MSRM MUNICH SCHOOL OF ROBOTICS AND MACHINE INTELLIGENCE

ISRR 2019

INCREASING THE CLOSED-LOOP DYNAMICS OF ROBOTICS RESEARCH

SAMI HADDADIN

Today

- Actual idea:
  - Defining what a robot should ideally be: standard Lagrangian dynamics (here)
  - Develop a reference platform: What do we want to have exactly?
  - Note:
    - I believe my argumentation holds for any robot type you want.
    - I am just taking the most basic form „robotics 1“

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- Use it to do research case study I: Learning dynamics
- Use it to do research case study II: Learning manipulation

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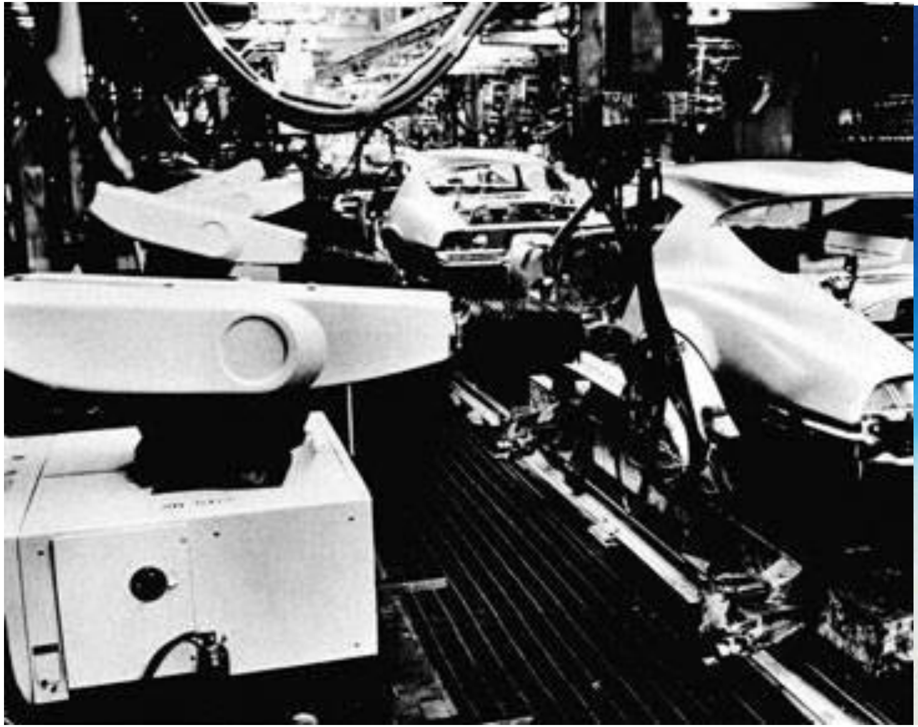
- Use it to do research case study I: **Learning dynamics**

The first robot generations

The first industrial robot
George Devol & Joseph Engelberger in 50’s



The first universally programmable robot
Victor Scheinman at Unimation

The ideal robot from „Robotics 1“

$$\boxed{\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q},\dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau}_{\mathrm{m}}}$$

The robot from „Reality 1“

??? ?

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \boldsymbol{\tau}_{\mathrm{m}} - \boldsymbol{\tau}_{\mathrm{f}} + \boldsymbol{\tau}_{\mathrm{ext}}$$

??? ??? ???

Fazit:
Let’s do position control.
I hate friction identification anyways and no one needs models.
PID actually just works fine.

State of the art

www.electronicsb2b.com

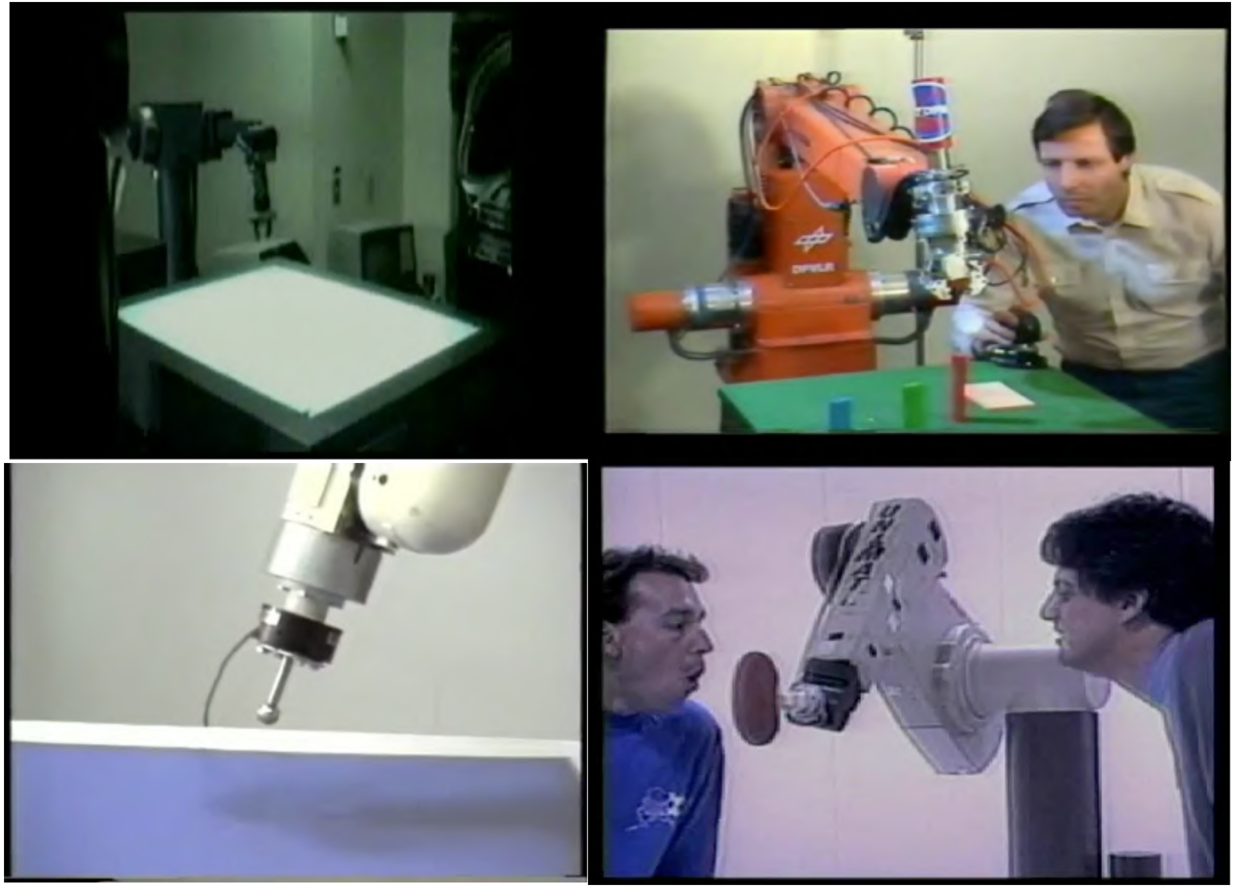
Spot welding and painting
> 300k€ per robot installation
Worldwide sales: 300k robots/ years

NO assembly, …

Source: Kulturpunkt.hr

Chapter I
-
Develop a reference system

The pioneers



Oussama Khatib, Stanford University
Gerd Hirzinger, DLR
Bruno Siciliano, University of Naples

The robot from „Reality 1“

??? ?

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau}_{\mathrm{m}} - \boldsymbol{\tau}_{\mathrm{f}} + \boldsymbol{\tau}_{\mathrm{ext}}$$

??? ??? ???

The robot from „Reality 1“ to „Reality 2“

offline lagfree estimation

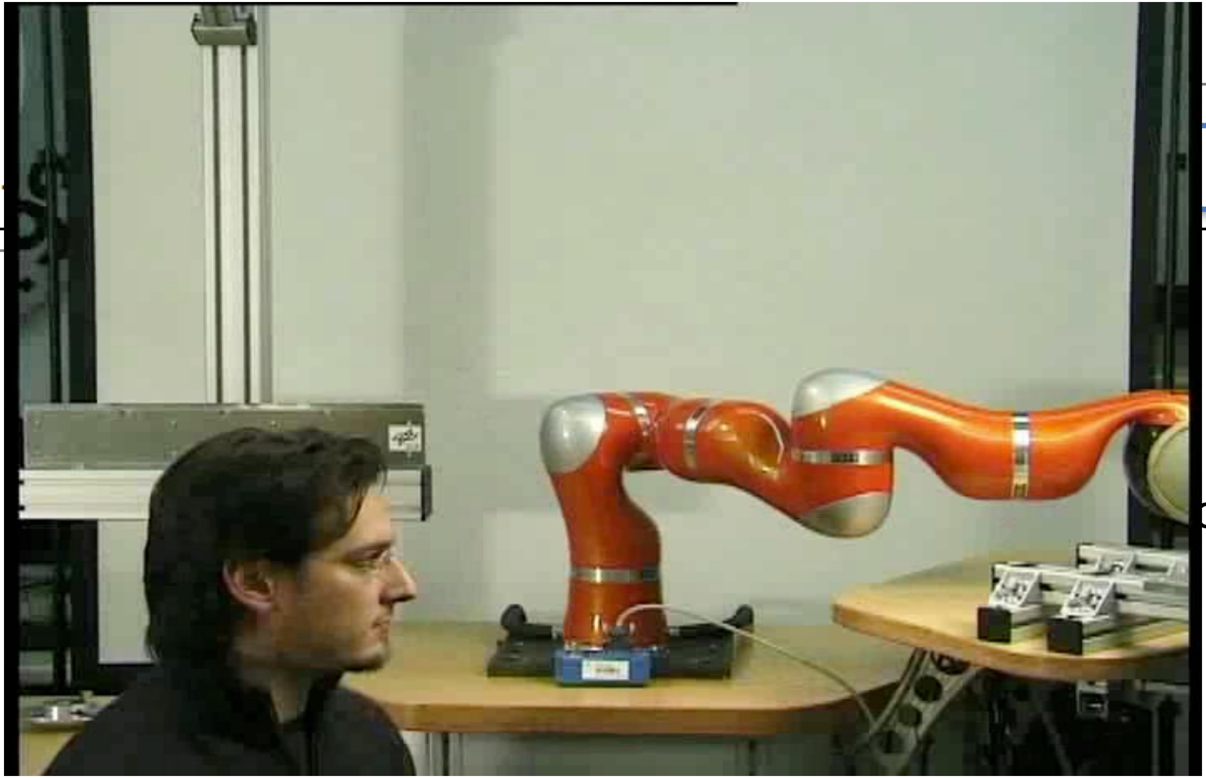
$$\underline{M(q)}\ddot{q} + \underline{C(q,\dot{q})}\dot{q} + \underline{g(q)} = \tau_{\mathrm{m}} \underline{\boxed{}} + \underline{\tau_{\mathrm{ext}}}$$

System identification

???

Joint torque sensing

The robot from „Reality 1“ to „Reality 2“ to „Reality 3“



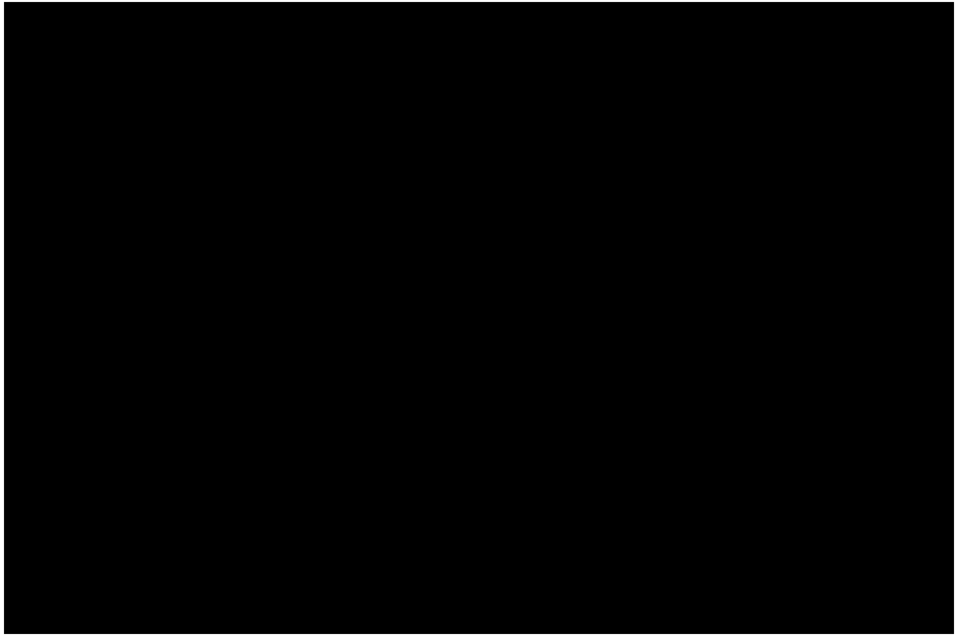
$+ \tau_{\text{ext}}$

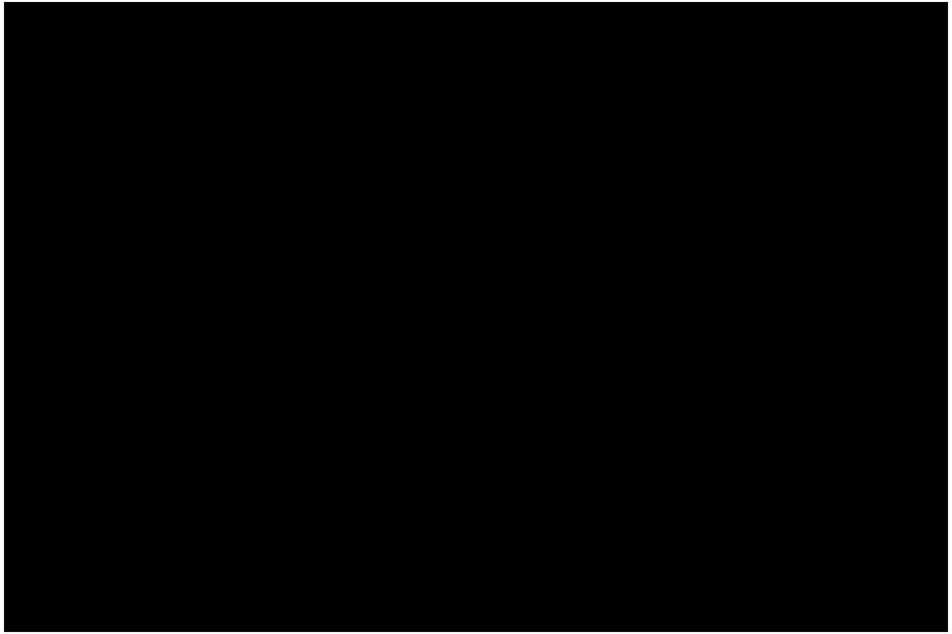
Momentum observer

orque sensing

Collision Handling

De Luca et al. IROS 2006
Haddadin et al. IROS 2009
Haddadin et al. TRO2017





The Paper

Towards the Robotic Co-Worker

Sami Haddadin, Michael Suppa, Stefan Fuchs, Tim Bodenmüller, Alin Albu-Schäffer, Gerd Hirzinger

sami.haddadin@dlr.de
Institute of Robotics and Mechatronics
DLR e.V. - German Aerospace Center
P.O. Box 1116, D-82230 Wessling, Germany

Summary. Recently, robots have gained capabilities in both sensing and actuation, which enable operation in the proximity of humans. Even direct physical interaction has become possible without suffering the decrease in speed and payload. The DLR Lightweight Robot III (LWR-III), whose technology is currently being transferred to the robot manufacturer KUKA Roboter GmbH, is such a device capable of realizing various features crucial for direct interaction with humans. Impedance control and collision detection with adequate reaction are key components for enabling "soft and safe" robotics. The implementation of a sensor based robotic co-worker that brings robots closer to humans in industrial settings and achieve close cooperation is an important goal in robotics. Despite being a common vision in robotics it has not become reality yet, as there are various open questions still to be answered. In this paper a solid concept and a prototype realization of a co-worker scenario are developed in order to demonstrate that state-of-the-art technology is now mature enough to reach this aspiring aim. We support our ideas by addressing the industrially relevant bin-picking problem with the LWR-III, which is equipped with a Time-of-Flight camera for object recognition and the DLR 3D-Modeller for generating accurate environment models. The paper describes the sophisticated control schemes of the robot in combination with robust computer vision algorithms, which lead to a reliable solution for the chosen problem. Strategies are devised for safe interaction with the human during task execution, state depending robot behav-

What is the goal?

Ideal I

Reference platform that is as highly **capable**, **affordable** and **accessible**

Ideal II

Behaves like Lagrangian dynamics and has the right interfaces

$$\boldsymbol{\tau}_{\text{in}} = M(\boldsymbol{q})\ddot{\boldsymbol{q}} + C(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q})$$

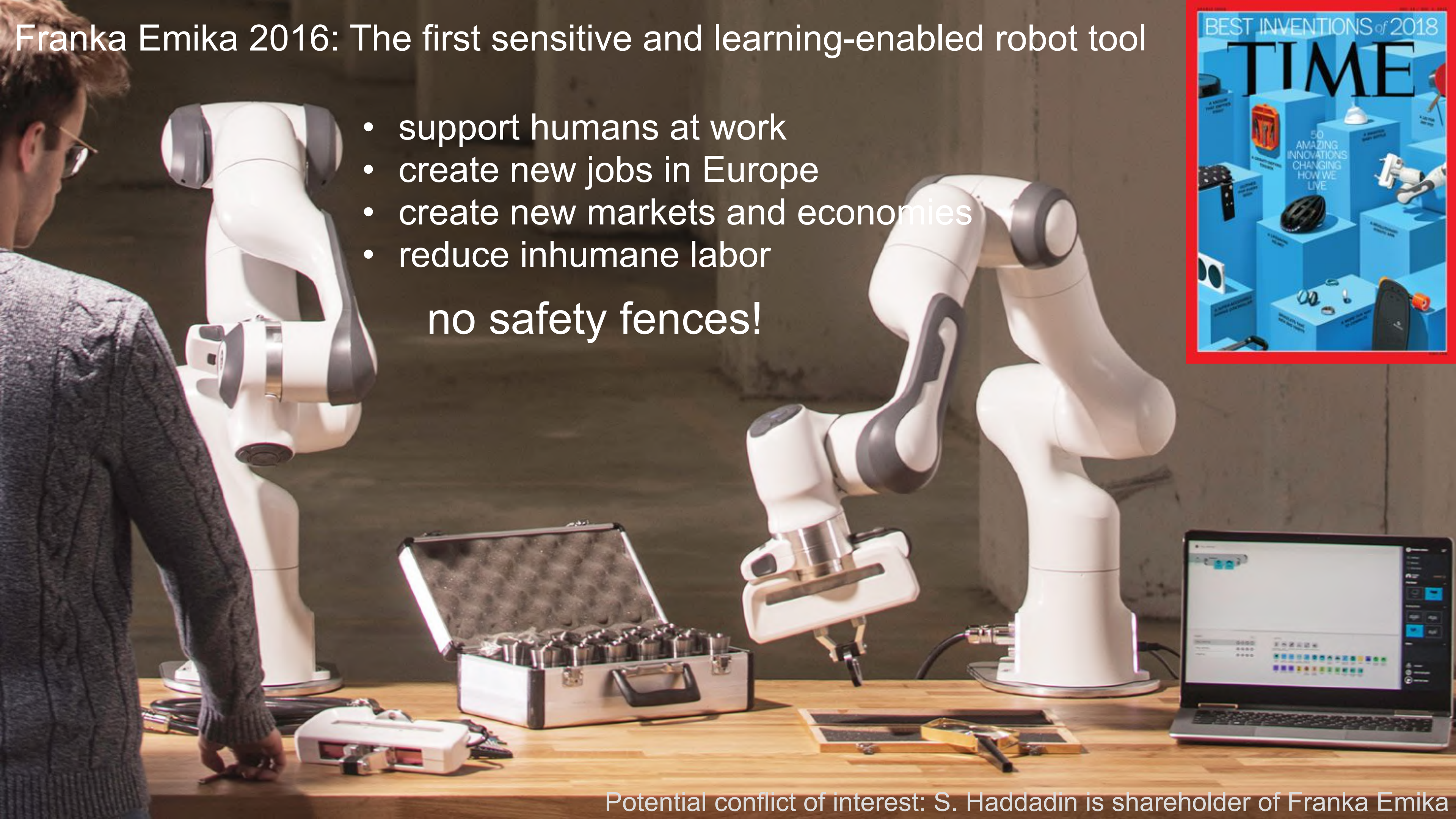
Ideal III: HIGH PERFORMANCE

- Presumably is able to perform all reference skills (initially ambitious and grows along the lines or research …)
- **Joint torque** (**not current**) interface
- Real-time control rate **1 kHz: joint torque** / velocity, …
- dexterity
- fast and accurate
- **Precise** torque, external torque and external wrench measurements << 1 N / Nm
- **Dynamic models available < 2% error**
- **Precise** position and velocity measurements < 0.1 mm

Franka Emika 2016: The first sensitive and learning-enabled robot tool

- support humans at work
- create new jobs in Europe
- create new markets and economies
- reduce inhumane labor

no safety fences!



Potential conflict of interest: S. Haddadin is shareholder of Franka Emika

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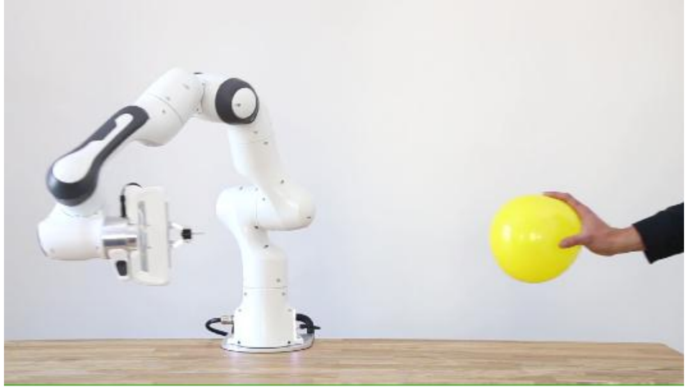
FRANKA EMIKA

human like dexterity

safe reflexes



sensitive assembly

sensitive insertion

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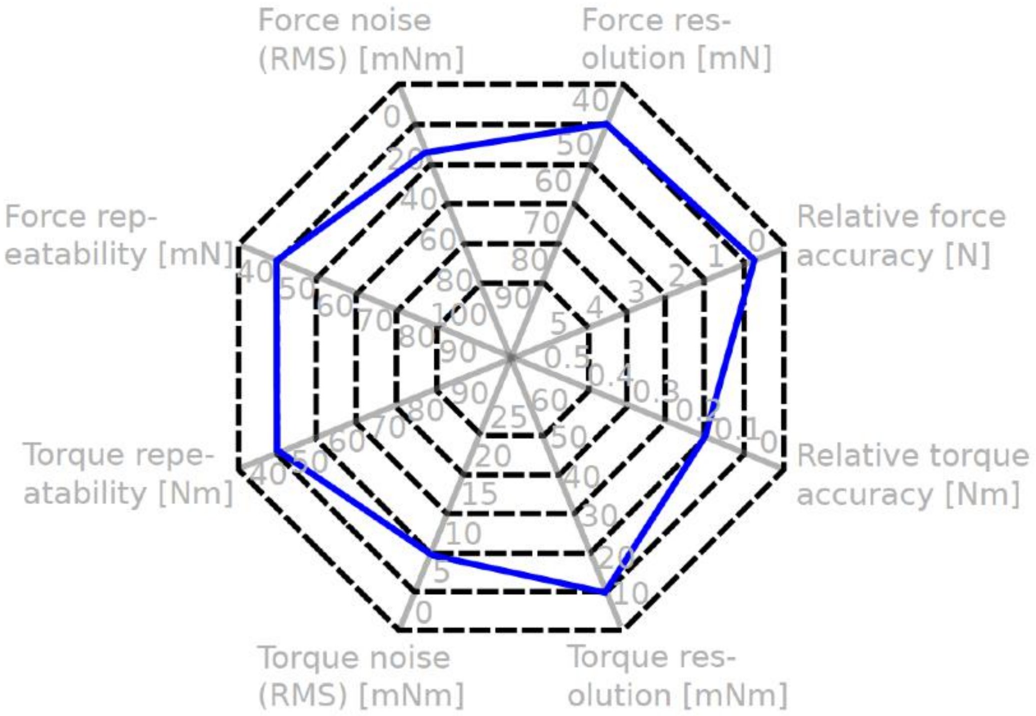
This is a new robot type. We need to redefine the robot data sheet



Redefining the robot data sheet

HARDWARE

Arm

Degrees of freedom	7
Payload	3 kg
Workspace	see backside
Maximum reach	855 mm
F/T Sensing	link-side torque sensors in all 7 axes
Expected nominal lifetime [3,4]	20,000 h
Joint position limits [°]	A1, A3, A5, A7: -166/166 A2: -101/101 A4: -176/-4 A6: -1/215
Mounting flange	DIN ISO 9409-1-A50
Installation position	upright
Weight	~ 17.8 kg
Moving mass	~ 12.8 kg
Protection rating	IP30
Ambient temperature [2]	15 – 25 °C (typical) 5 – 45 °C (extended)
Air humidity	20 – 80 % non-condensing
Power consumption	• max. ~ 350 W • typical application ~ 60 W
Interfaces	• ethernet (TCP/IP) for visual intuitive programming with Desk • input for external enabling device • input for external activation device or safeguard • Control connector • Connector for end-of-arm tooling

Control

Controller size (19”)	355 x 483 x 89 mm (D x W x H)
Supply voltage	100 – 240 V_{AC}
Mains frequency	47 – 63 Hz
Power consumption	~ 80 W
Active power factor correction (PFC)	yes
Weight	~ 7 kg
Protection rating	IP20
Ambient temperature	15 – 25 °C (typical) 5 – 45 °C (extended)
Air humidity	20 – 80 % non-condensing
Interfaces	• ethernet (TCP/IP) for internet and/or shop-floor connection • power connector IEC 60320-C14 (V-Lock) • Arm connector

Redefining the robot data sheet

SOFT-ROBOT PERFORMANCE

Motion

Joint velocity limits [°/s]	A1, A2, A3, A4: 150 A5, A6, A7: 180
Cartesian velocity limits	up to 2 m/s end effector speed
Pose repeatabillity	<+/- 0.1 mm (ISO 9283)
Path deviation [3]	<+/- 1.25 mm

Force

Sensing [3]

Force resolution	<0.05 N
Relative force accuracy	0.8 N
Force repeatability	<0.15 N
Force noise (RMS)	<0.035 N
Torque resolution	<0.02 Nm
Relative torque accuracy	0.15 Nm
Torque repeatability	<0.05 Nm
Torque noise (RMS)	<0.005 Nm

1 kHz Control [3]

Minimum controllable force (Fz)		0.05 N
Force controller bandwidth (-3 dB)		10 Hz
Force range [N]	Nominal case	Best case
Fx	-125 – 95	-150 – 115
Fy	-100 – 100	-275 – 275
Fz	-50 – 150	-115 – 155
Torque range [Nm]	Nominal case	Best case
Mx	-10 – 10	-70 – 70
My	-10 – 10	-16 – 12
Mz	-10 – 10	-12 – 12

Interaction

Guiding force	~ 2 N
Collision detection time	<2 ms
Nominal collision reaction time [3,4]	<50 ms
Worst case collision reaction time [3]	<100 ms
Adjustable translational stiffness	0 – 3000 N/m
Adjustable rotational stiffness	0 – 300 Nm/rad
Monitored signals	Joint position, velocity, torque Cartesian position, velocity, force

Force measurement without force sensor

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Impedance Control

Force Control F_d = 7.8 N

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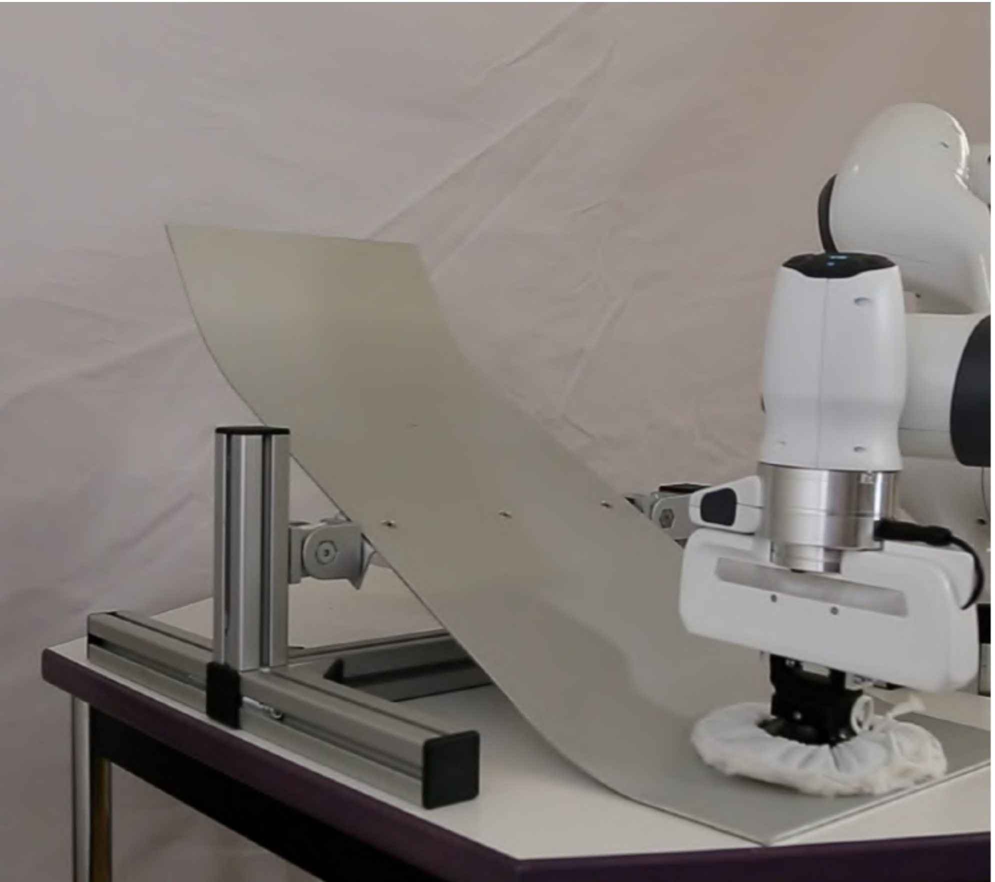
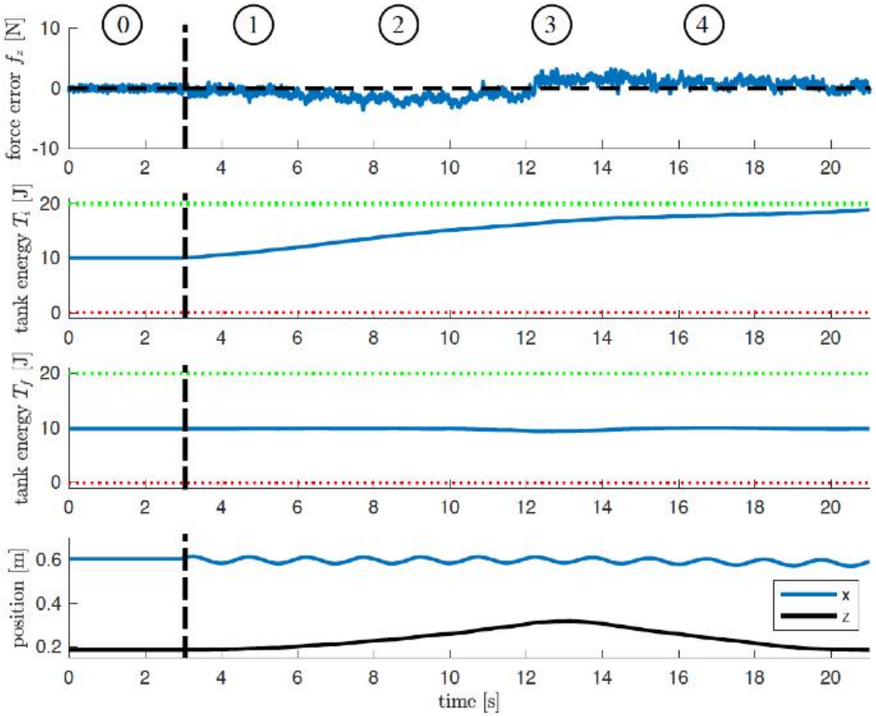
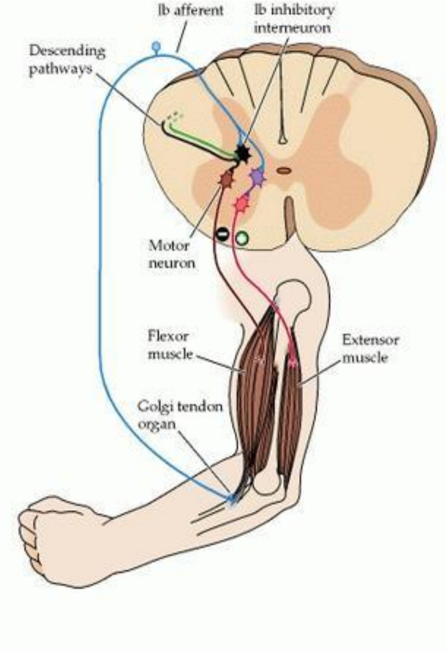
Wrench control with contact loss stabilization

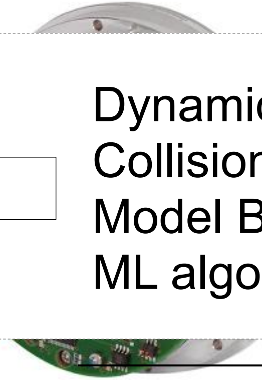
Force tracking



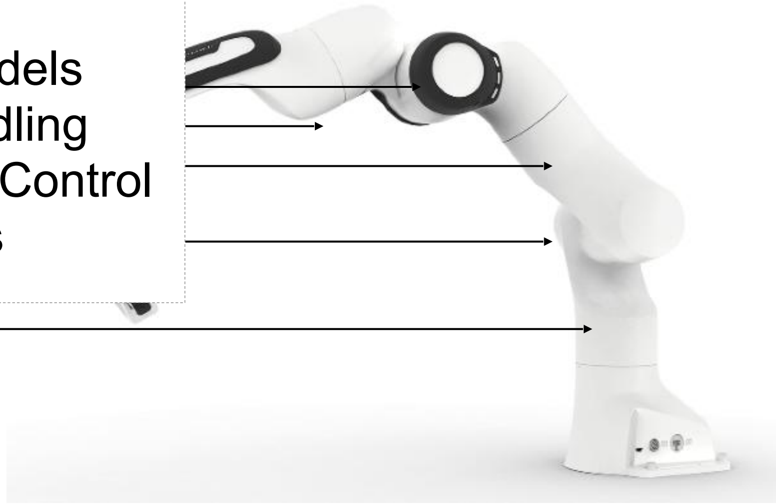


The key to sensitivity + manipulation





Dynamics Models
Collision Handling
Model Based Control
ML algorithms



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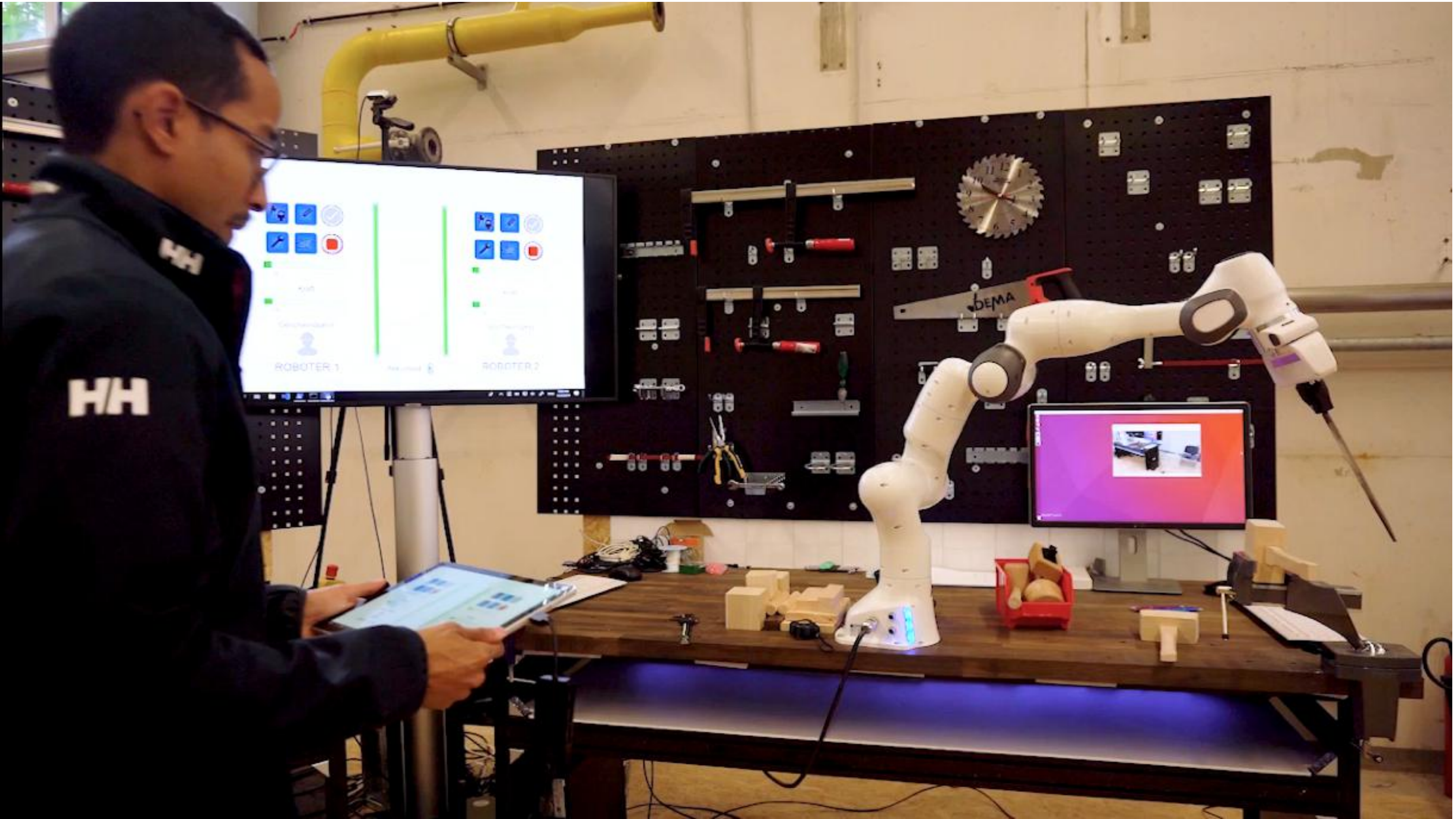
Human-Robot Collaboration 10 years after



Chapter II
-
Increasing Research Closed-Loop Dynamics

Why a reference platform?

Manipulation learning and control approaches are difficult to compare and validate.

Amazon picking challenge

So far: Benchmark **tasks instead of skills**

Why a reference platform?

Manipulation learning and control approaches are difficult to compare and validate.

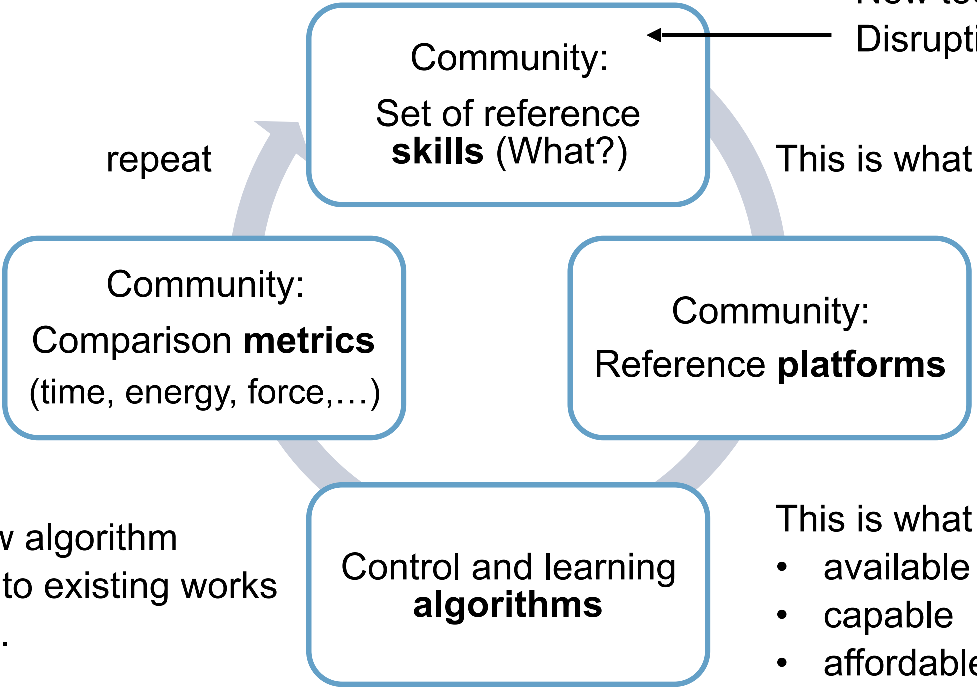
Amazon picking challenge

Enable *objective comparisons* and reproducible results with a ***reference platform***

This is not a one-time effort. This is a community mission!

The reference system-skill loop

New robots
New technologies
Disruptive ideas



repeat

This is what I probably need.

This is what I can currently get:

- available
- capable
- affordable

This is my new algorithm

- comparable to existing works
- papers at ….

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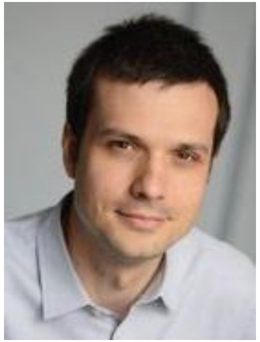
International Conference on
Robotics and Automation

ICRA Workshop: Bringing perception-based manipulation to the real world: standardizing robot manipulation learning



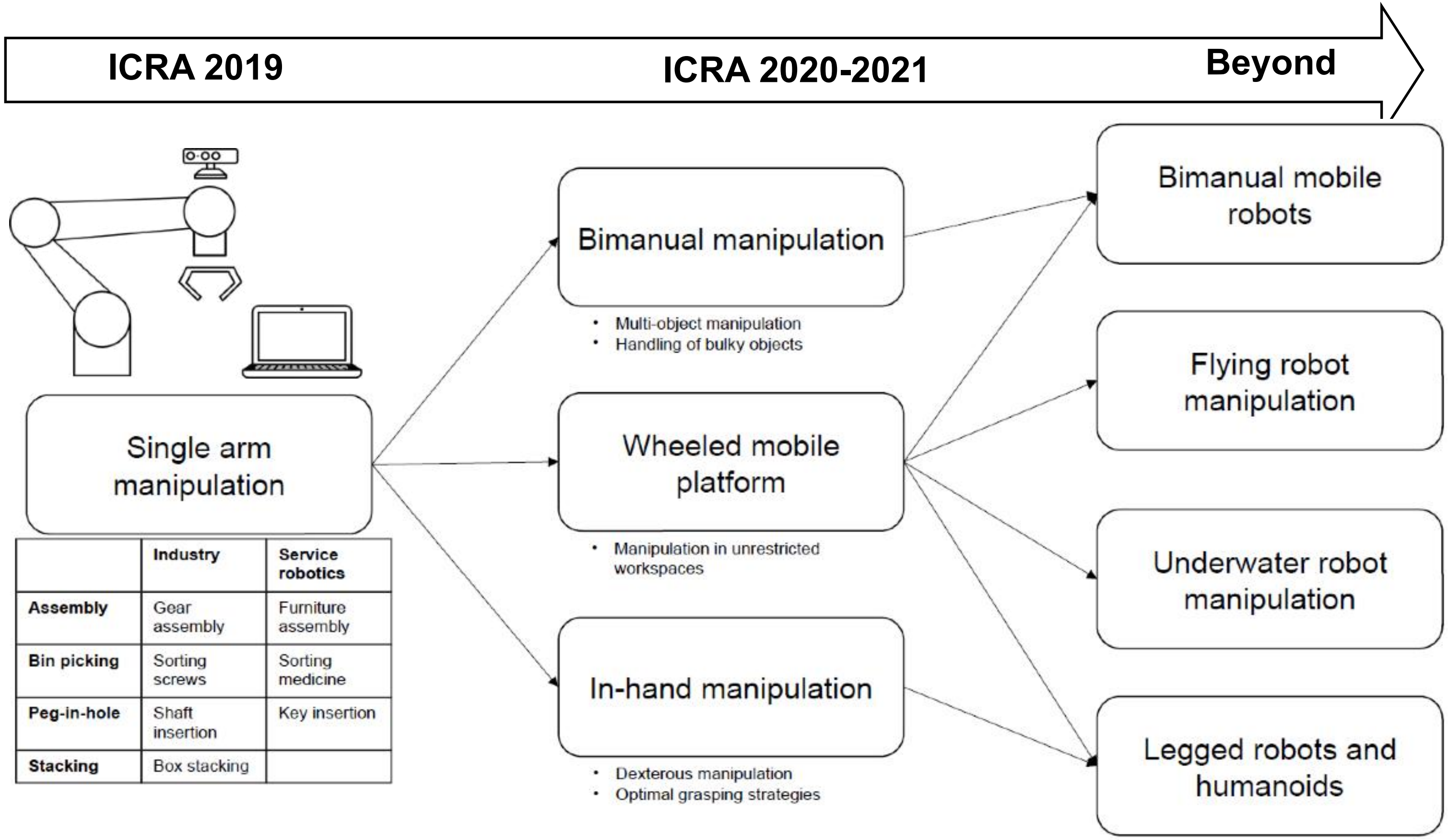








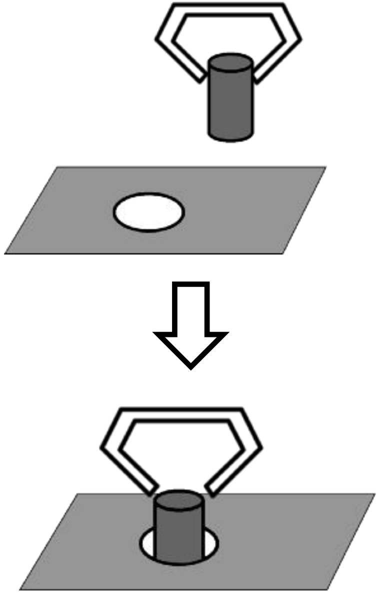
Roadmap for manipulation platforms and reference skills



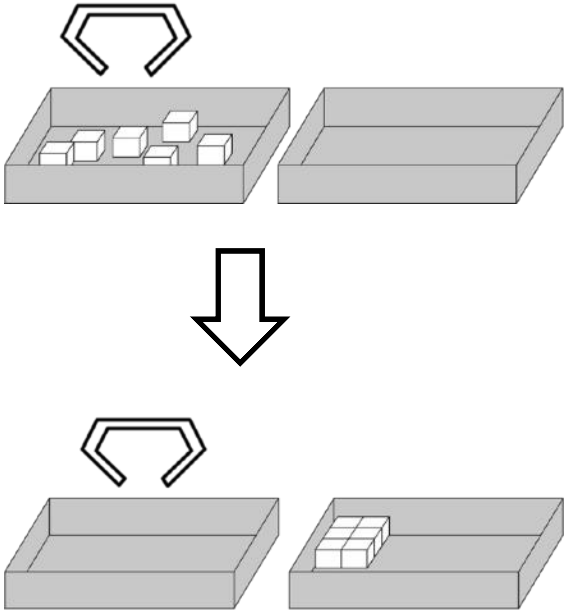
	Industry	**Service robotics**
Assembly	Gear assembly	Furniture assembly
Bin picking	Sorting screws	Sorting medicine
Peg-in-hole	Shaft insertion	Key insertion
Stacking	Box stacking	

Industrial reference skills I

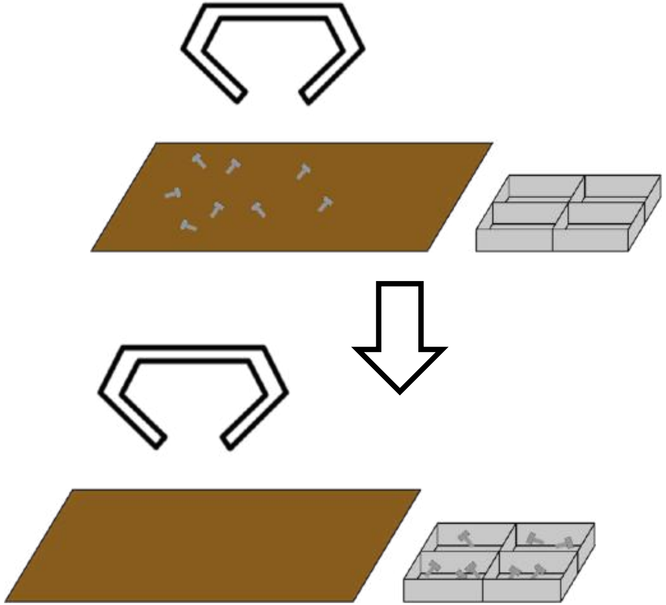
Shaft insertion



Sorting and stacking



Sorting screws



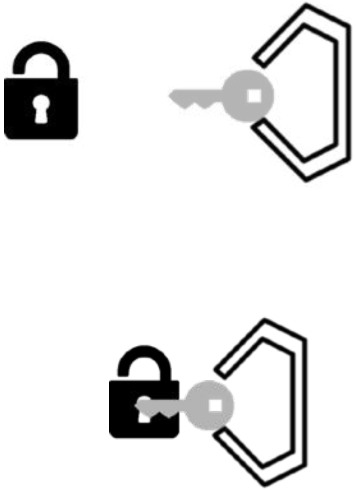
Industrial reference skills II

Gear assembly

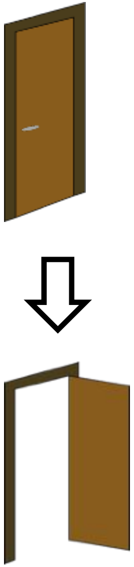
Cabling

Household reference skills I

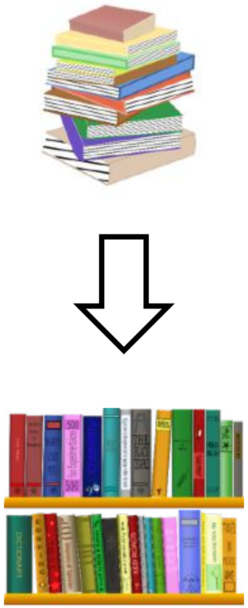
Key insertion



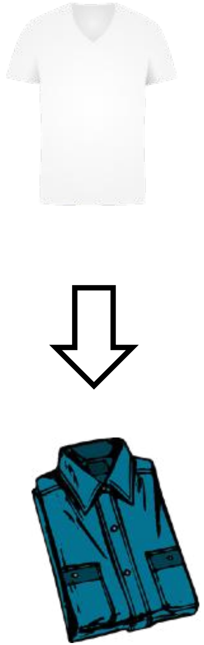
Open door



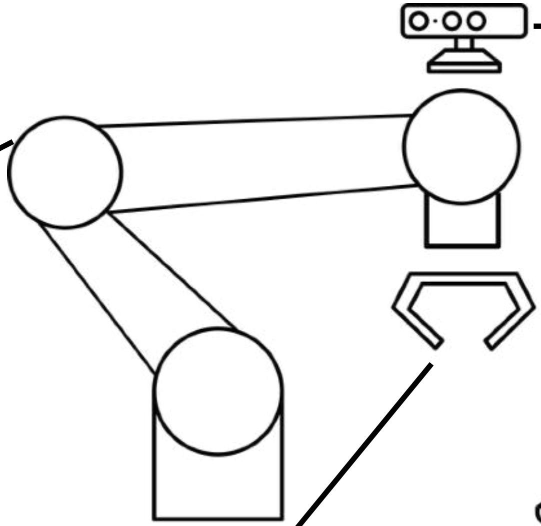
Book stacking



Folding clothes



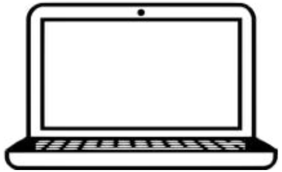
Platform requirements



A.3 Camera
- Minimum requirements:
  - RGB-D camera
  - Resolution 640 x 480
  - Refresh rate 15 Hz
- Ideal requirements:
  - Resolution 1920 x 1080
  - Refresh rate 60 Hz

A.1 Robot manipulator
- Minimum requirements:
  - At least 6 DoF
  - Joint velocity interface
  - Payload 1 kg
  - Control API
  - Position and velocity measurements
- Ideal requirements:
  - 7 DoF
  - Joint torque interface
  - Control rate 1 kHz
  - At least 3 kg at 0.5 m/s
  - Position, velocity, torque, external torque and external wrench measurements

A.2 End effector
- Minimum requirements:
  - Two finger gripper
  - Position controlled
- Ideal requirements:
  - Dexterous hand
  - Torque controlled
  - Control rate 1 kHz



Specify a suitable computer system to control the proposed full setup

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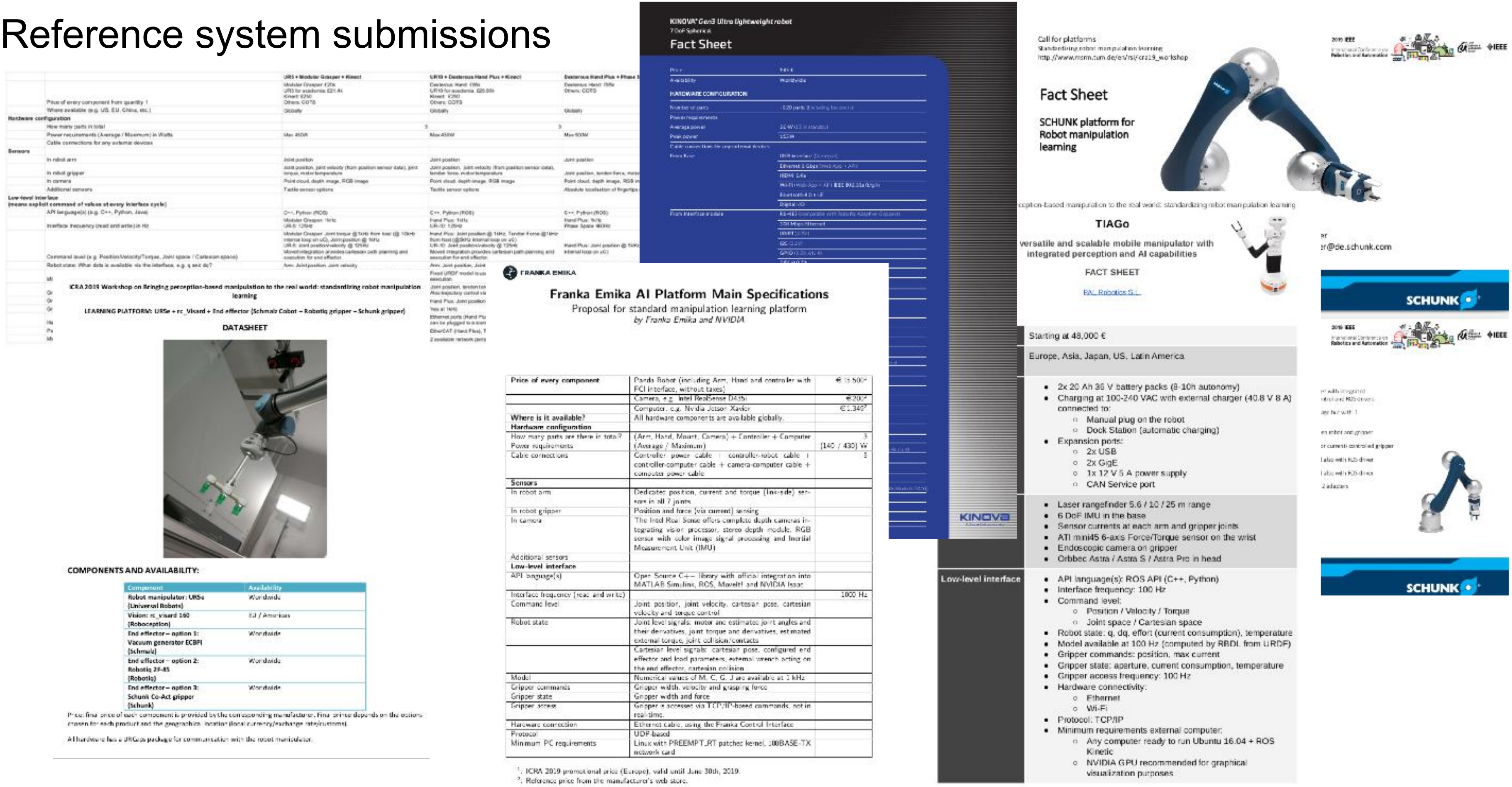
Reference system submissions



What is the (first!) GPU in Robotics?

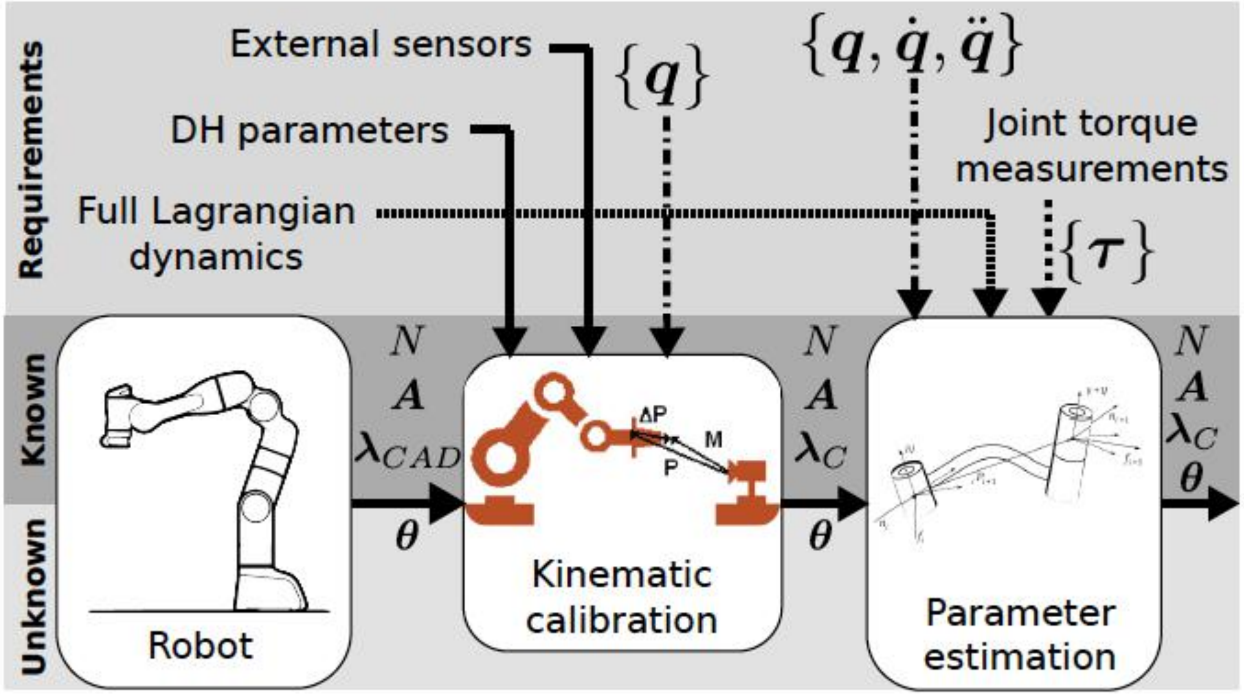
Chapter III
-
Robot Learning: Dynamics

Standard Problem: Learning Dynamics (never worked)

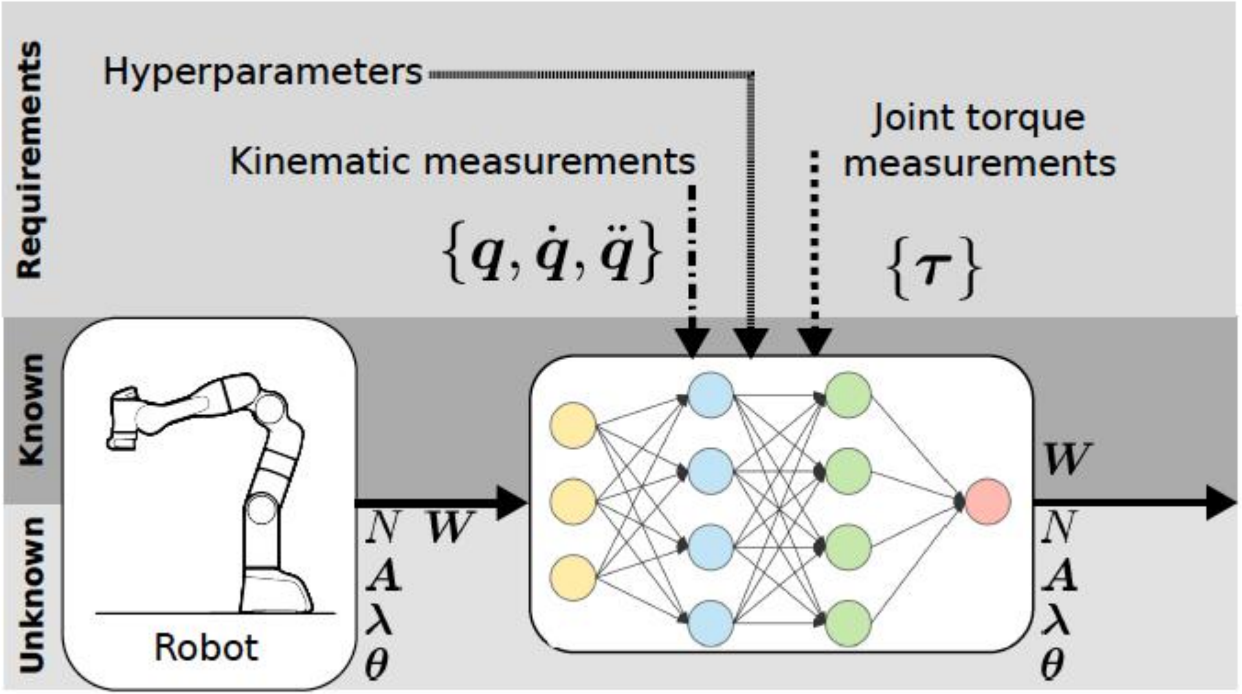
CAN WE LEARN ROBOT DYNAMICS?

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau}_{\mathrm{m}}$$

System identification



Neural Networks based



Typical challenges in neural networks

- Approaches rely on approximation capabilities of the specific network
- Weights usually no physical meaning
- Only little leveraging of available system knowledge
- Architecture choice depends on skilled human architect
- Generalization requires training sets to cover vast regions of input-output space

ROBOT DYNAMICS: LINEAR REGRESSION FORM

Overall energies: $T = \sum_{j=1}^{n} T_j$ & $U = \sum_{j=1}^{n} U_j$

Lagrangian function: $L = T - U$

Euler-Lagrange equation: $\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\boldsymbol{q}}}\right) - \frac{\partial L}{\partial \boldsymbol{q}} = \boldsymbol{\tau}$

$$\downarrow$$

$$\boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{C}(\boldsymbol{q}, \dot{\boldsymbol{q}})\dot{\boldsymbol{q}} + \boldsymbol{g}(\boldsymbol{q}) = \boldsymbol{\tau}_{\mathrm{m}}$$

Khalil, W., & Dombre, E. (2004). Modeling, identification and control of robots. Butterworth-Heinemann.

ROBOT DYNAMICS: LINEAR REGRESSION FORM

Overall energies: $$T = \sum_{j=1}^{n} T_j \quad \& \quad U = \sum_{j=1}^{n} U_j$$

Lagrangian function: $$L = T - U$$

Euler-Lagrange equation: $$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\boldsymbol{q}}}\right) - \frac{\partial L}{\partial \boldsymbol{q}} = \boldsymbol{\tau}$$

n-D input joint torque vector

10n-D **inertial parameters vector**:

$$X^T = [X_1^T, \dots, X_n^T]$$

$$\boldsymbol{\tau} = Y(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})X$$

n x 10n block upper triangular **regressor matrix**:

$$\begin{bmatrix} Y_{1,1} & Y_{1,2} & \dots & Y_{1,n} \\ 0 & Y_{2,2} & \dots & Y_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & Y_{n,n} \end{bmatrix}$$

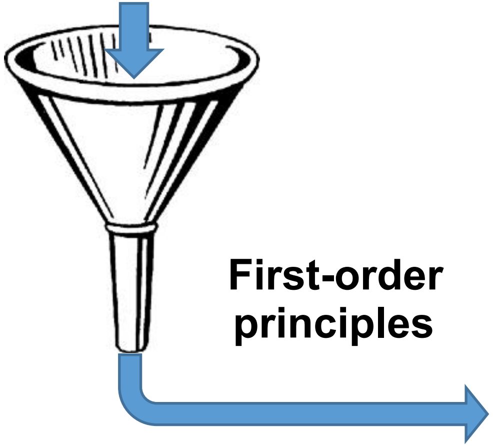
1 x 10 row vector

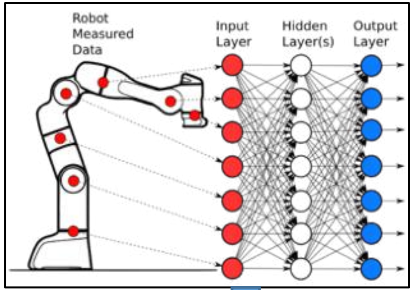
Khalil, W., & Dombre, E. (2004). Modeling, identification and control of robots. Butterworth-Heinemann.

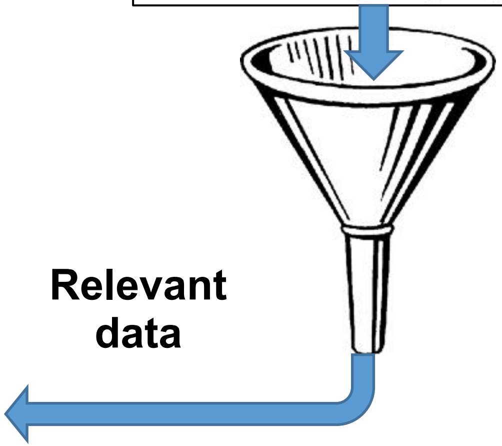
IDEA FOPnet

$$f = m\dot{v}$$

$$\tau = I\dot{\omega} + \omega \times I\omega$$







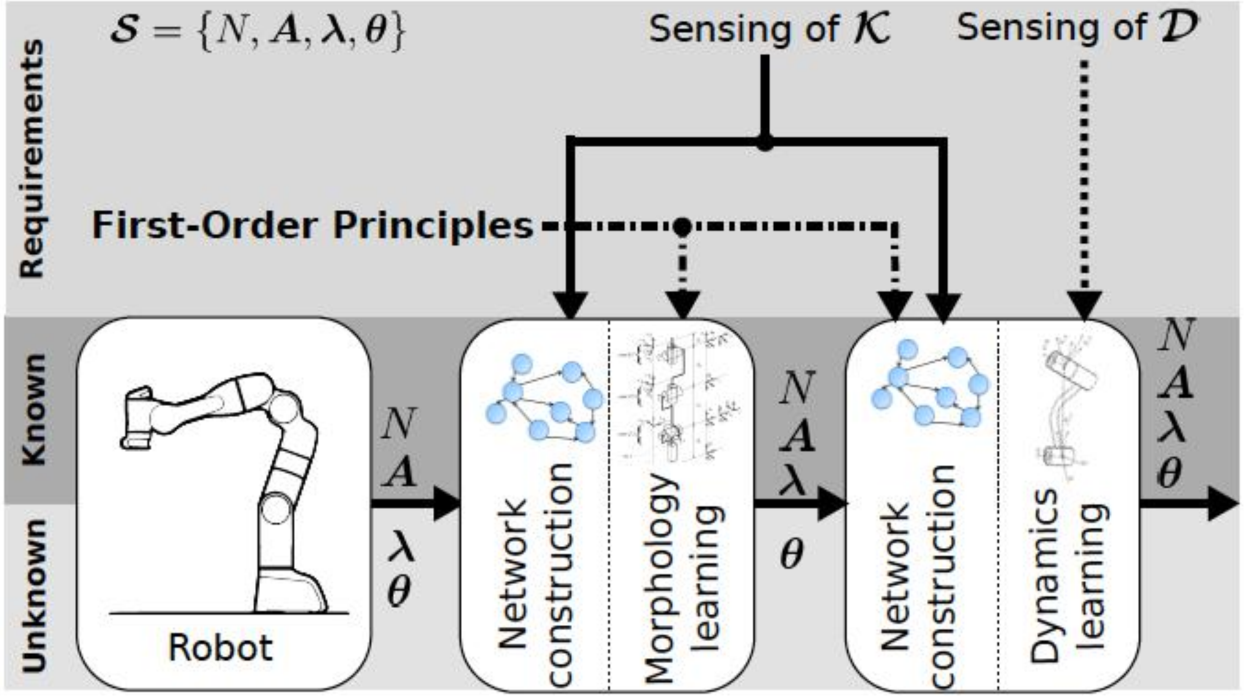
First-order principles

Relevant data

FOPnet

Diaz & Haddadin, Humanoids 2017

First-Oder Principles Network



ROBOT DYNAMICS: WHAT ARE THE FOPs?

$$\left.\begin{aligned}\boldsymbol{\tau}_m &= \boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \boldsymbol{c}(\boldsymbol{q},\dot{\boldsymbol{q}}) + \boldsymbol{g}(\boldsymbol{q}) \\ \boldsymbol{\tau}_m &= \boldsymbol{Y}(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}};\boldsymbol{\lambda})\boldsymbol{\theta}\end{aligned}\right\} \quad \boldsymbol{\tau}_m = f(\boldsymbol{q},\dot{\boldsymbol{q}},\ddot{\boldsymbol{q}};\boldsymbol{\lambda},\boldsymbol{\theta})$$

Compositionality

$$\boldsymbol{k}_i = f(q_i,\dot{q}_i,\ddot{q}_i;\boldsymbol{\lambda}_i)$$

$$\boldsymbol{w}_{ii} = f(\boldsymbol{k}_i;\boldsymbol{\theta}_i)$$

$$\boldsymbol{w}_i = f(\boldsymbol{q},\boldsymbol{w}_{ij};\boldsymbol{\lambda})$$

Learning of: $\boldsymbol{\theta}$

$$\boldsymbol{\tau}_m = \boldsymbol{w} \circ \boldsymbol{k}$$

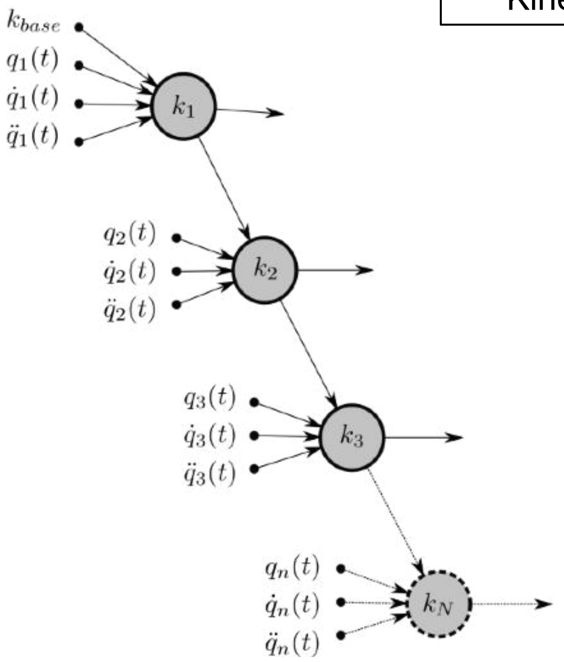
Learning of: $\boldsymbol{\lambda}$

Diaz & Haddadin, Humanoids 2017

ROBOT DYNAMICS: FOP TOPOLOGY

Kinematics are learned first

Measured →Training signal



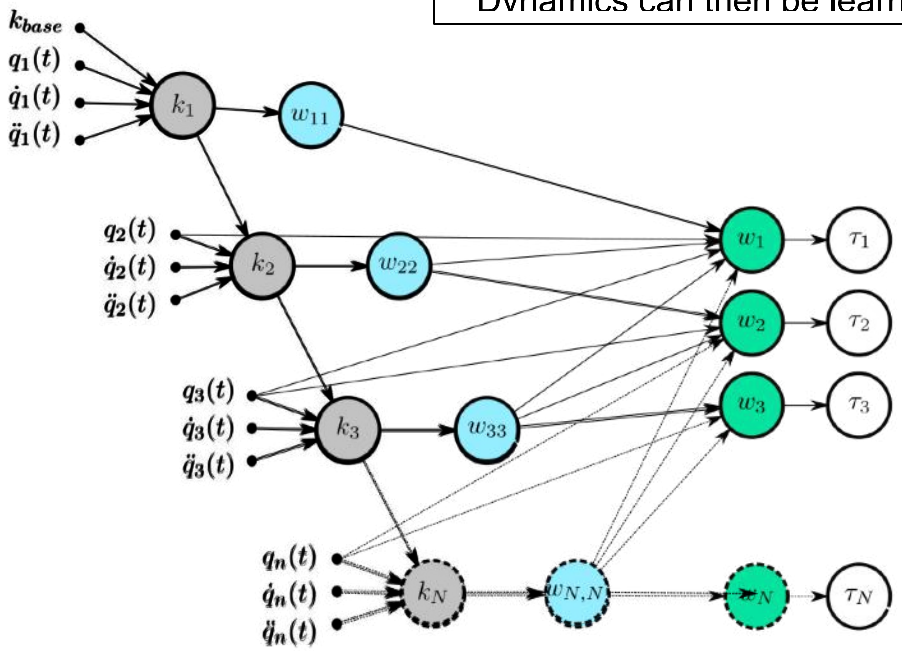
$$\boldsymbol{k} = f(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}; \boldsymbol{\lambda})$$

$\boldsymbol{\lambda}$

$\hat{\lambda}$ Kinematics related parameters

ROBOT DYNAMICS: FOP TOPOLOGY

Dynamics can then be learned

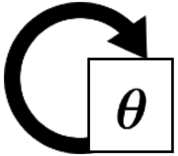


$\hat{\theta}$ Dynamics related parameters $\hat{\lambda}$ Kinematics related parameters

$$\boldsymbol{k} = f(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}; \boldsymbol{\lambda})$$

$$\boldsymbol{w} = f(\boldsymbol{q}, \boldsymbol{k}; \boldsymbol{\lambda}, \boldsymbol{\theta})$$

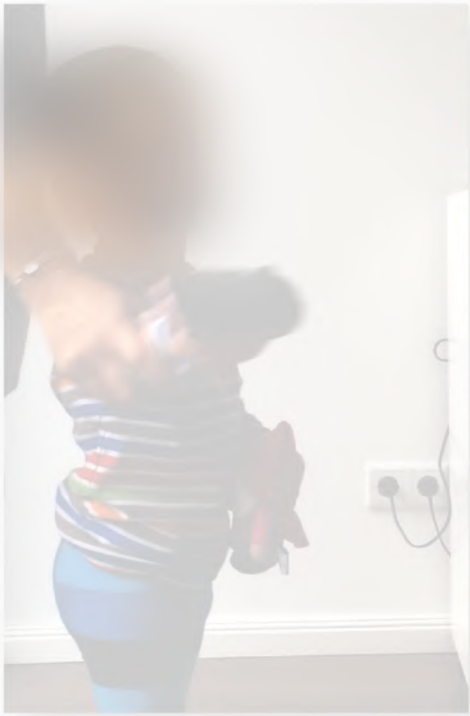
$$\boldsymbol{\tau} = C(\boldsymbol{w} \circ \boldsymbol{k})$$

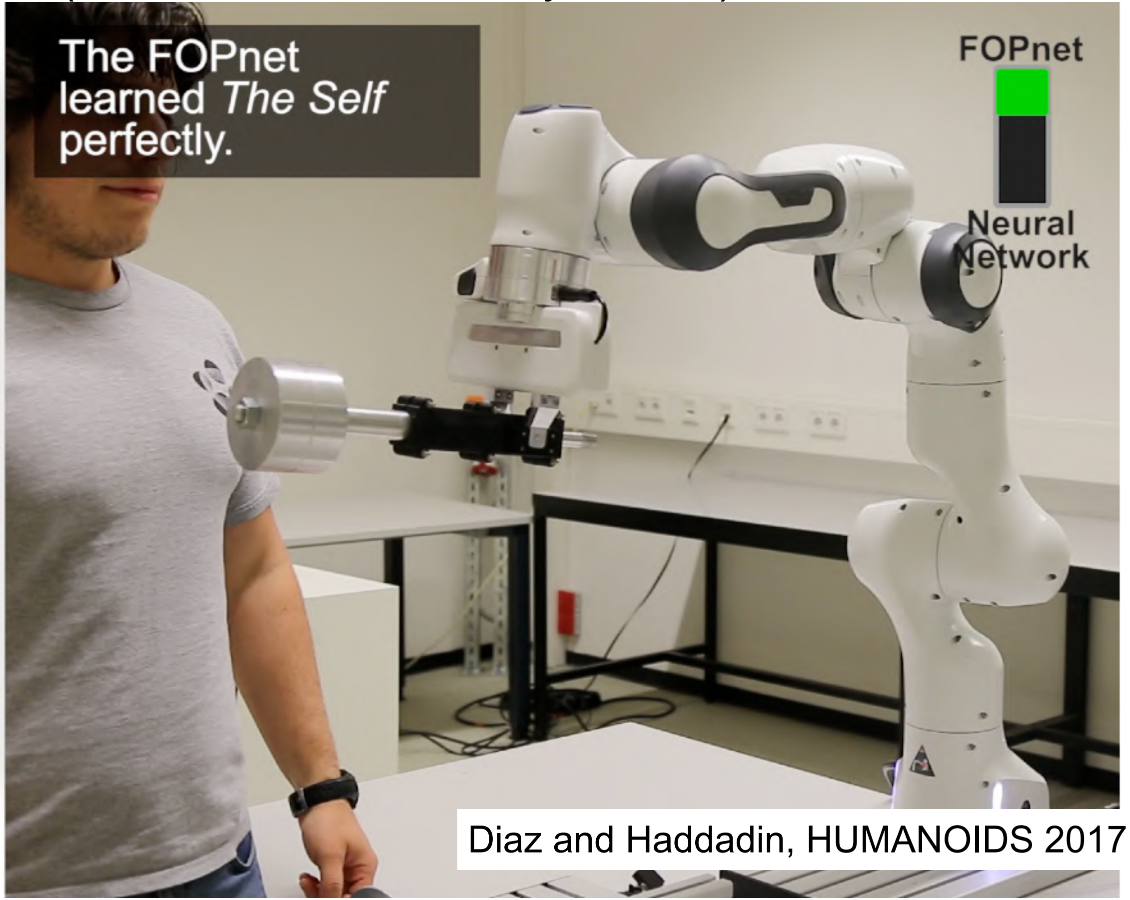


Measured→ Training signal

Diaz & Haddadin, Humanoids 2017

LEARNING THE SELF (i.e., Kinematics and Dynamics)



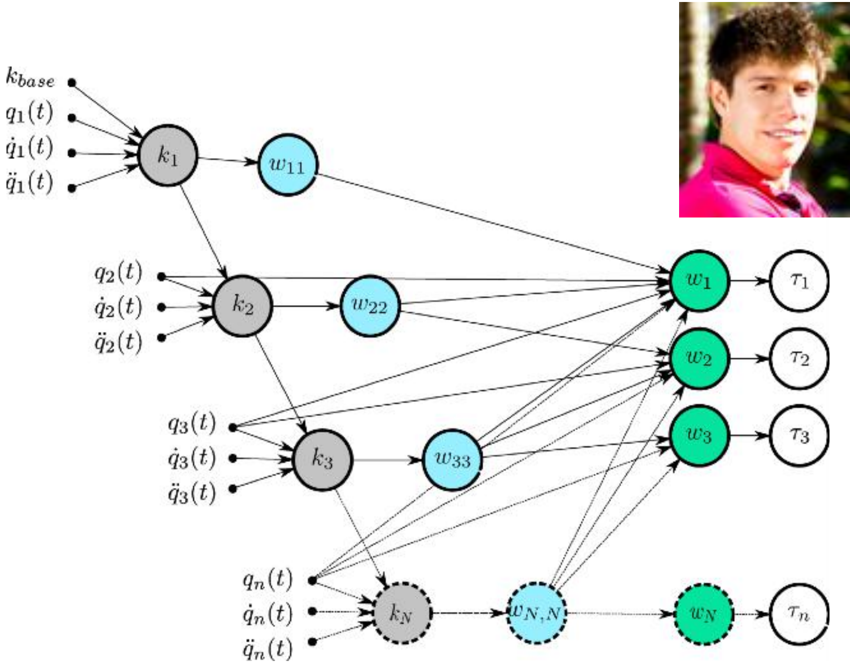


Diaz and Haddadin, HUMANOIDS 2017

Constructive architecture

- NE-formulation used for network structure
- Three subnetworks:
  1. Kinematics network (**gray**):
     links rigid body velocities and accelerations
  2. Self-dynamics network (**blue**):
     wrench due to link inertial parameters
  3. Inter-dynamics network (**green**):
     includes wrenches from succeeding links

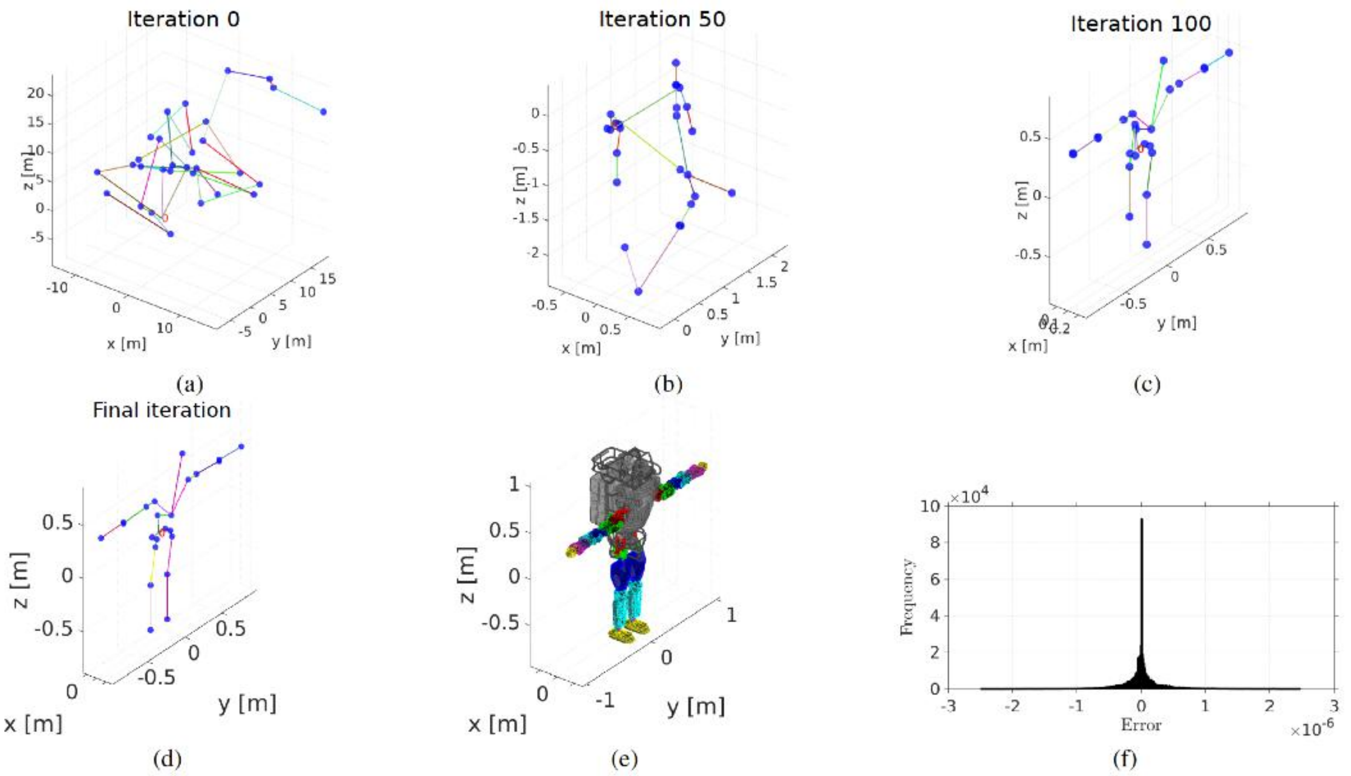
The network outputs joint torques



Each node is itself a net

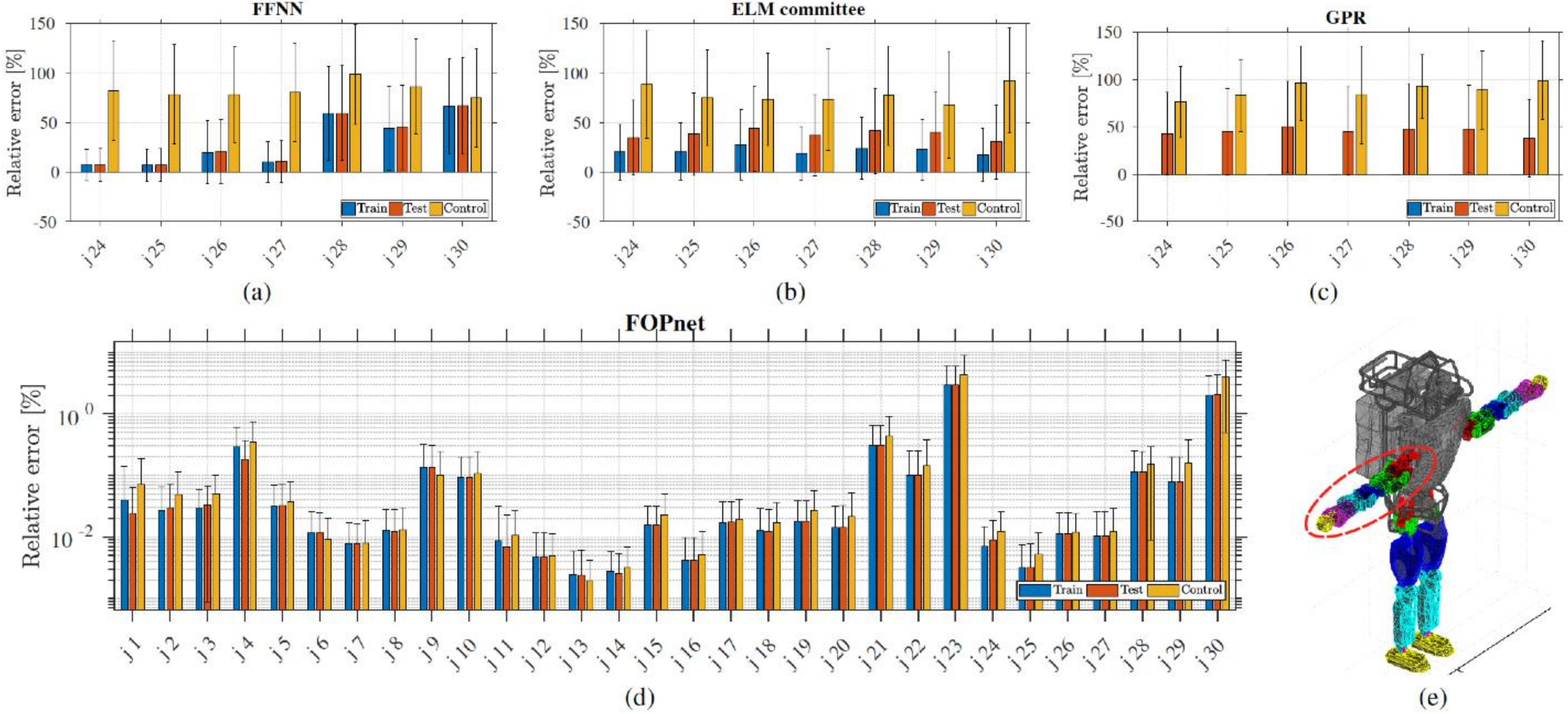
Diaz & Haddadin, Humanoids 2017

Learning Humanoid Dynamics



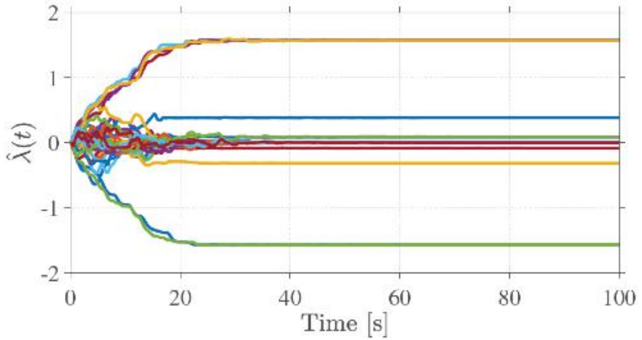
Diaz & Haddadin, Humanoids 2018

Learning Humanoid Dynamics

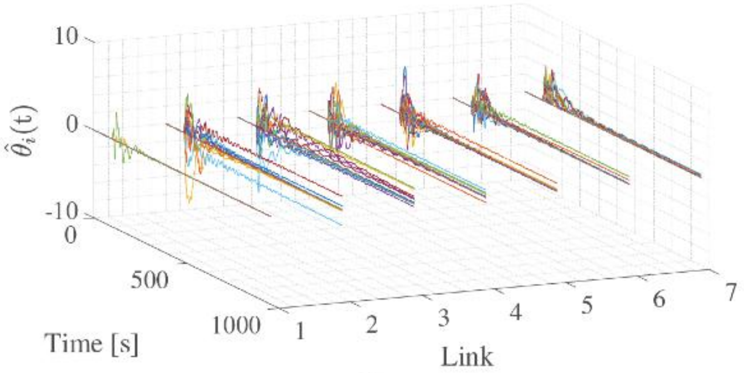


Diaz & Haddadin, Humanoids 2018

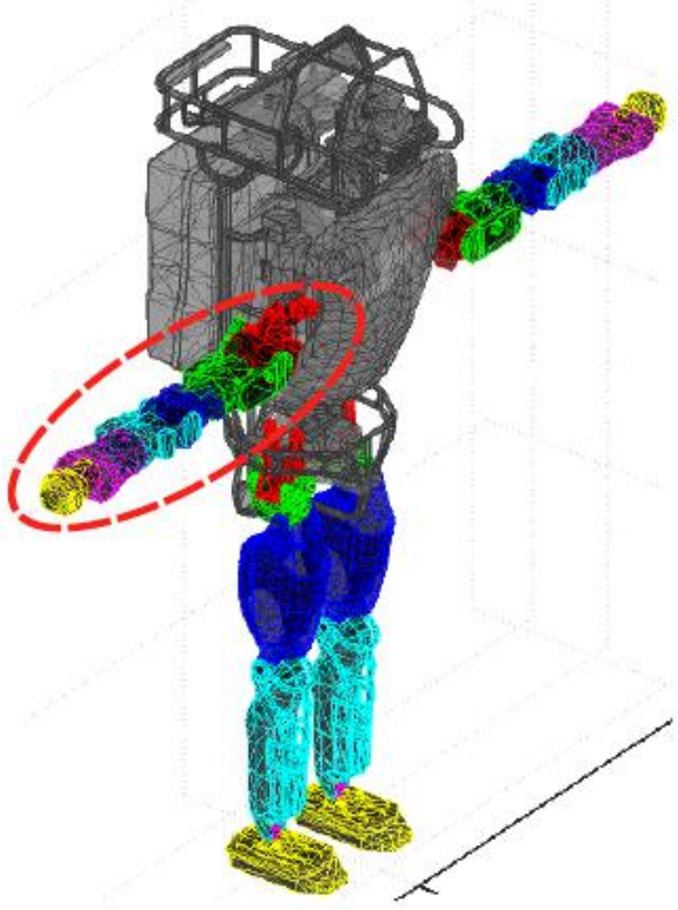
Learning Humanoid Dynamics



(a)



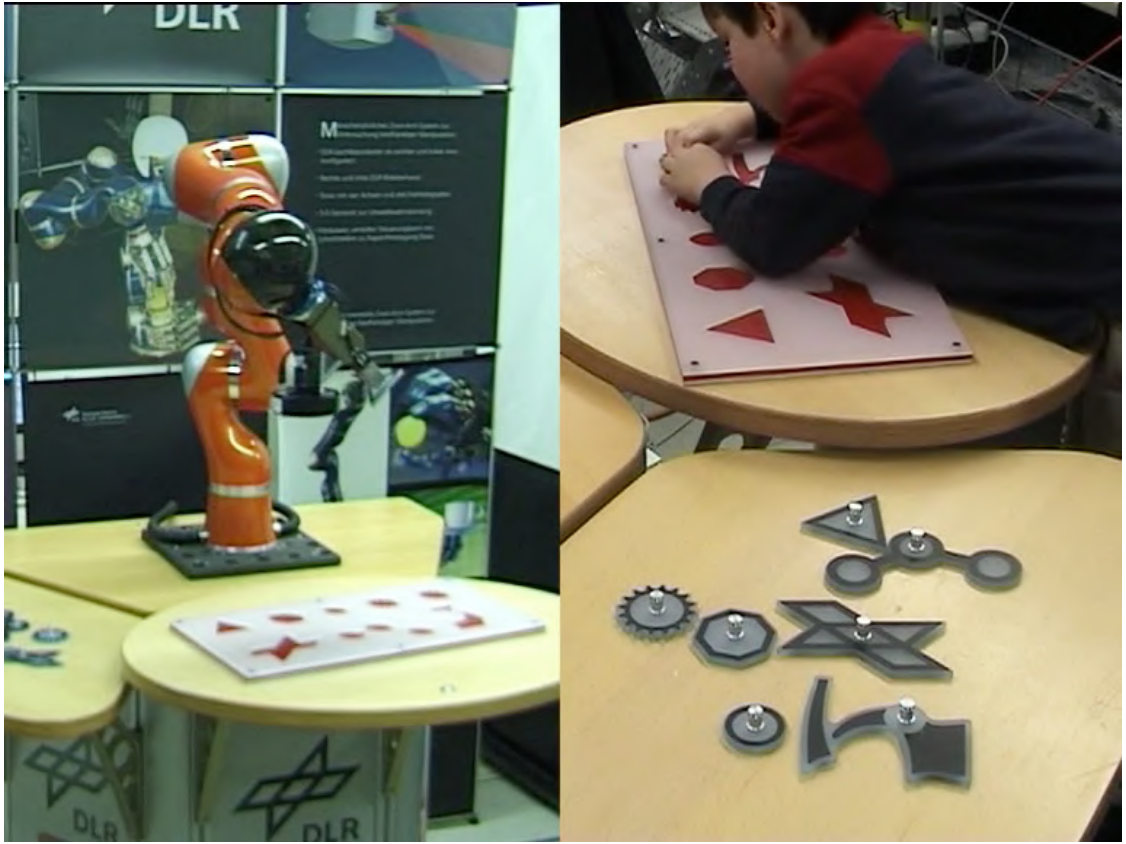
(b)



Diaz & Haddadin, Humanoids 2018

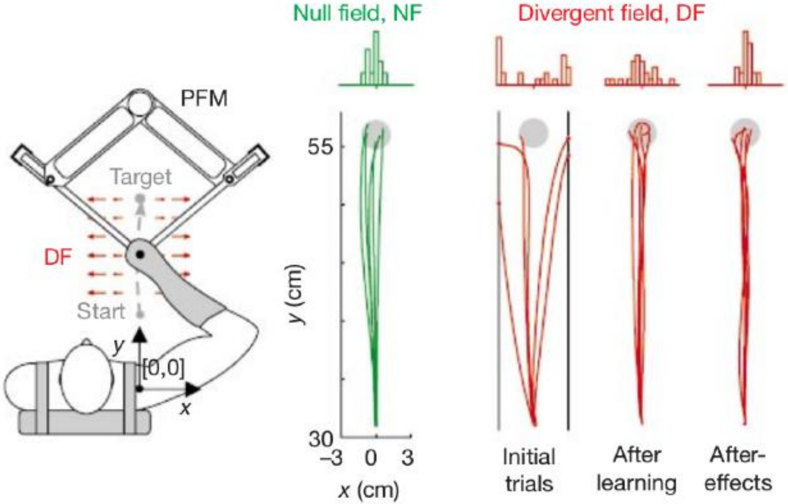
Chapter III
-
Robot Learning: Manipulation

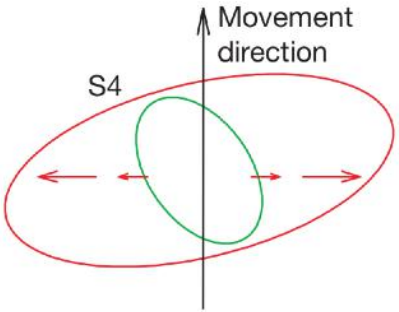
The DLR Papas experiment



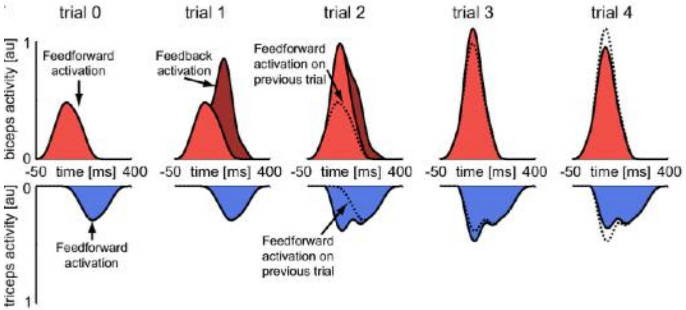
Andreas Stemmer & Paolo Robuffo Giordano, DLR

Human impedance and force learning



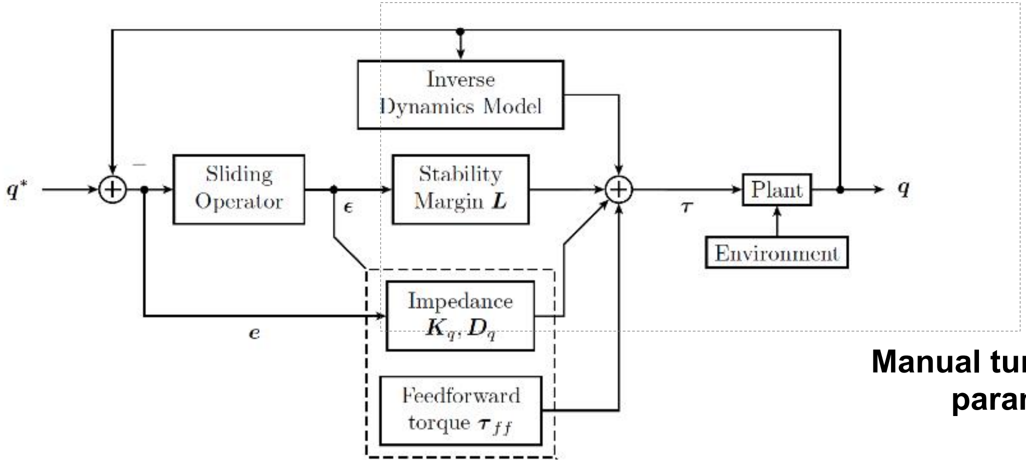


Burdet, E., Franklin, D. W., & Milner, T. E. (2013). Human robotics: neuromechanics and motor control. MIT press.



Yang et. al. TRO2011, Jarasse et. Al. ICRA2012

Bio-inspired adaptive impedance control



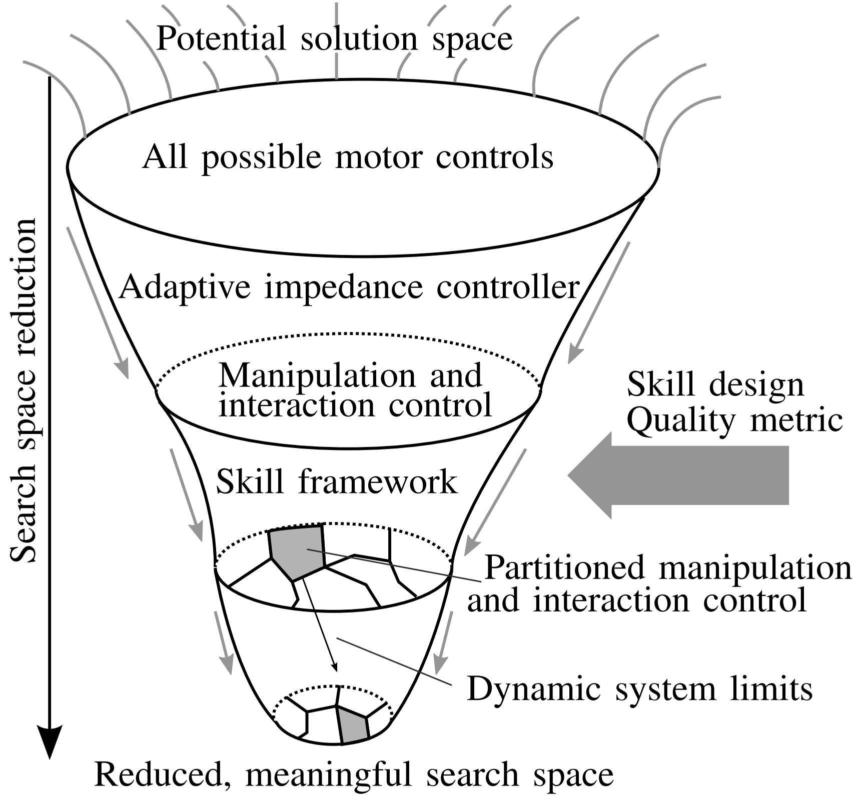
Manual tuning of meta parameters!

$$\tau(t) = \tau_{ff}(t) - K_q(t)e(t) - D_q(t)\dot{e}(t) - L(t)\varepsilon(t) + \tau_r(t)$$
$$\varepsilon = \dot{e}(t) + \kappa e(t),$$

$$\delta K_q(t) = K_q(t) - K_q(t-T) = Q_{K_q}(\varepsilon(t)e(t)^T - \gamma(t)K_q(t))$$

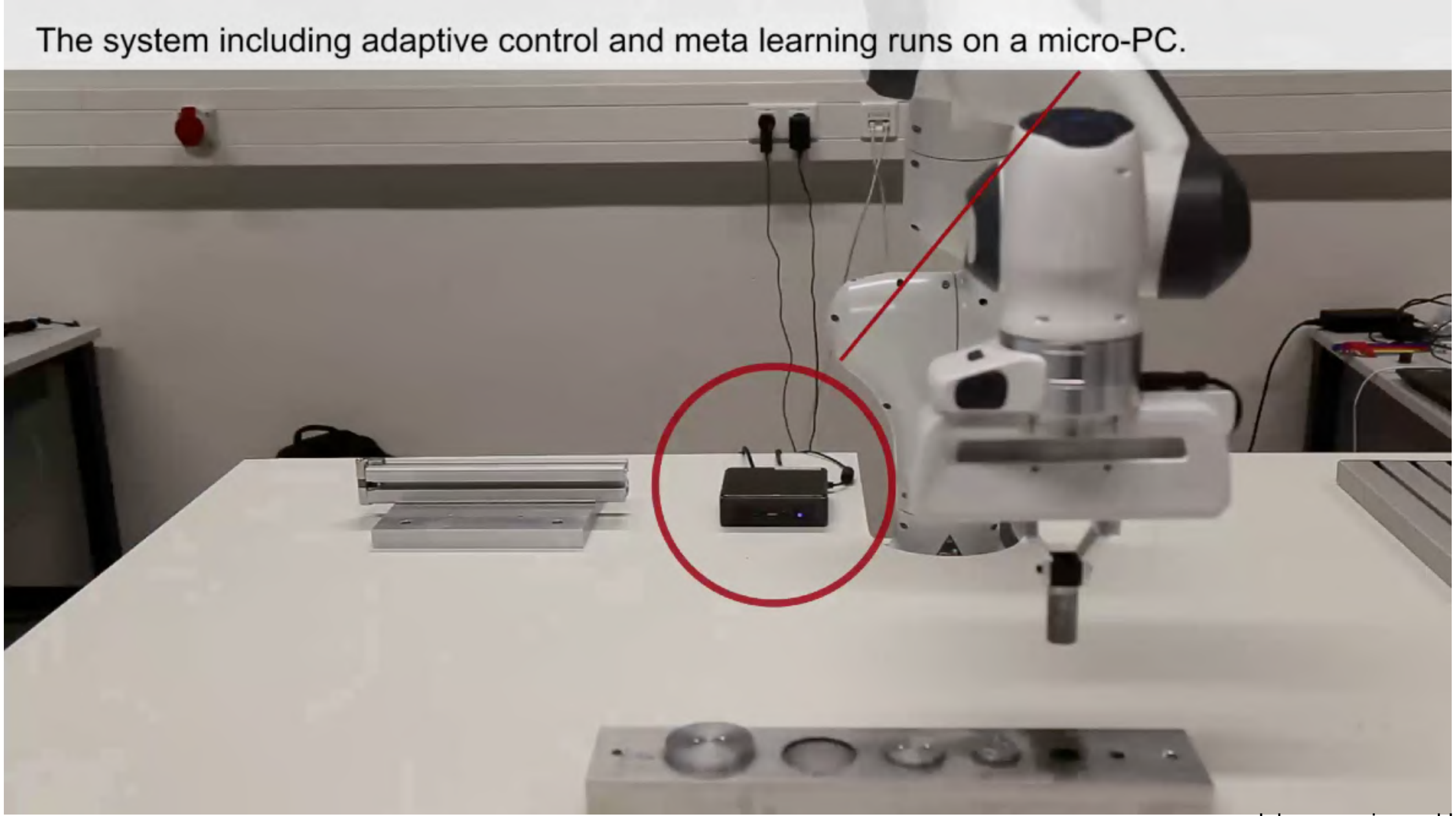
Yang et. al. TRO2011, Jarasse et. Al. ICRA2012

Skill framework I



Johannsmeier and Haddadin, ICRA 2018, IROS 2019

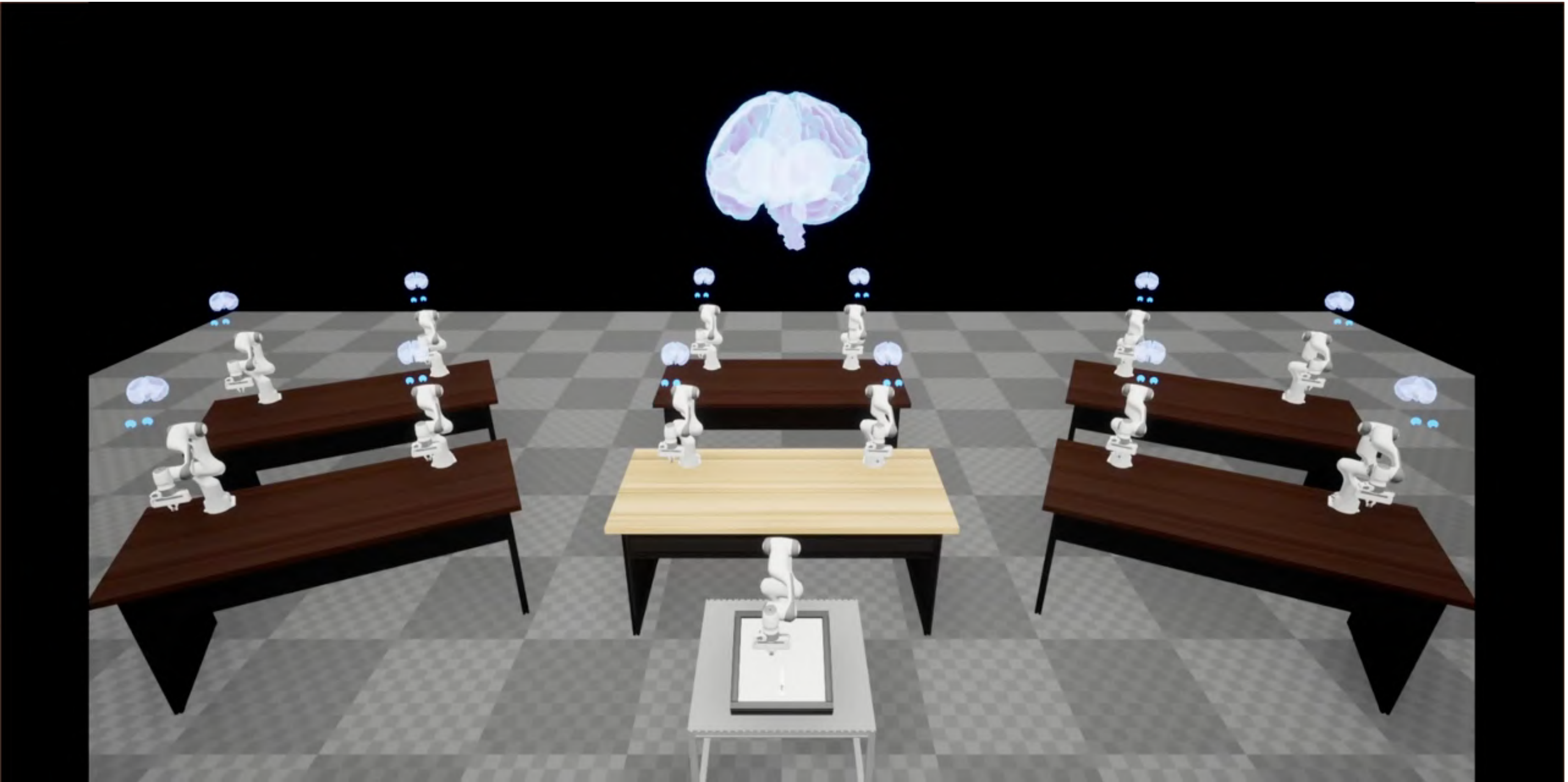
Learning peg in hole



Johannsmeier and Haddadin, ICRA 2018, IROS 2019

Collective Learning: „n robots learn m keys“

Collective Learning




ILIAD
SoftPro
TEAM VIGR
FRANKA
EMIKA

ISRR 2019

THANK YOU VERY MUCH!

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SIXTH FRAMEWORK
PROGRAMME

SEVENTH FRAMEWORK
PROGRAMME

HORIZON 2020

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HRK Hochschulrektorenkonferenz
Die Stimme der Hochschulen