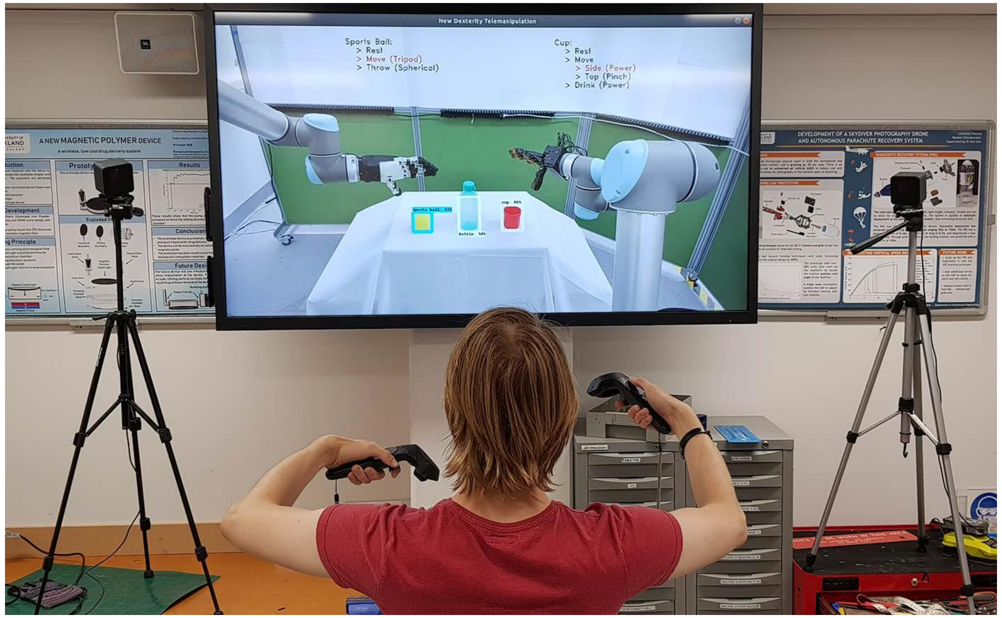




Necessity of advanced robotic technologies (full or semi- autonomy)

- Very interesting/complex manipulative tasks - Quite slow and painstaking with tele-operation
- Reduce the safety risks on human workers
- Most importantly: operational cost reduction and increase in productivity

Tele-manipulation



Input device: Natural Hand movements

Scene perception: Scene cameras

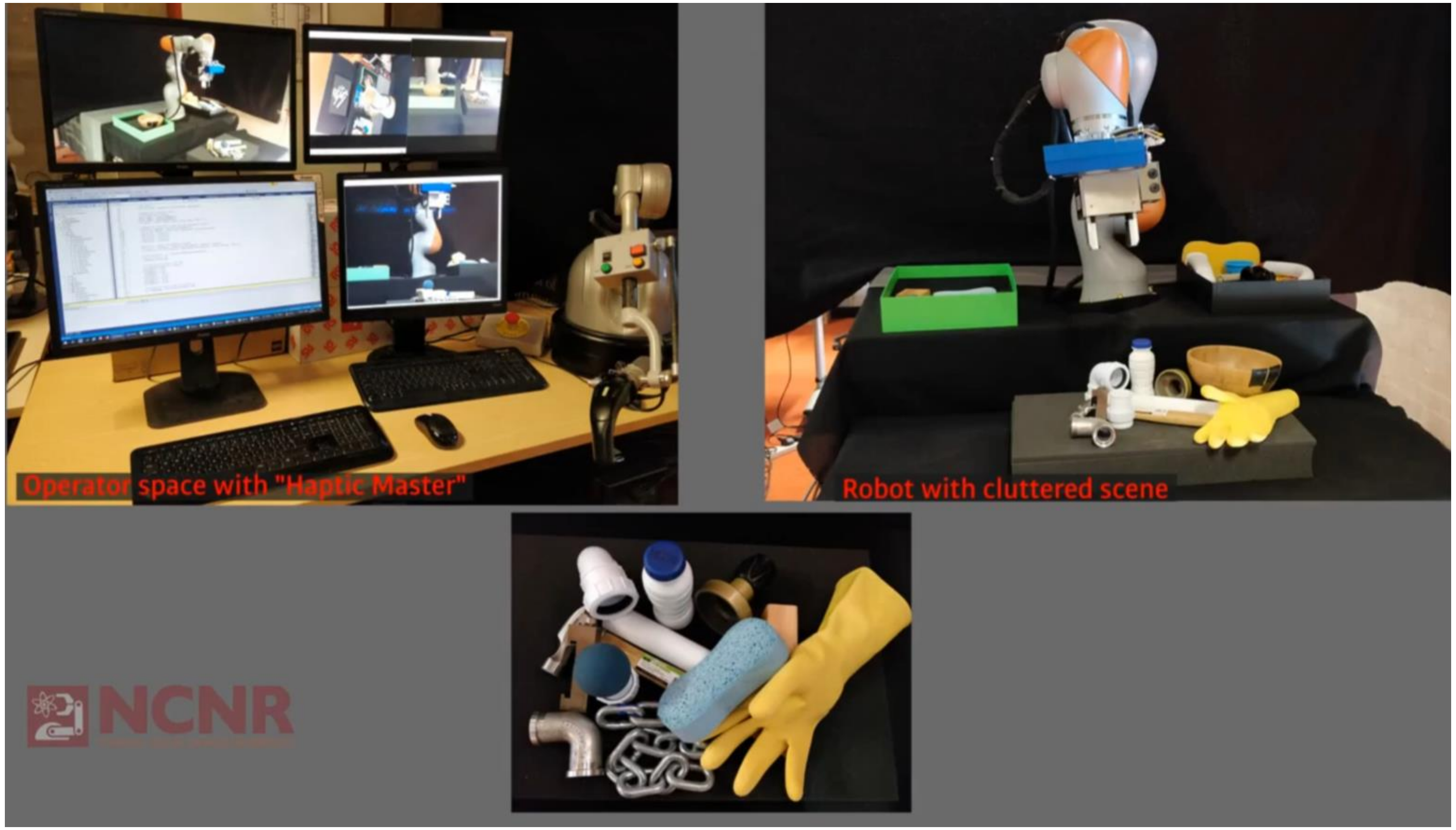
Force Feedback: None

Input device: Haptic device

Scene perception: Direct view

Force Feedback: Yes

Tele-manipulation

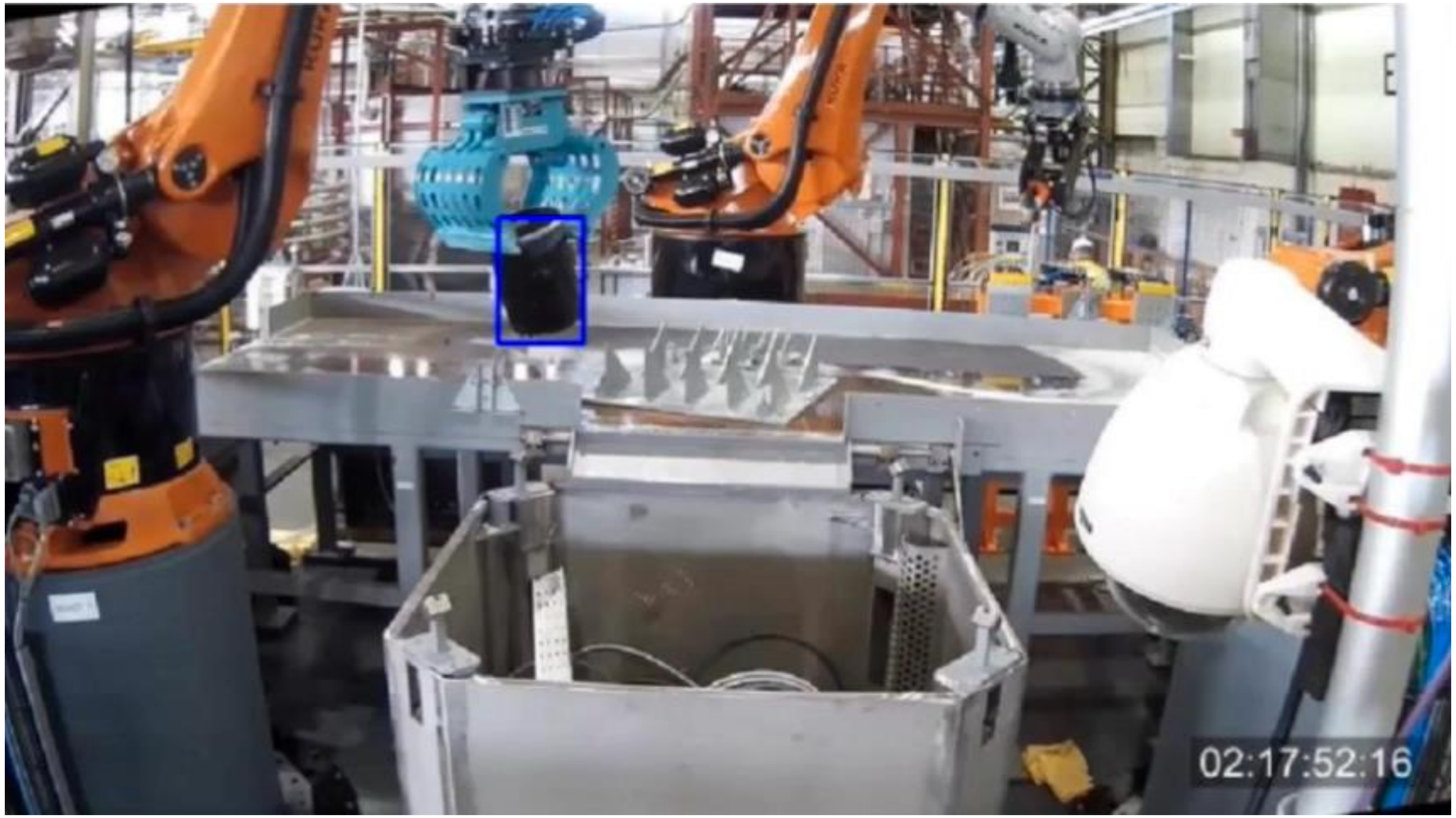


Input device: Haptic device

Scene perception: Scene cameras

Force Feedback: Yes

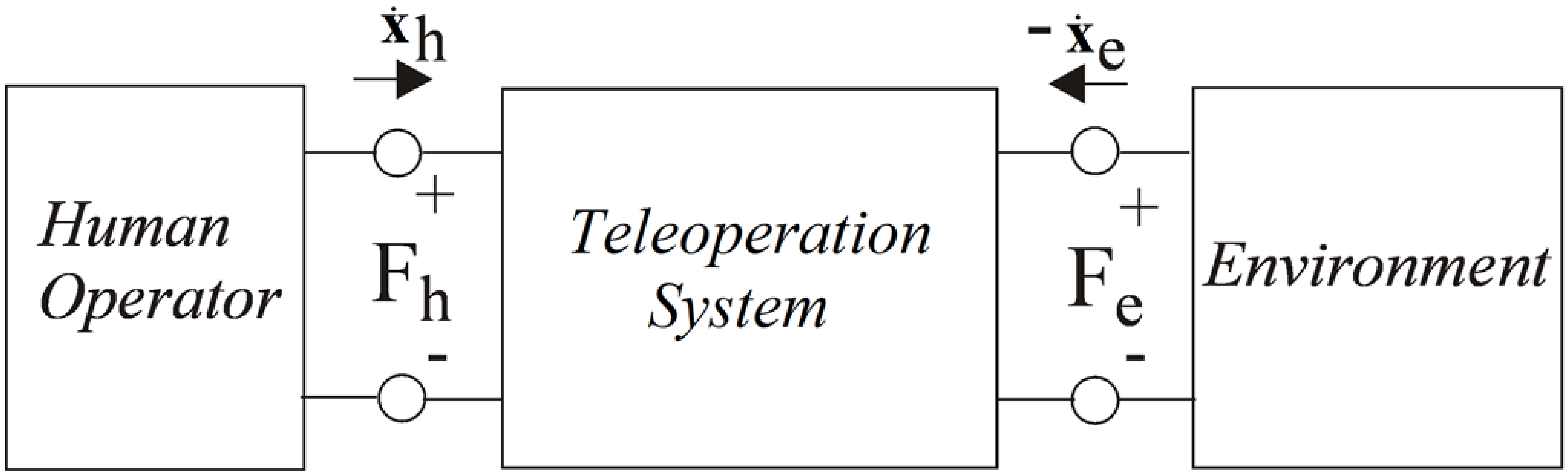
Tele-manipulation



State of the Art Tele-manipulation in the Nuclear Industry

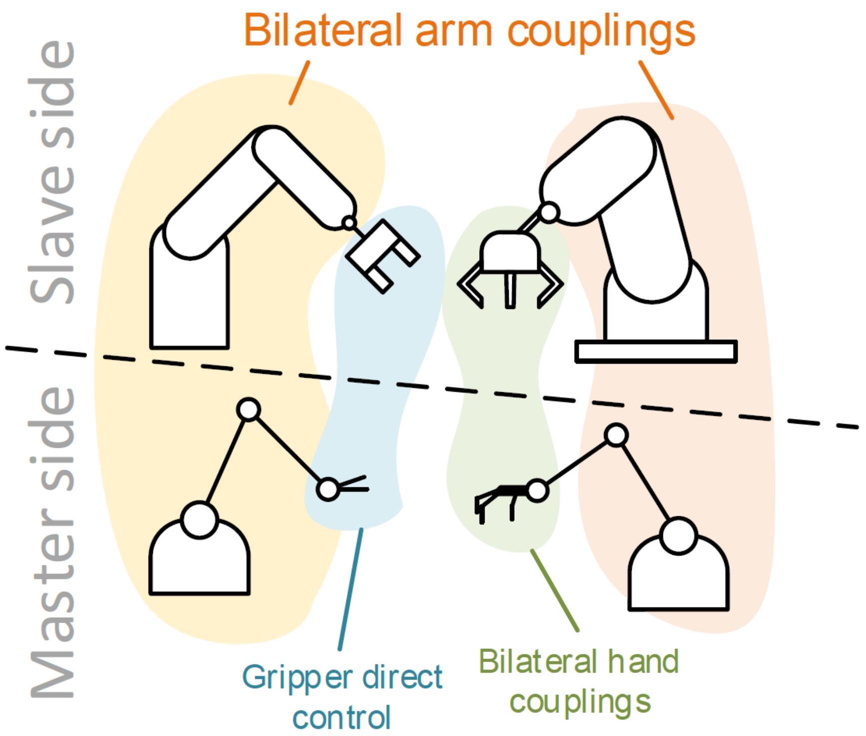
Input device: Joysticks **Scene perception:** Scene cameras **Force Feedback:** No

Tele-manipulation



1. Operator uses an input device
2. Controls a remote or collocated robot
3. Receive visual and/or haptic feedback from robot's environment

Tele-manipulation



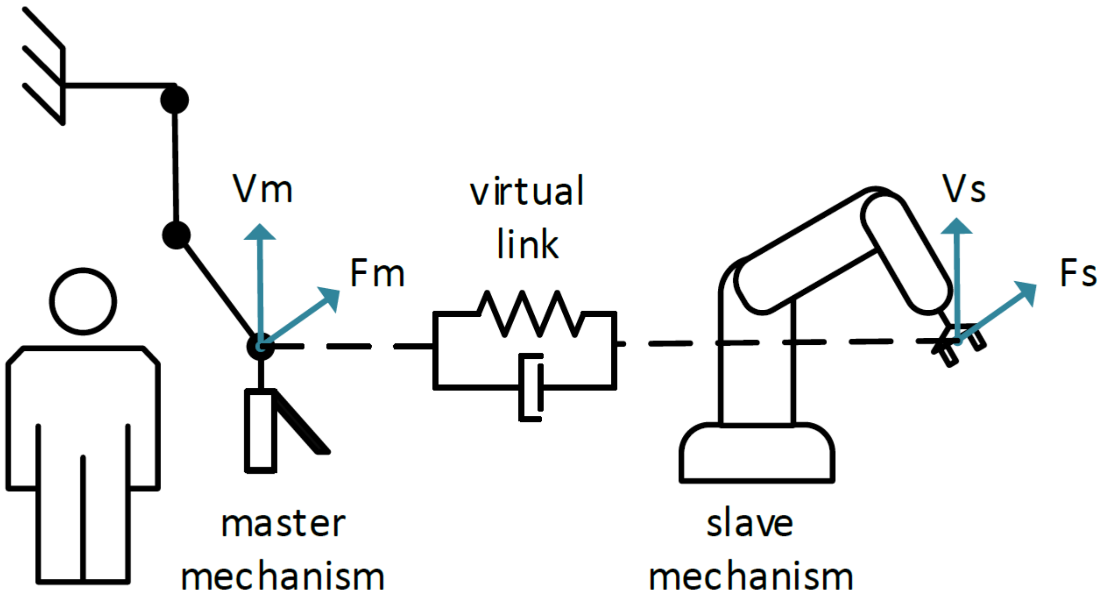


Fig. 7. Basic principle of bilateral coupling

- Generic controller
- No task related information used

Autonomous Grasping

- Robotic grasping of cluttered objects remain an open research problem
- Classical grasping methods require detailed knowledge of objects'

    E.g. shape, mass, friction coefficients etc.

- Learning approaches seek to encode a more direct link but require
    - large training data (some more and some less)
    - prototypical grasps to be taught beforehand ...

Autonomous Grasping

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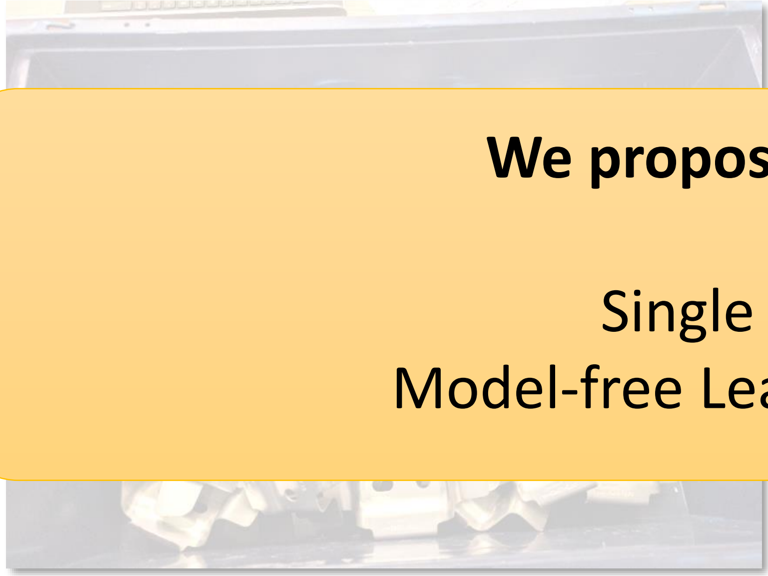
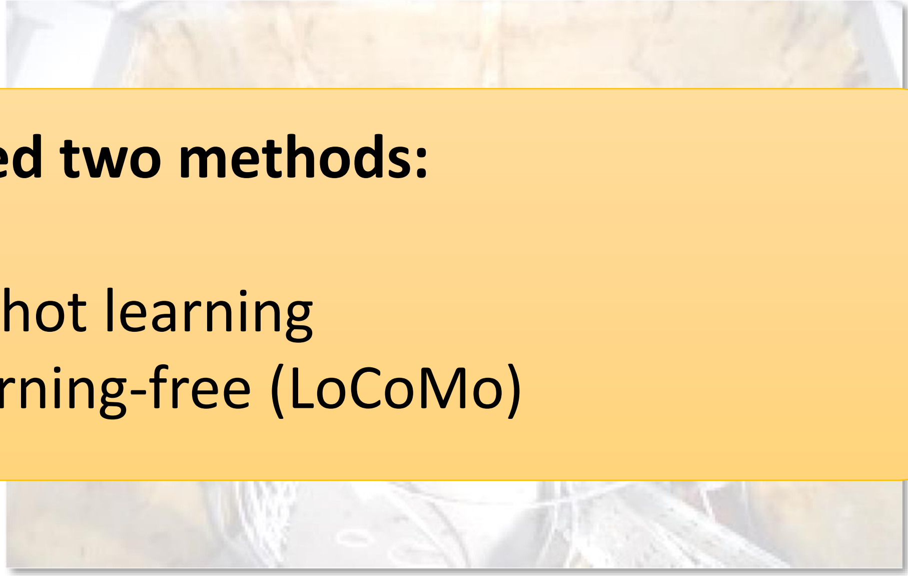
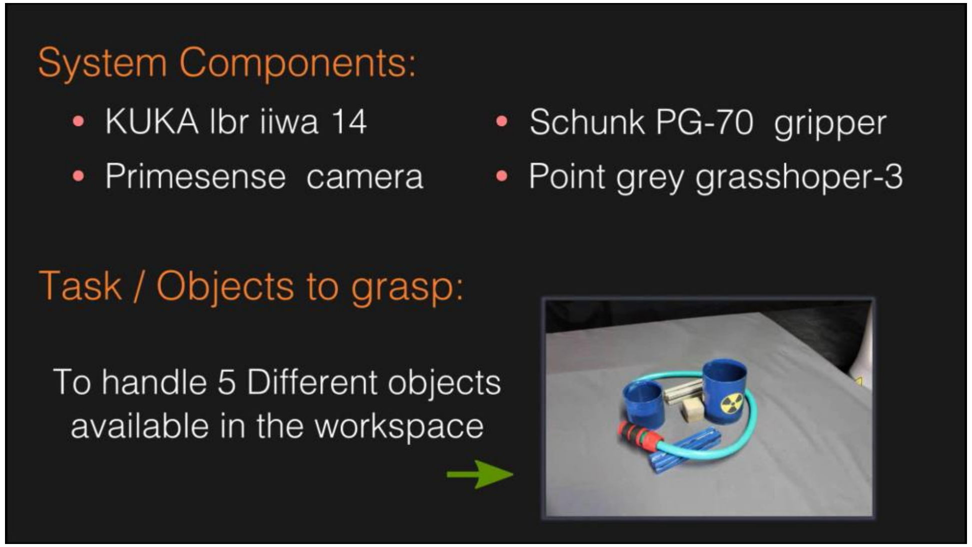



We proposed two methods:

Single shot learning
Model-free Learning-free (LoCoMo)

Autonomous Grasping



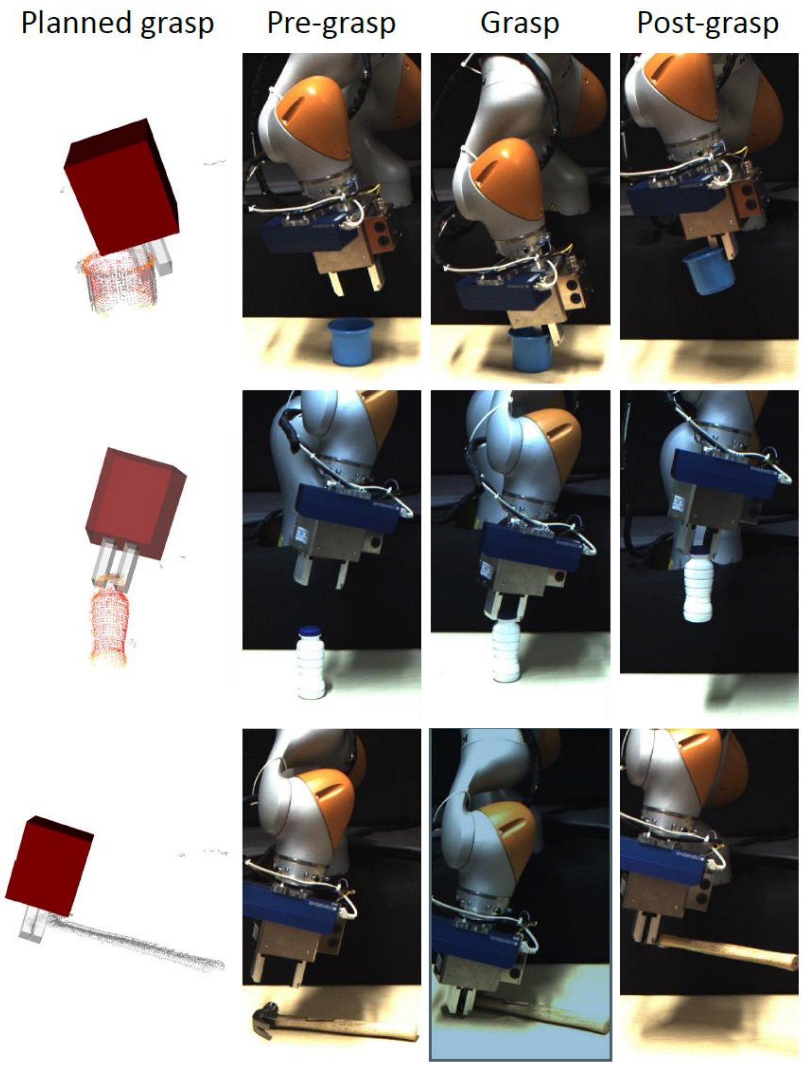
Marek Kopicki et al.
One shot learning and generation of dexterous grasps for novel objects (IJRR 2015)

- Learning on single object, generalise on new unseen objects
- Arbitrary shape
- Deformable
- Moderately cluttered heaps

Maxime Adjigble et al.
Model-free and learning-free grasping by local contact moment matching (IROS 2018)

- Different gripper geometry
- Unknown objects
- Arbitrary shape
- Deformable
- Moderately cluttered heaps

Autonomous Grasping

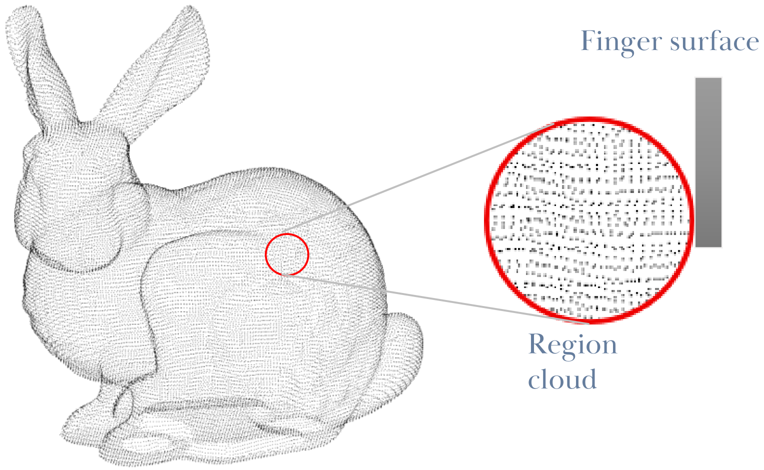


Object	Success Rate 1^{st} Grasp (5 Trials)
bleach cleanser	80% (4/5)
racquetball	100% (5/5
blue cup	80% (4/5)
aluminium profile	100% (5/5)
plastic bottle	100% (5/5)
bamboo bowl	100% (5/5)
spring clamp	100% (5/5)
electric hand drill	80% (4/5)
gas knob	100% (5/5)
golf ball	100% (5/5)
hammer	100% (5/5)
plastic lemon	80% (4/5)
mustard container	100% (5/5)
plastic nectarine	100% (5/5)
gray pipe	100% (5/5)
potted meat can	40% (2/5)
screwdriver	100% (5/5)
plastic strawberry	100% (5/5)
multi-head screwdriver	100% (5/5)
white pipe	60% (3/5)
wood block	100% (5/5)
Success Rate	**91.43%** (96/105)

Model-free and learning-free grasping tested (YCB Object Dataset)

Autonomous Grasping

LoCoMo:



$$n_\rho = M_\rho^0(\xi) - X$$

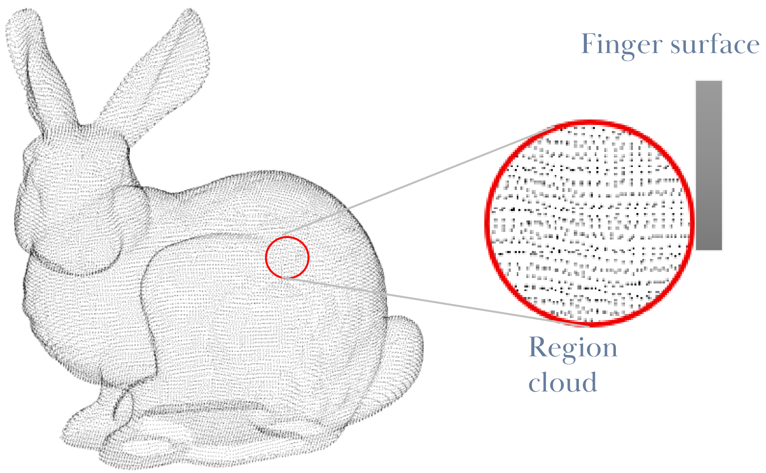
$$M_\rho^0(\xi) = \frac{1}{N}\sum_{n=1}^{N} X_i$$

$$\boldsymbol{\varepsilon} = \boldsymbol{n}_\rho^1 - \boldsymbol{n}_\rho^2$$

$$C_\rho = ((2\pi)^n\,|\Sigma|)^{\frac{1}{2}}\,\phi(\varepsilon;\vec{0},\Sigma)$$

Autonomous Grasping

LoCoMo:

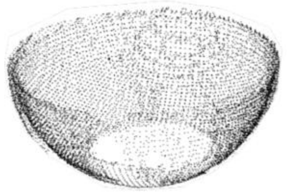


$$C_\rho = ((2\pi)^n \, |\Sigma|)^{\frac{1}{2}} \phi(\varepsilon; \vec{0}, \Sigma)$$

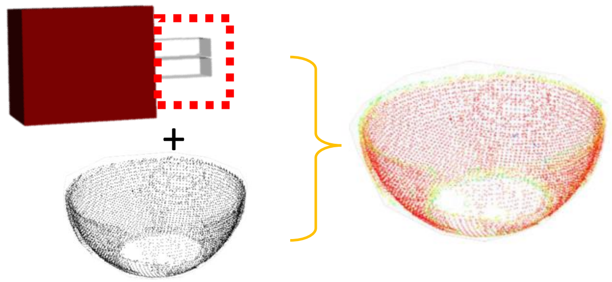
$$C_i = \frac{1}{N_s} \sum_{i=1}^{n} C_\rho^{i,Xi}$$

$$\mathcal{R} = k \prod_{i=1}^{n_f} C_i^{w_i}$$

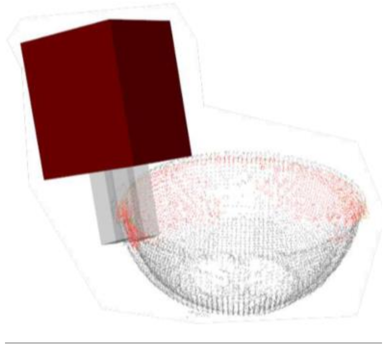
Grasping Pipeline:



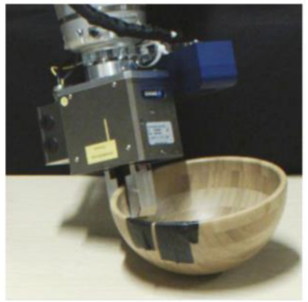
1. Acquire scene cloud



2. Compute LoCoMo



3. Generate grasp hypotheses



4. Execute best grasp

How to combine Teleoperation and Autonomous grasping for a better Tele-manipulation?

Teleoperation

- Complete control of robot's movements
- Natural movements translated into robot movements
- Force\Visual feedback
- Hard to operate
- 3D Visual perception/understanding challenging

Autonomous Grasping

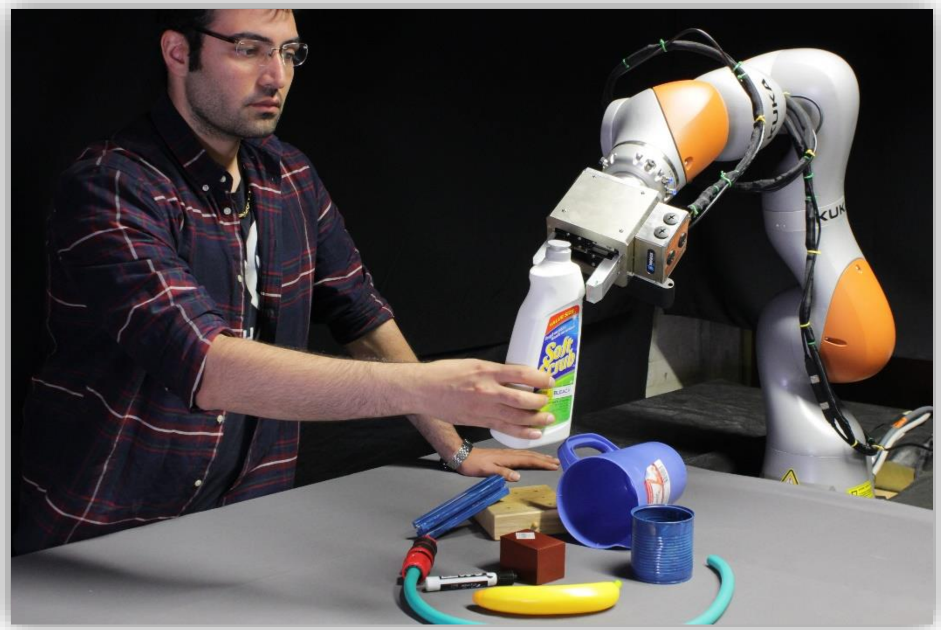
- Trajectory planner available
- Easy to operate
- Multiple grasp poses available
- Probabilistic
- High success rate but still not acceptable for high consequence applications

HRI Assisted Tele-manipulation

Some tasks requires human robot interaction

Manipulation by human hand-over

- Robot follows the human hand and collects the objects
- Multiple dynamic problems combined:
    - Continuous pose update
    - Real-time stable grasp pose update
    - Real-time motion planning to maintain *reach-to-grasp*
- Developed to use for problems in automotive industry



HRI Previous Work

Dynamic grasp and trajectory planning for moving objects

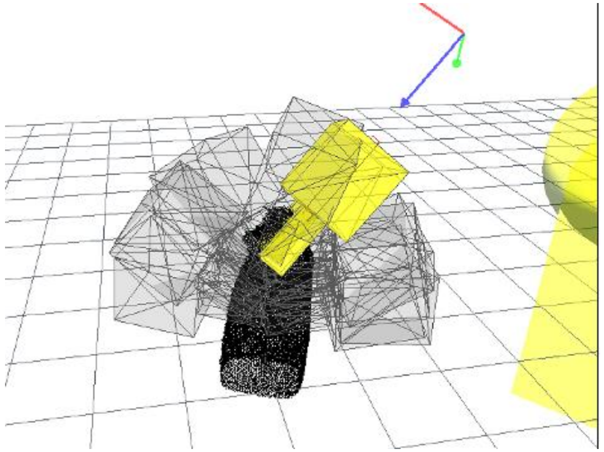
- Grasp precomputed
- Object tracked
- Grasps re-ranked online

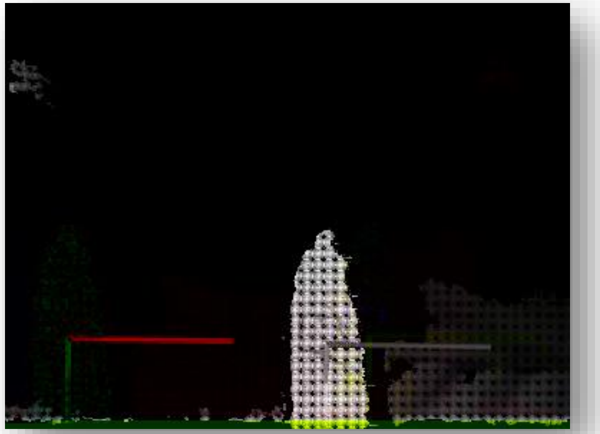
$\mathcal{K}^{for} : \mathbb{R}^{N^a} \longrightarrow SE(3)$ from the approximate solution $\tilde{c}^a$,

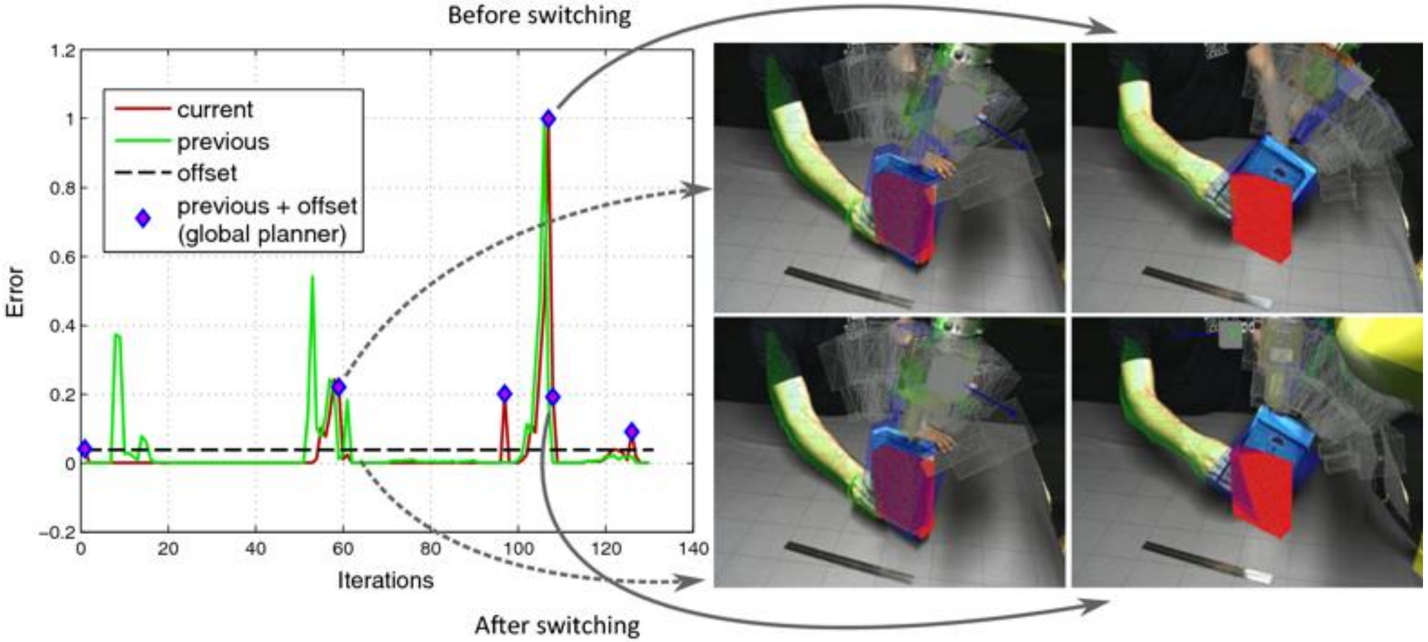
$$\epsilon_{ij} = (1-a)\,||\mathtt{lin}(sv^w_{ij}) - \mathtt{lin}(\mathcal{K}^{for}(\tilde{c}^a_{ij}))||^2 + a\,(1 - |\mathtt{ang}(sv^w_{ij}) \cdot (\mathtt{ang}(\mathcal{K}^{for}(\tilde{c}^a_{ij})))^{-1}|)$$

$$\epsilon_j = \frac{1}{m_j}\sum_{i=1}^{m_j} \epsilon_{ij}$$

HRI Previous Work







- Get initial pose of the object and generate initial grasp trajectories
- Track and update object pose when moved by human
- Compute feasible arm trajectories maintaining stable grasp tracking
    - Compute Inverse kinematics
- Select **k**th grasp trajectory with the smallest error and set as reference

Assisted Grasping with LoCoMo

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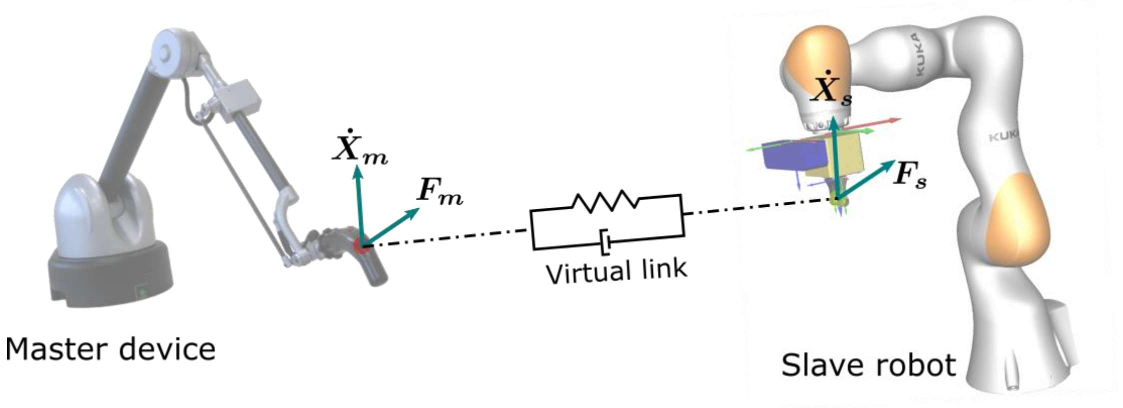
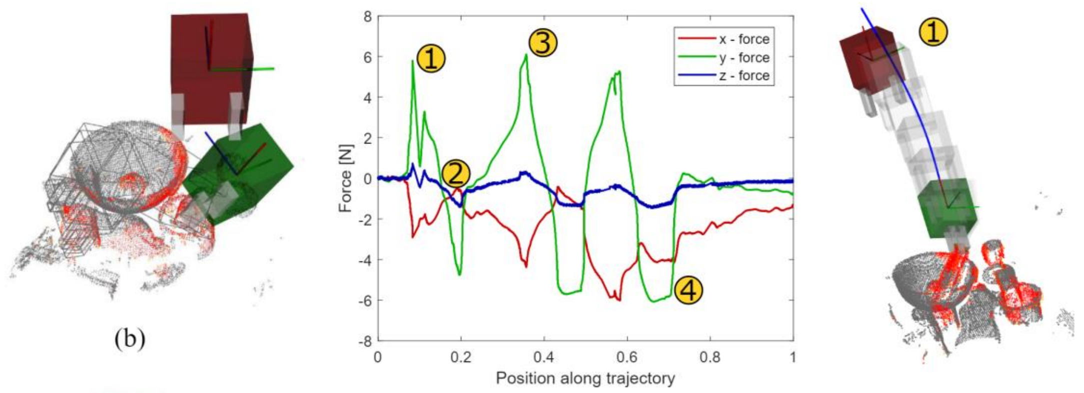
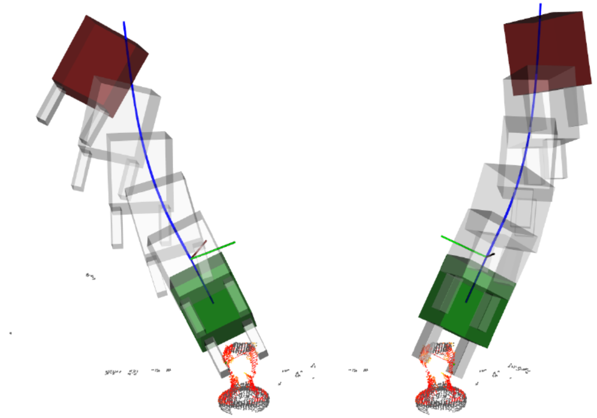




- Standard Teleoperation enhanced by grasp suggestions
- Force feedback includes shortest trajectory to grasp
- Grasp Reranking online based on state of the slave robot
- Combined with LoCoMo grasping to do assisted grasping
- Integrated shared control for automatic orientation alignment



$$\mathcal{R}_j^{'} = \frac{(d_{max} - d_j)}{(d_{max} - d_{min}))}\mathcal{R}_j$$

$$\boldsymbol{F}_m = -\boldsymbol{F}_s = -K_s(\boldsymbol{X}_m - \boldsymbol{X}_s) - K_d(\dot{\boldsymbol{X}}_m - \dot{\boldsymbol{X}}_s)$$

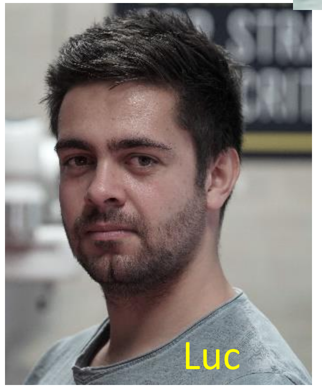
Assisted Grasping with LoCoMo

Test at ERL Laboratory:
- Kuka IIWA
- Haption Virtuose 6D
- Schunk PG70
- Ensenso N35
- Household objects

2-4X productivity increase
Reduced cognitive load
Usable by non expert users

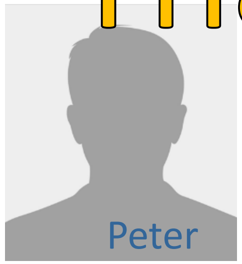
Test at NNL Laboratory:
- Kuka KR180 R2900
- Haption Virtuose 6D
- Zimmer GEH8660
- Ensenso N35
- Nuclear Mockup objects

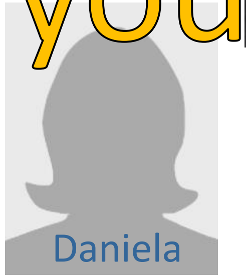
The Team

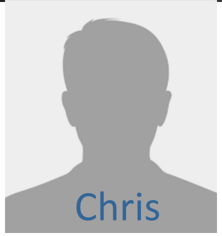


Thank you!!

Yasemine (alumni)







Marek (alumni)