ISTITUTO ITALIANO
DI TECNOLOGIA
SOFT ROBOTICS FOR HUMAN
COOPERATION AND REHABILITATION

CENTRO "E. PIAGGIO"
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Antonio Bicchi

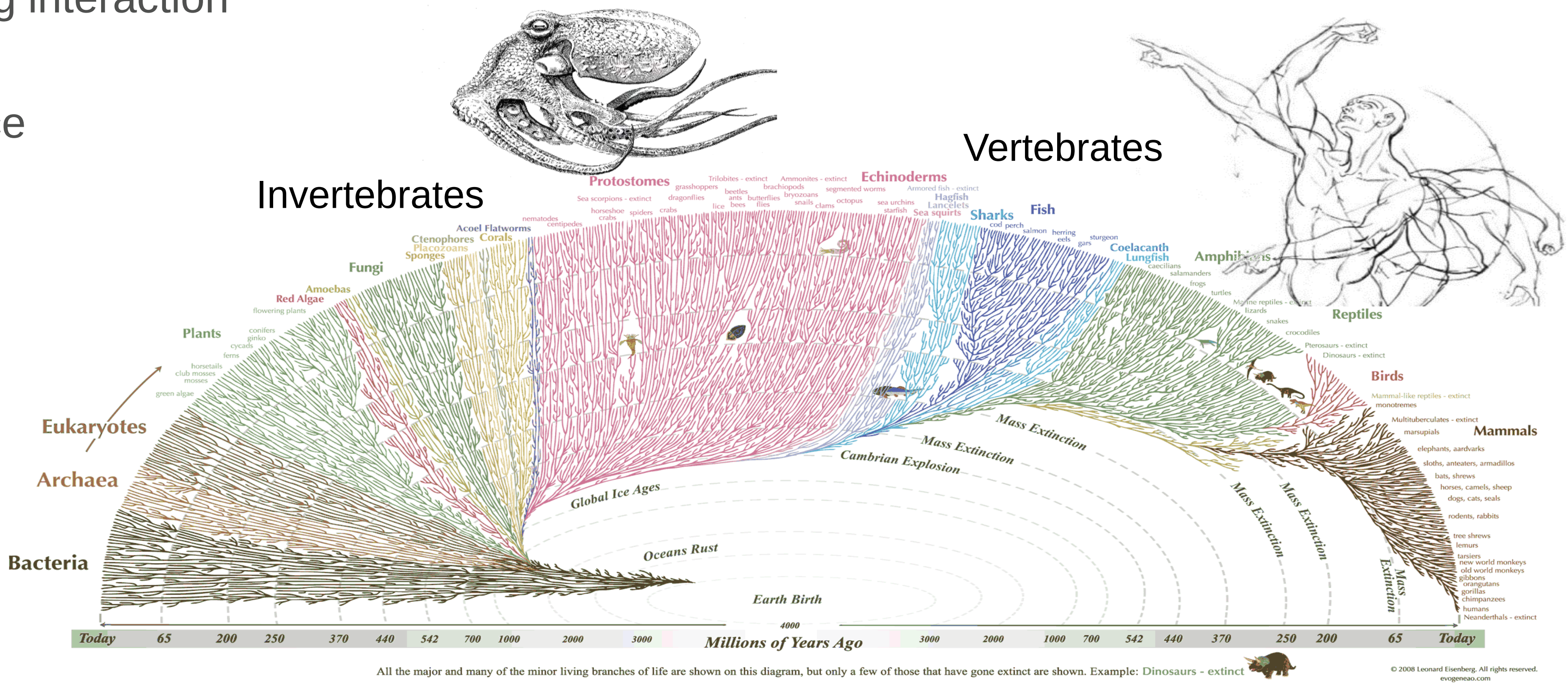
Planning and Learning Interaction with Variable Impedance.

Compliance in Natural Systems

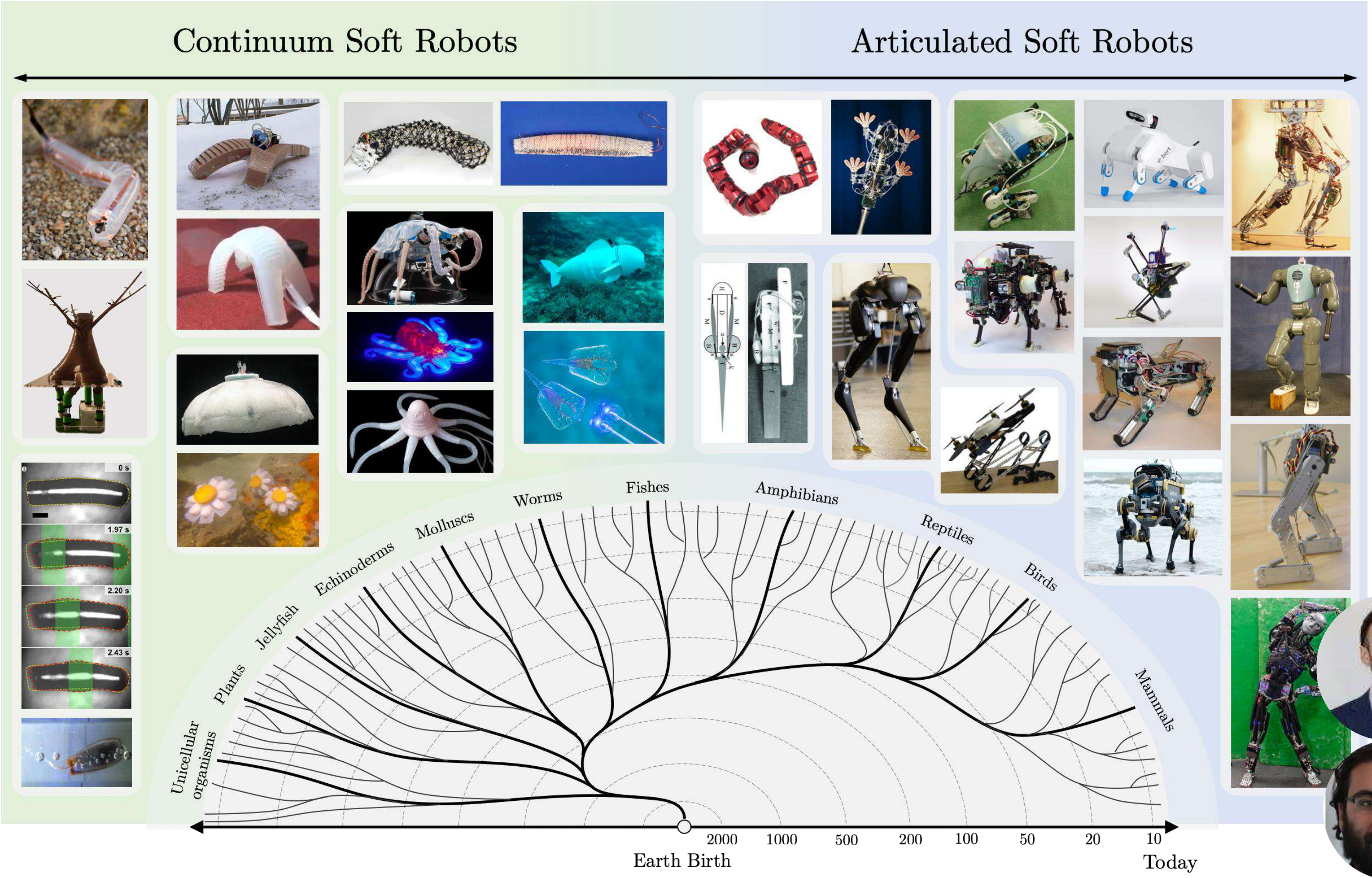
Compliance in Natural Systems

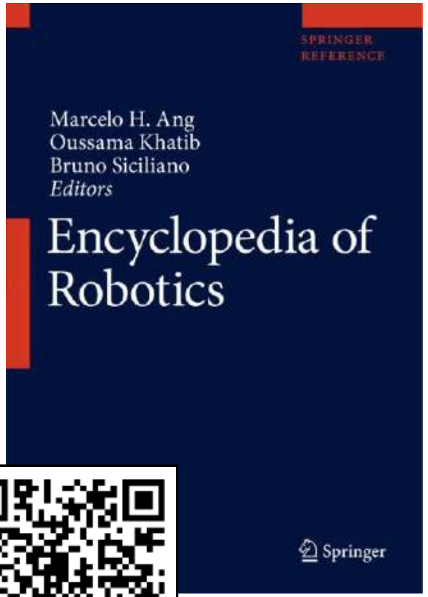
Key enabler for adaptivity

- Versatility for different applications
- Tolerance to errors and imprecisions
- Safety
- Robustness during interaction
- Energy efficiency
- Better performance



Soft robots are robotic systems embedding in their mechanical structure purposefully designed compliant elements.





C. Della Santina, M. G. Catalano, A. Bicchi, ”Soft Robotics, definition of” Springer Encyclopedia of Robotics (2021)

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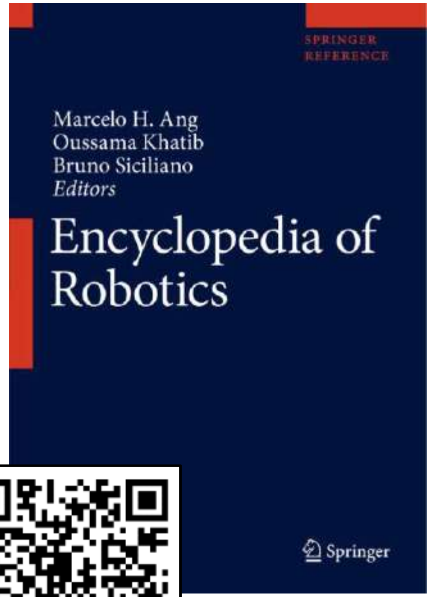

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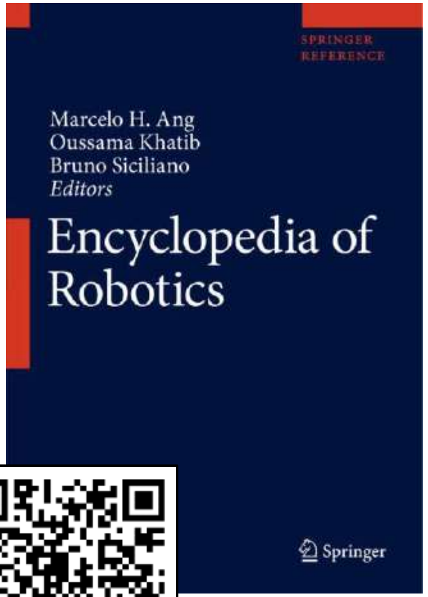


C. Della Santina, **M. G. Catalano**, A. Bicchi, ”Soft Robotics, definition of” Springer Encyclopedia of Robotics (2021)

Stiffness of muscles

Characterized by

- Force / deformation
- Force / velocity
- Force / moto-neuron firing rate

Descriptive models e.g.

- Gribble Muscle Model:

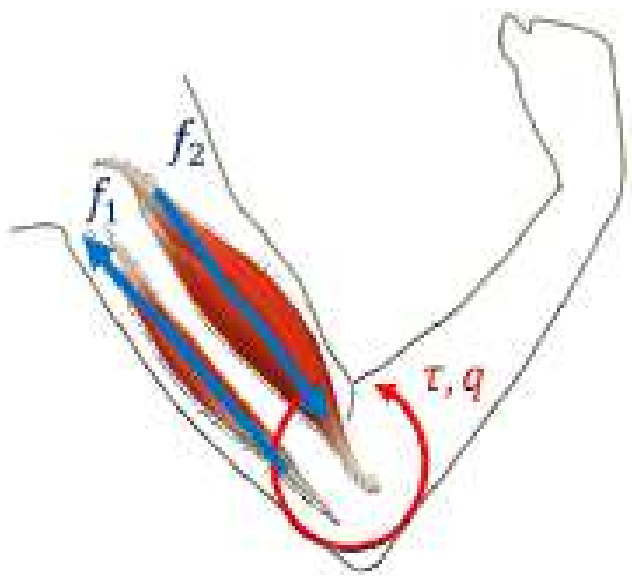
  $\boldsymbol{Flexor\ force}: f_1 = \rho(e^{\delta A_1} - 1)$

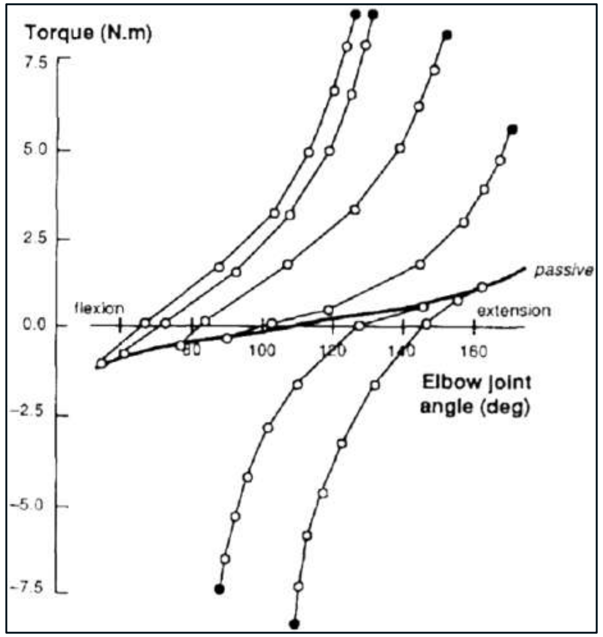
  $\boldsymbol{Extensor\ force}: f_2 = -\rho(e^{\delta A_2} - 1)$

- An open topic in literature

Stiffness of limbs

Human Antagonistic Muscles Characteristics



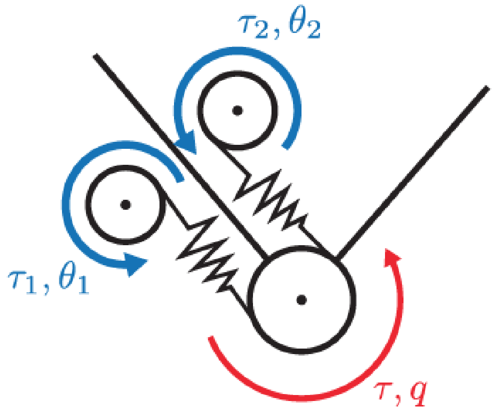


Gribble Muscle Model:

$\boldsymbol{Flexor\ force}$: f_1= ρ($e^{\delta A_1}$ −1)

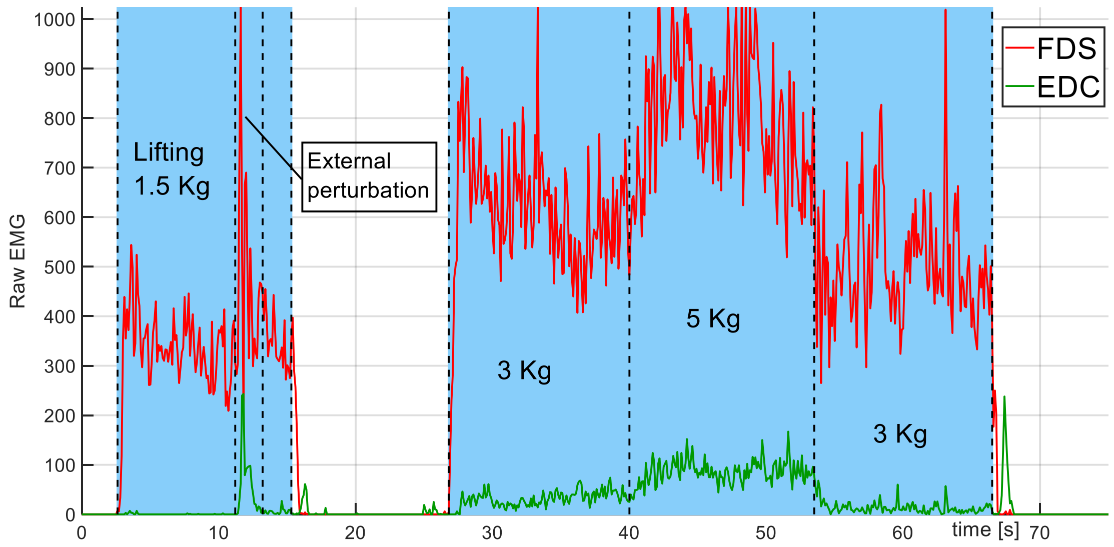
$\boldsymbol{Extensor\ force}$: f_2= -ρ($e^{\delta A_2}$ −1)

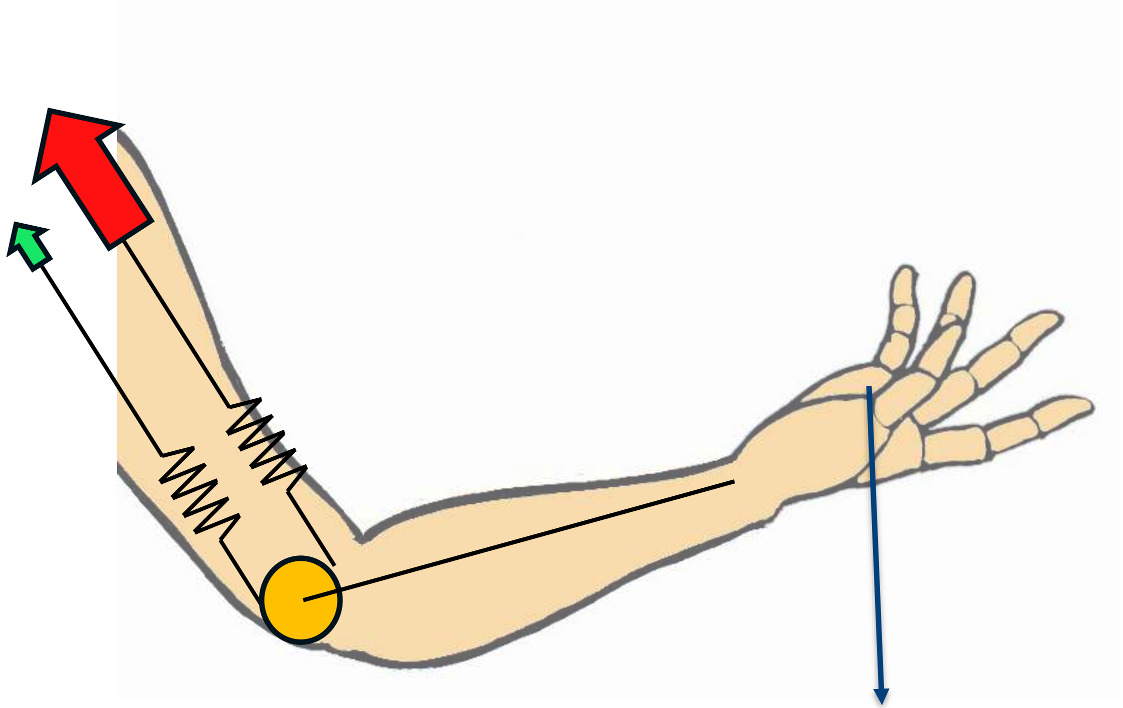
The stiffness of all the muscles that act on a given joint contribute to defining also the stiffness of the joint



Stiffness changes in Humans

Stiffness changes
involuntarily and voluntarily

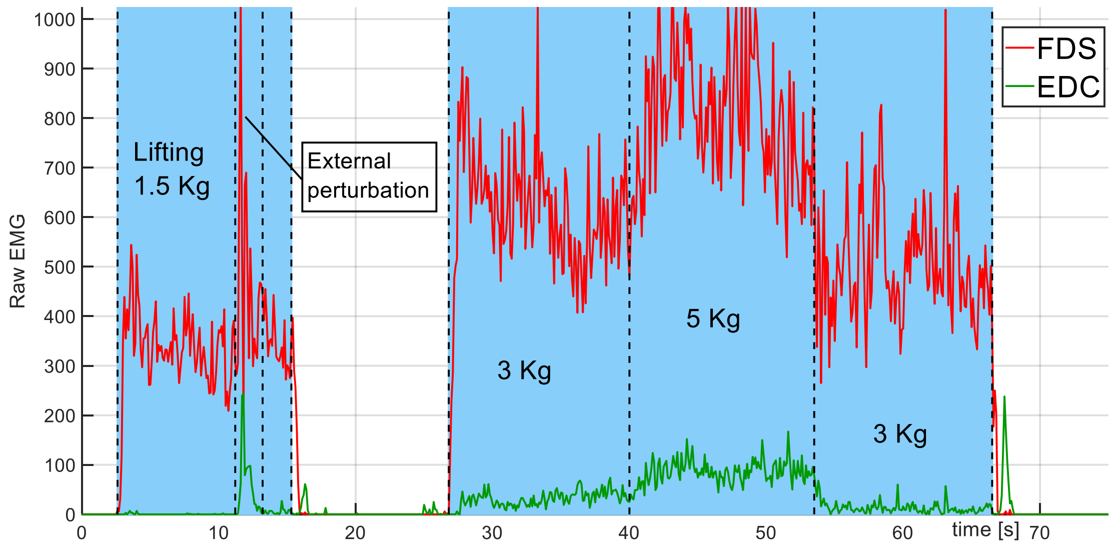


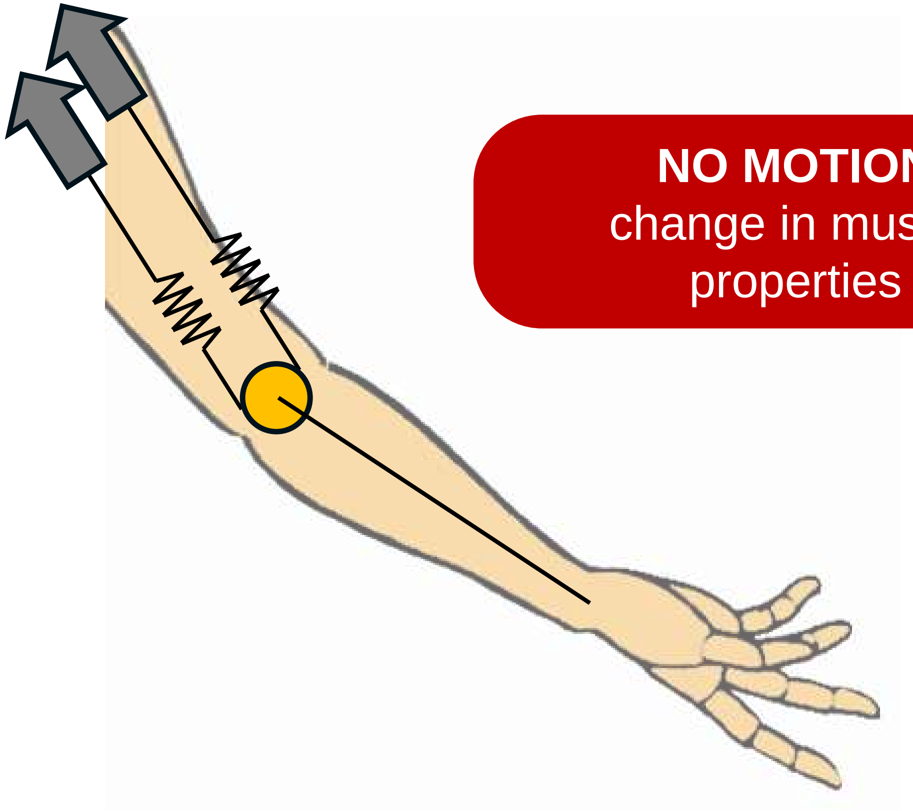


The stiffness of a human arm increases when lifting heavy weighs

Humans change stiffness

Stiffness changes involuntarily and voluntarily



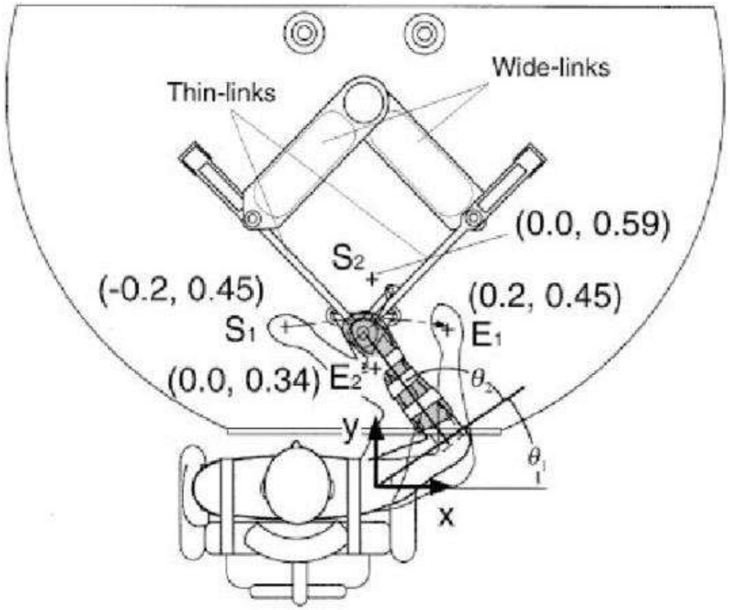


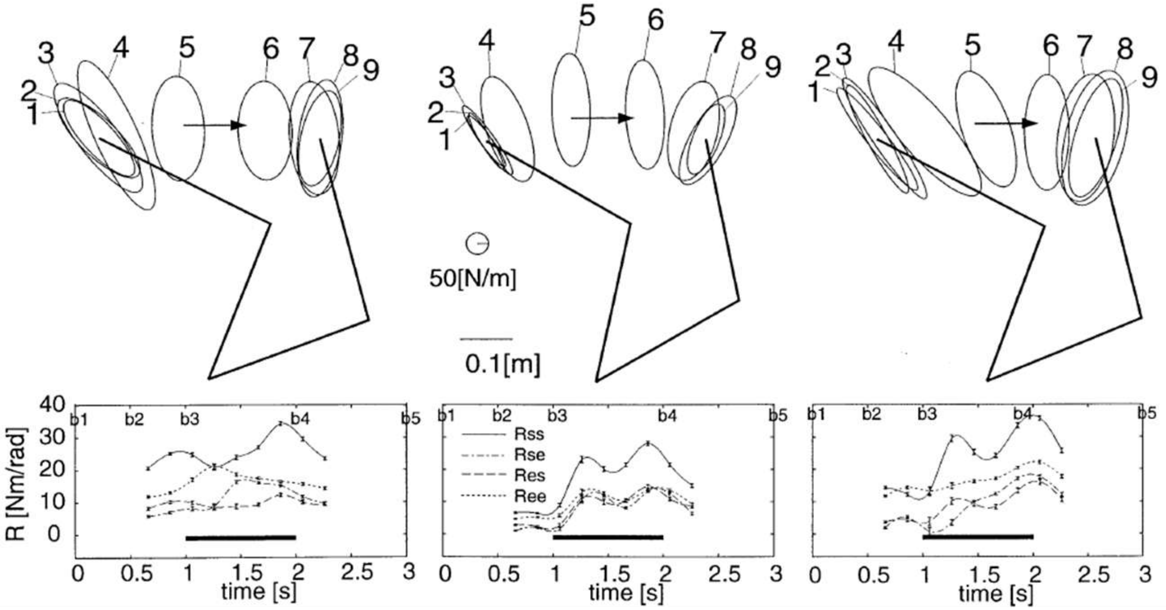
NO MOTION
change in muscle properties

Humans can change the stiffness of their limbs to adapt to different tasks

How do humans control stiffness?

Experiments show that humans can learn after many repeated trials to change their stiffness profile along a given learned path to counteract disturbances





Gomi and Kawato, 1997

N Hogan, "Adaptive control of mechanical impedance by coactivation of antagonist muscles" IEEE Transactions on automatic control 29 (8), 681-690, 1984

Gomi, H, Yasuharu K., Kawato, M.. "Human hand stiffness during discrete point-to-point multi-joint movement." *IEEE Engineering in Medicine and Biology Society*. Vol. 4., 1992.

Burdet, E., et al. "A method for measuring endpoint stiffness during multi-joint arm movements." Journal of biomechanics 33.12, 2000.

How do humans change stiffness?

However, there is strong correlation between the activation patterns of muscles that move a limb. This affects how the stiffness of a limb is modulated.

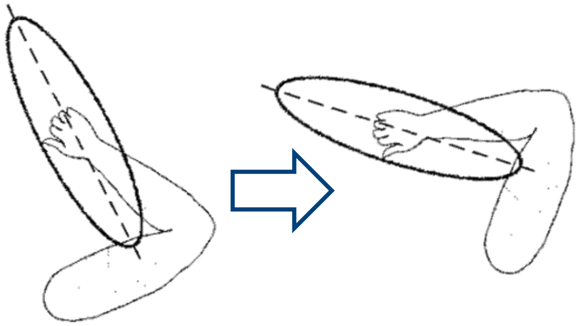
E. Perreault, R. Kirsch, and P. Crago, “Voluntary control of static endpoint stiffness during force regulation tasks,” Journal of Neurophysiology, vol. 87, pp. 2808–2816, 2002.

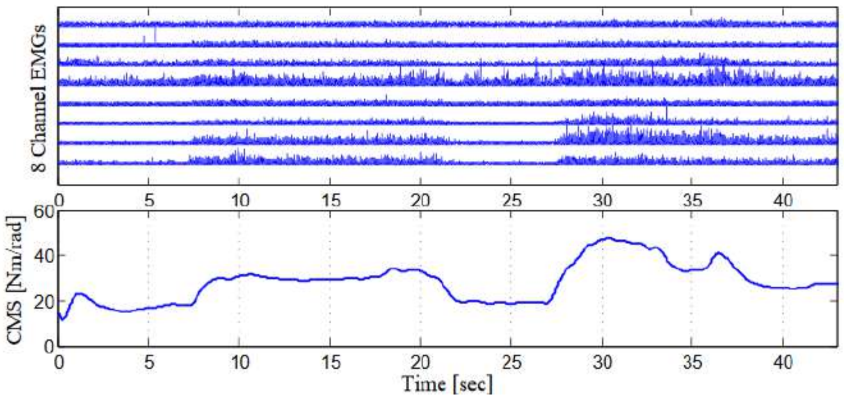
To a first approximation, humans control their stiffness ellipsoid simply:

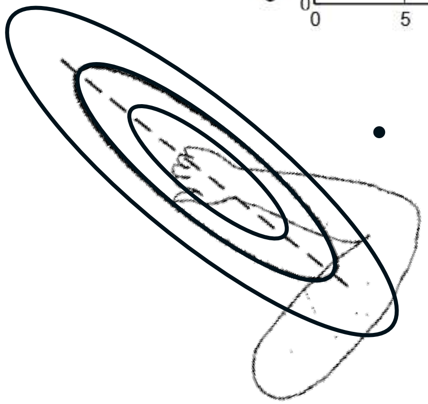
- Posture dominates the *shape*
- Coactivation controls the *volume*

A. Ajoudani, Gabiccini, M., Tsagarakis, N. G., Albu-Schaeffer, A., and Bicchi, A., “Tele-Impedance: Exploring the Role of Common-Mode and Configuration-Dependant Stiffness”, Humanoids 2012.

- **Configuration Dependent Stiffness (CDS)**
  - changes with posture
  - gives the shape of the stiffness ellipsoid
  - exploits redundancy

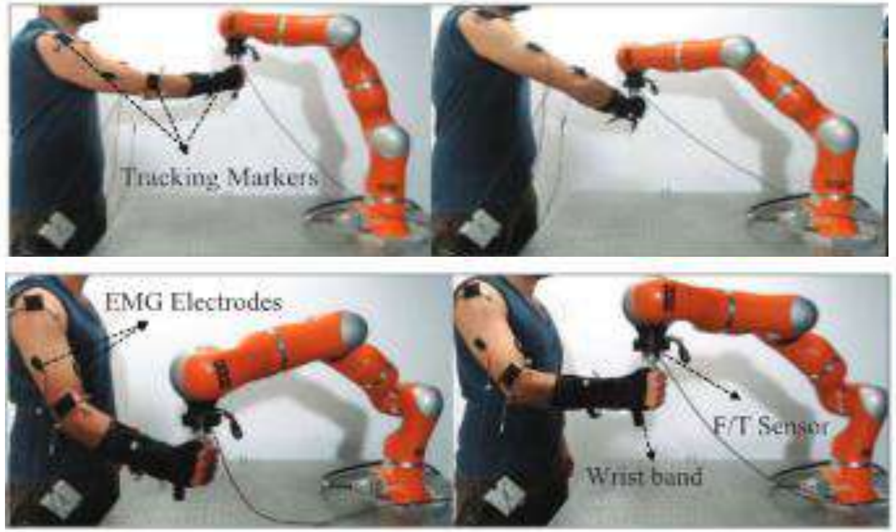




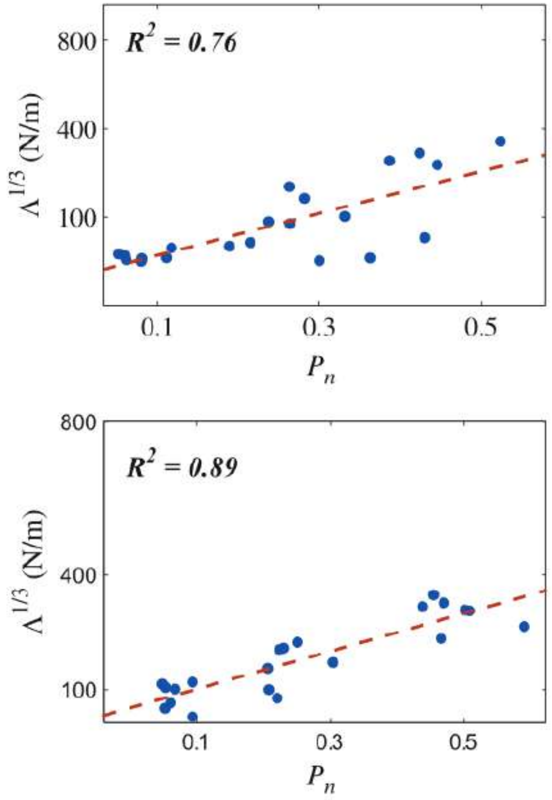


- **Common Mode Stiffness CMS**
  - changes with co-contraction
  - gives the size of the ellipsoid

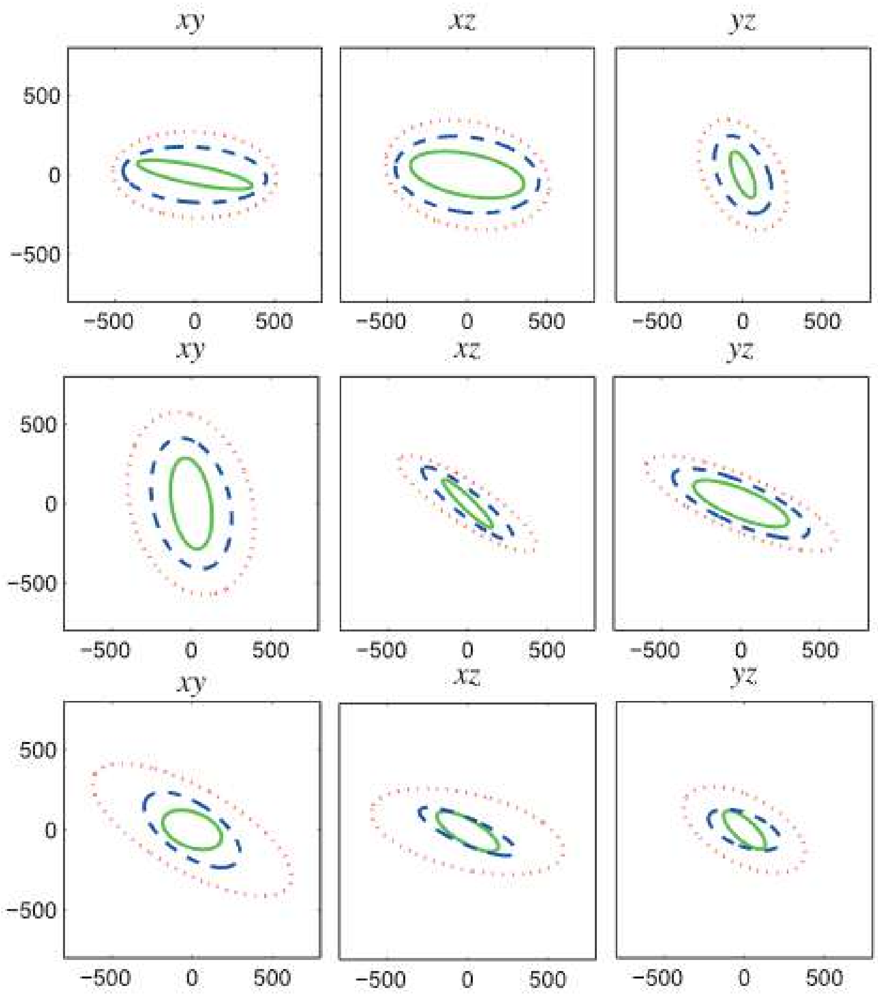
Common Mode Stiffness

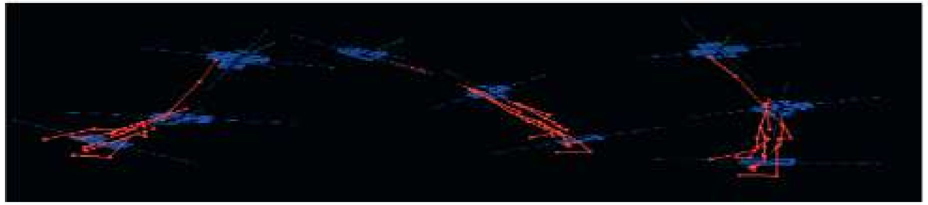


Experimental Validation Setup
(robot used as a shaker)



Ellipsoid volume vs co-contraction





A. Ajoudani, Fang, C., Tsagarakis, N. G., and Bicchi, A., “Reduced-Complexity Representation of the Human Arm Active Endpoint Stiffness for Supervisory Control of Remote Manipulation”, International Journal of Robotics Research, vol. 37, no. 1, 2017.

Variable Impedance in Robots

Methods to vary Impedance

Software:

Variable Impedance Control

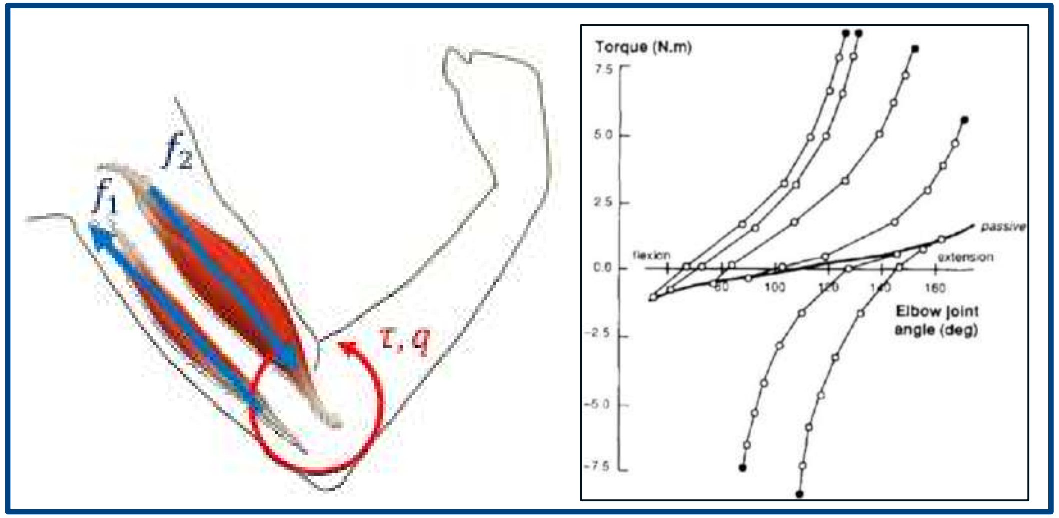
Hardware:

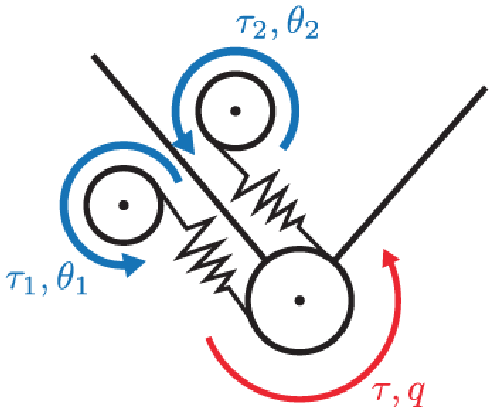
Variable Impedance Actuators

HW: Varable Stiffness Actuators

Inspired by nature

Human Antagonistic Muscles Characteristics





Gribble Muscle Model:

$\boldsymbol{Flexor\ force}$: $f_1 = \rho(e^{\delta A_1} - 1)$

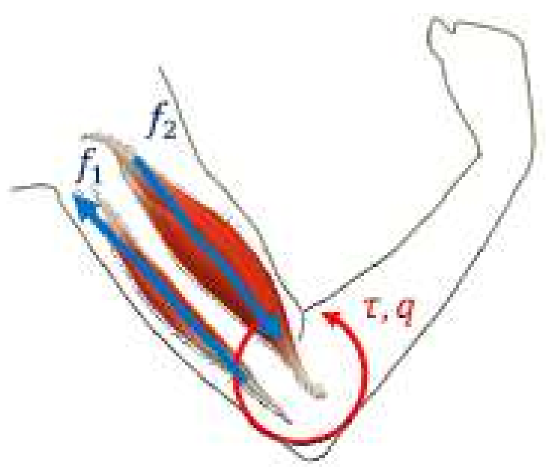
$\boldsymbol{Extensor\ force}$: $f_2 = -\rho(e^{\delta A_2} - 1)$

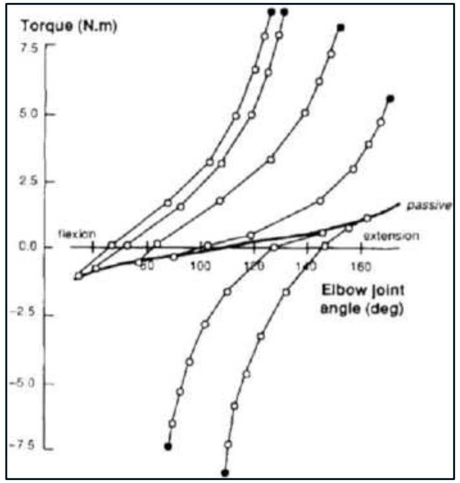
HW: Varable Stiffness Actuators

VSA-CubeBot: A modular variable stiffness platform for multiple degrees of freedom robots
MG Catalano, **G Grioli**, M Garabini, F Bonomo, M Mancini, N Tsagarakis, ...
2011 IEEE international conference on robotics and automation, 5090-5095

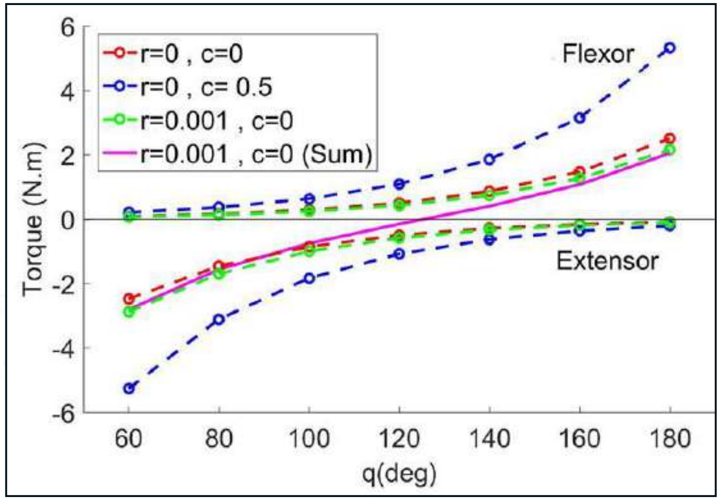
Inspired by nature

Human Antagonistic Muscles Characteristics





Antagonistic-Antagonistic VSA Characteristics



Gribble Muscle Model:

$\textit{Flexor force}: f_1 =$

$\textit{Extensor force}: f_2 = -\rho(e^{\delta A_2} - 1)$

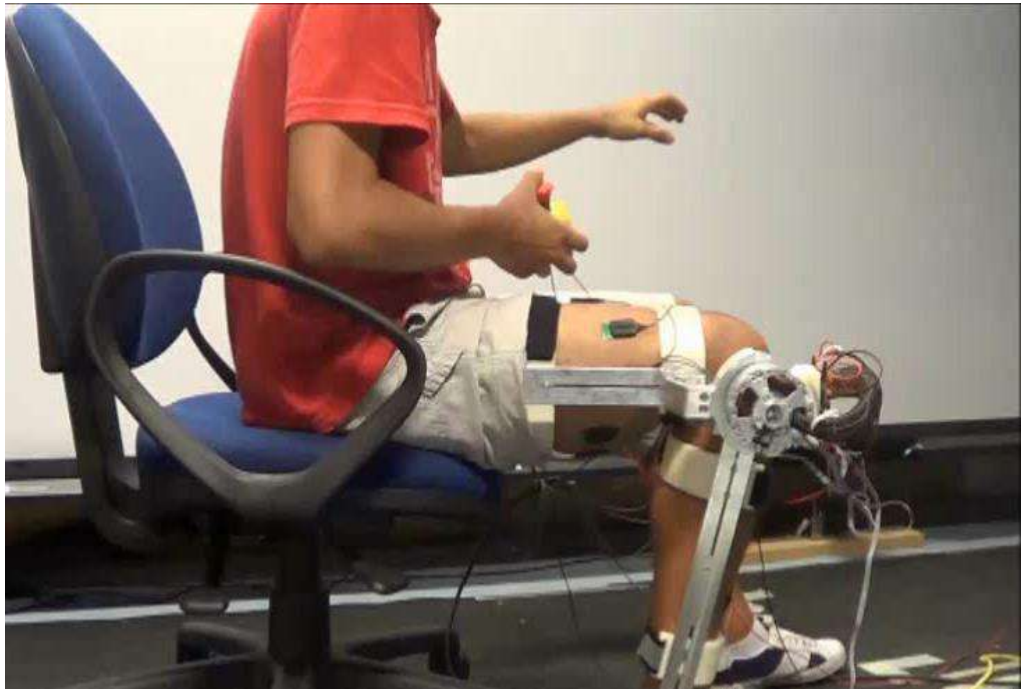
ANALOGY	Muscle	VSA
Equilibrium Position	$\frac{\lambda_1 + \lambda_2}{2R}$	$\frac{\Theta_1 + \Theta_2}{2}$
Stiffness	$2\rho\delta R^2 e^{\delta\frac{\lambda_2 - \lambda_1}{2}}$	$2\gamma\beta e^{\beta\frac{\Theta_2 - \Theta_1}{2}}$

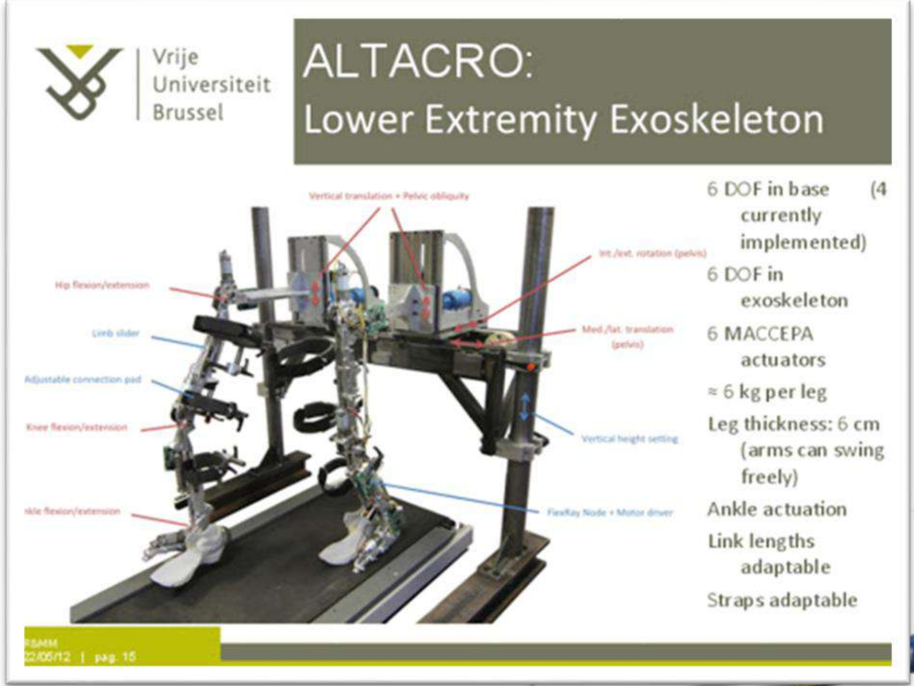
Agonistic-Antagonistic VSA Dynamics:
Motor 1,2 output torque:

$\tau_{1,2} = \pm\gamma e^{\pm\beta(q - \Theta_1)} \pm\mu$

VSA for Rehabilitation: Exoskeletons

Beyl, P., Naudet, J., Van Ham, R, Lefeber, D.. Mechanical Design of an Active Knee Orthosis for Gait Rehabilitation IEEE ICoRR - Rehabilitation Robotics (2007)





N. Karavas, A. Ajoudani, Tsagarakis, N. G., Saglia, J., Bicchi, A., and Caldwell, D., "Tele- Impedance based Assistive Control for a Compliant Knee Exoskeleton: Stiffness Augmentation and Motion Assistance", Robotics and Autonomous Systems, vol. 73 part A, pp. 78-90, 2015.

S. Mghames, al. "Design, control and validation of the variable stiffness exoskeleton FLExo", ICORR 2017

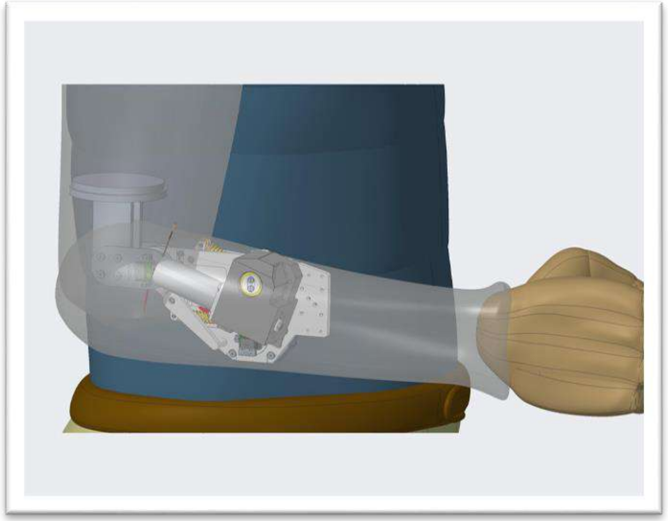
VSA for Rehabilitation: Prostheses

VS Elbow

Design of an elbow joint with variable stiffness actuation, i.e. inherent compliance.

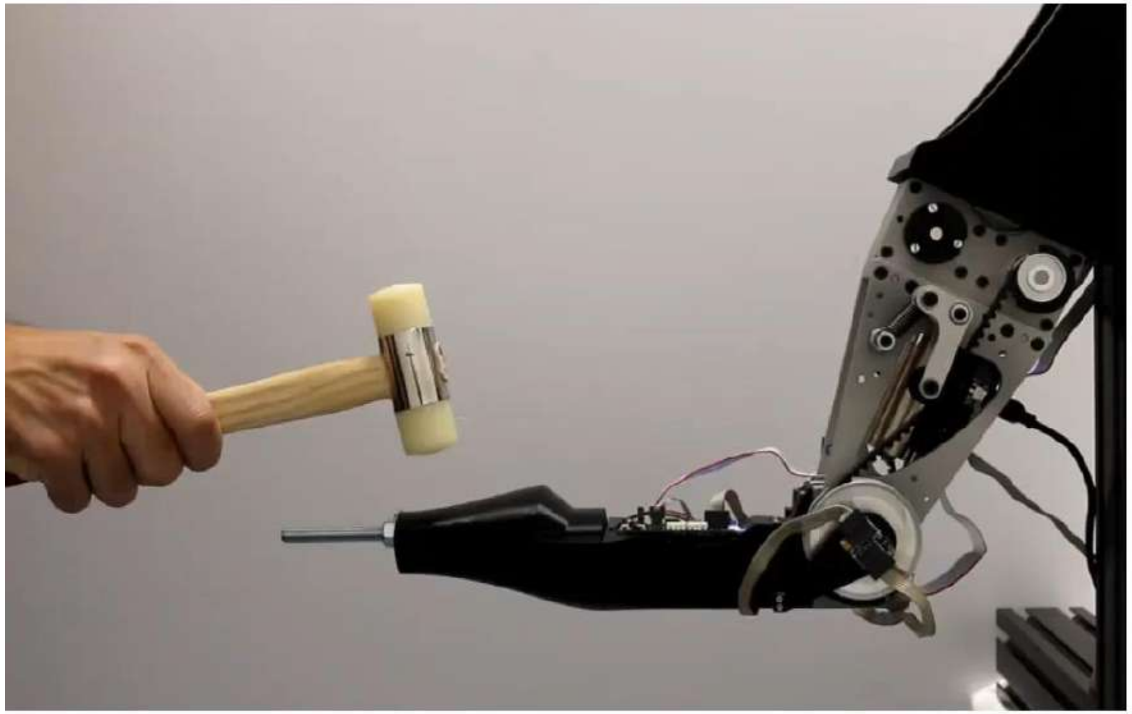
Two approaches

Distributed approach	**Antagonistic approach**
Independent setup (explicit stiffness variation)	Antagonistic setup

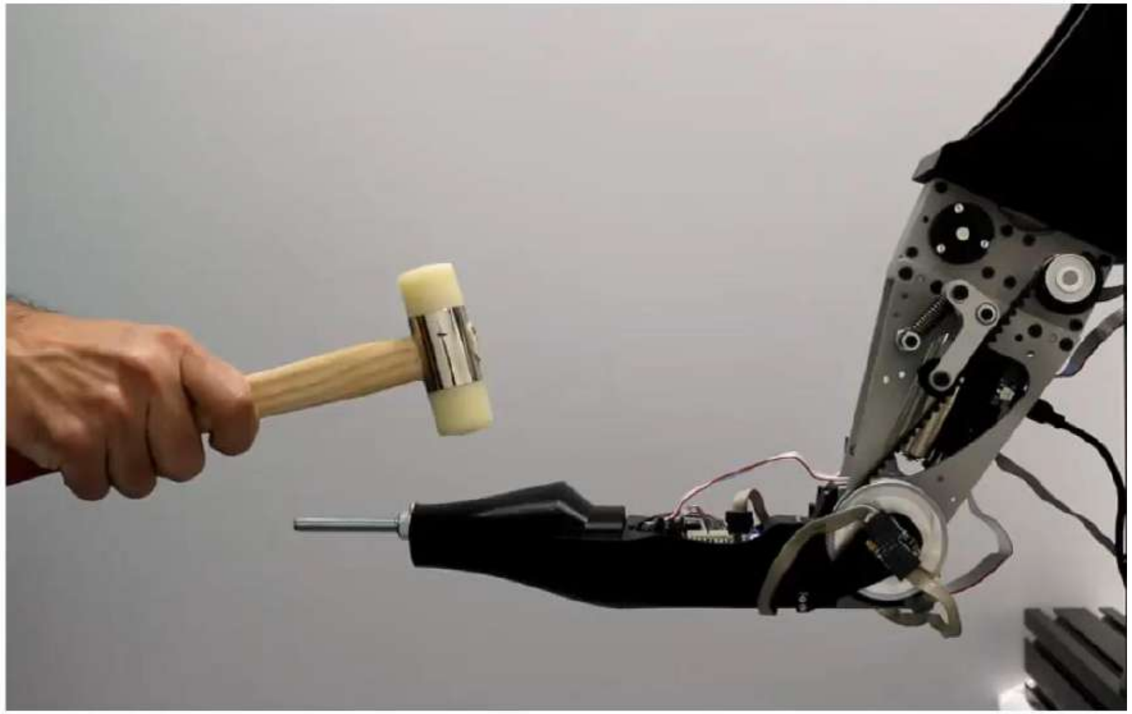


VS Elbow Joint

Low stiffness configuration



High stiffness configuration

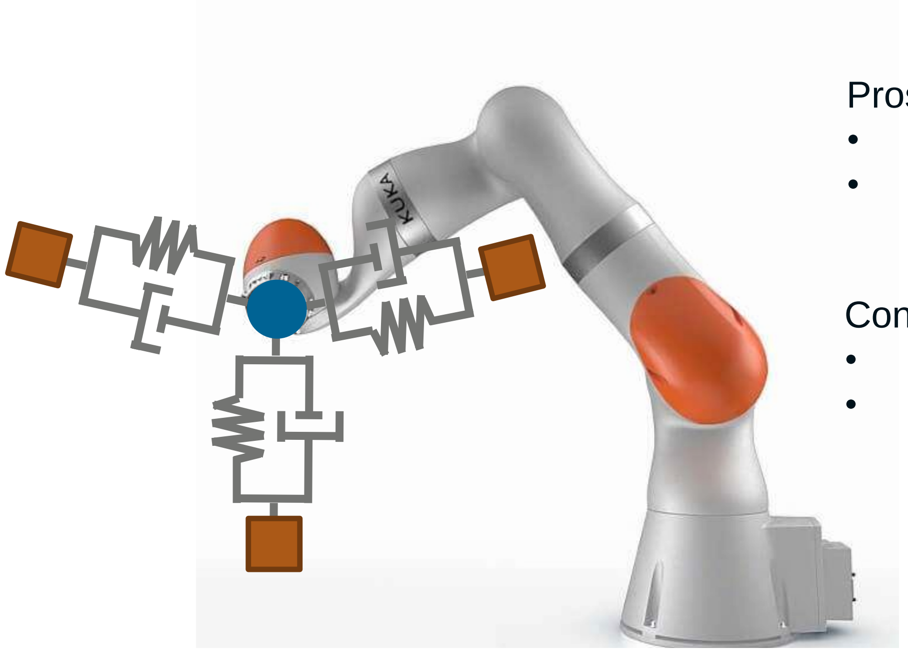


A Variable Stiffness Elbow Joint for Upper Limb Prosthesis
S Lemerle, G Grioli, A Bicchi, MG Catalano
2019 IEEE/RSJ International Conference on Intelligent Robots and Systems

SW: Variable Impedance Control

$$M(q)\ddot{q} + h(q, \dot{q}) = \tau + J(q)^{\mathrm{T}} F_{\mathrm{ext}}$$

$$M_{\mathrm{c}}(\ddot{x} - \ddot{x}_{\mathrm{d}}) + D_{\mathrm{c}}(\dot{x} - \dot{x}_{\mathrm{d}}) + K_{\mathrm{c}}(x - x_{\mathrm{d}}) = F_{\mathrm{ext}}$$



Pros
- Configurable
- Precise and compliant

Cons
- Not resilient
- Not energy efficient

Impedance Control in Reality

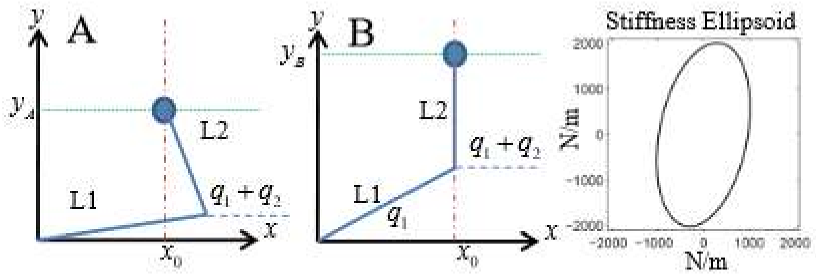


Fig. 2: Two-link manipulator in configuration A (left) and B (middle). Even if both configurations realize a similar desired Cartesian stiffness profile (most right plot), interaction Boundaries of the Cartesian force/stiffness control in the presence of external disturbance are different.

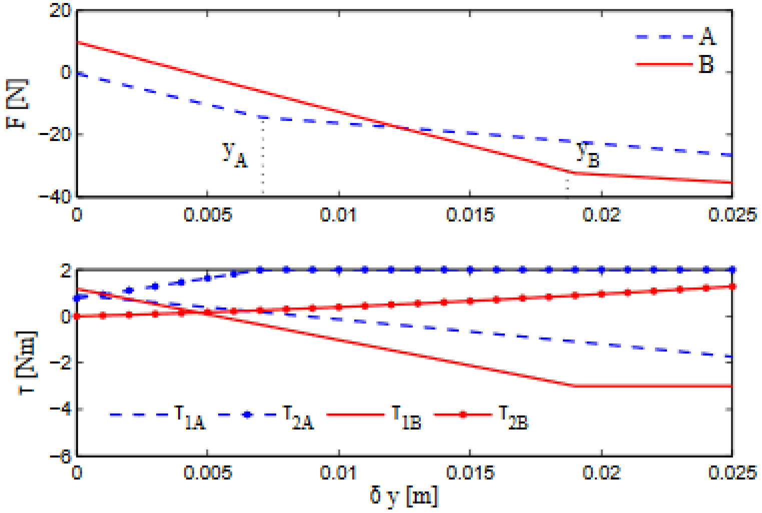


Fig. 3: Endpoint forces vs. displacements along $-y$ direction in manipulators A and B (upper plot), and the corresponding joint torques (lower plot). Initial force offsets refer to the effect of gravity at y direction of the endpoint.

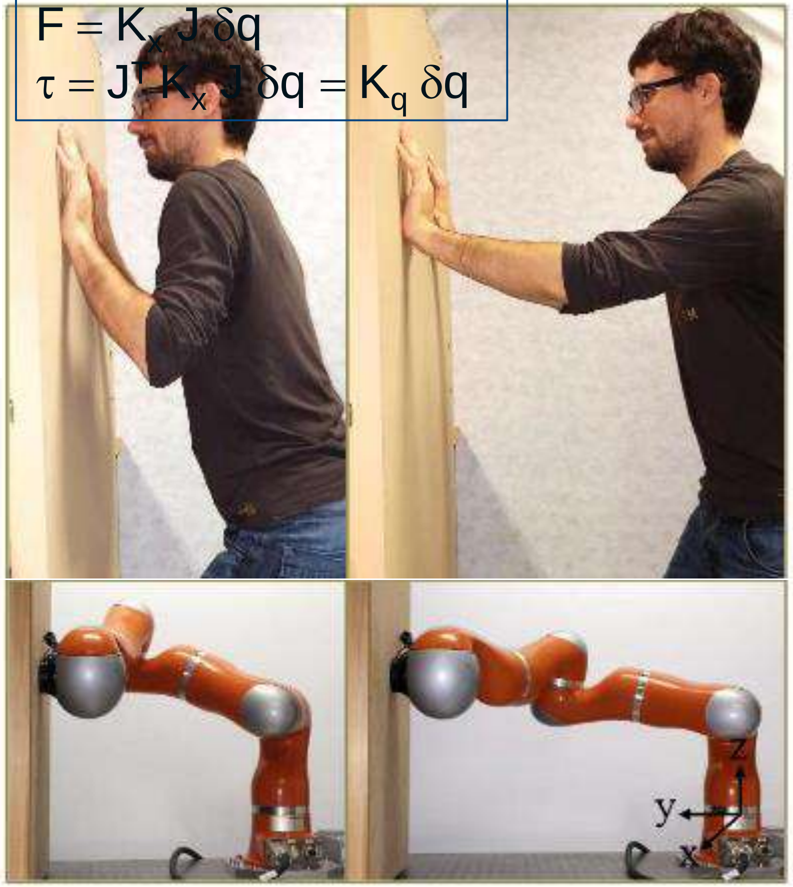
In theory, a robot can attain arbitrary stiffness ellipsoids in any posture

Not in Reality

$\tau = J^T \delta x$

$F = K_x J \delta q$

$\tau = J^T K_x J \delta q = K_q \delta q$



A. Ajoudani, Tsagarakis, N. G., and Bicchi, A., “Choosing Poses for Force and Stiffness Control”, IEEE Transactions on Robotics, 2017.

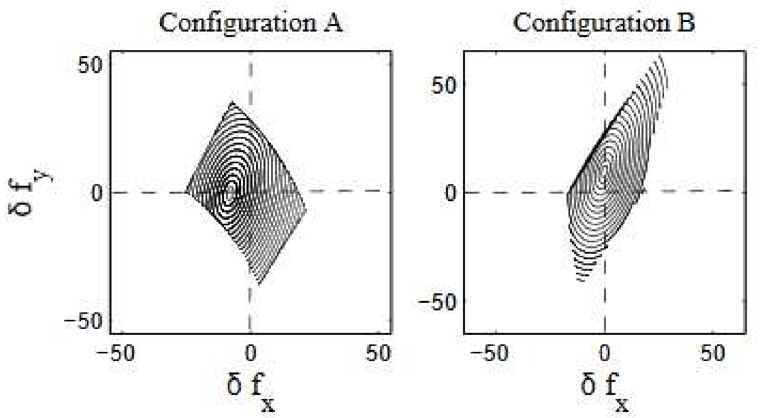


Fig. 4: The locus of $||f||$ for the growing displacement norm for the two-link manipulator in configuration A (left plot), and B (right plot) hit the limits caused by two configuration dependent force boundaries. The spatial translation of the centre of the ellipsoids w.r.t. the origin can be observed in the plots.

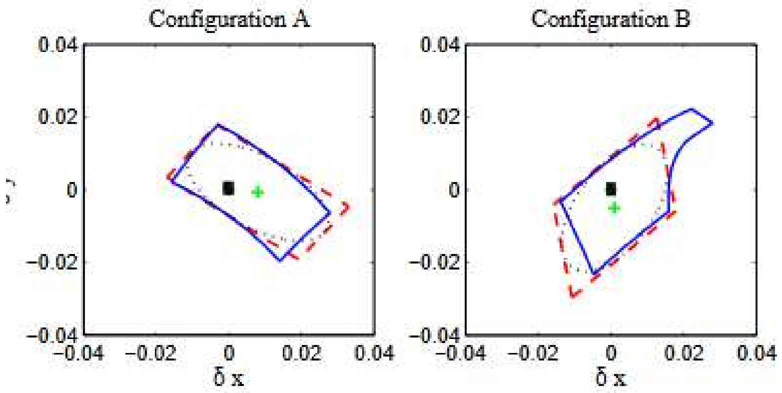
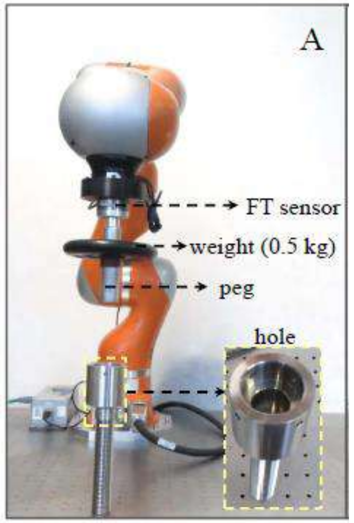
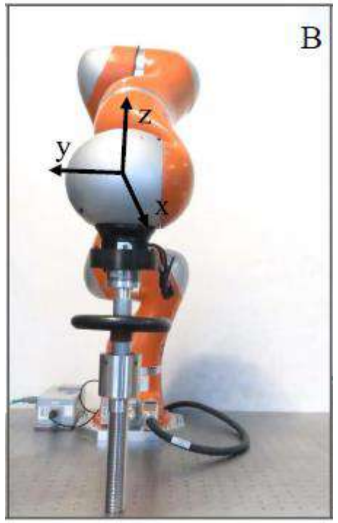


Fig. 5: Blue (solid) plots illustrate the stiffness feasibility regions (SFRs) for configuration A (left) and B (right), while corresponding polytopes are plotted in red (dashed). Stiffness feasibility ellipsoids (SFEs) are plotted in black (dotted), for both configurations. The units are in [m].

Choosing poses to change impedance





A. Ajoudani, M. Gabiccini, N. Tsagarakis, A. Albu-Schaffer, A. Bicchi “Exploring the Roles of Common Mode and Configuration Dependent Stiffness Control” Humanoids 2012.

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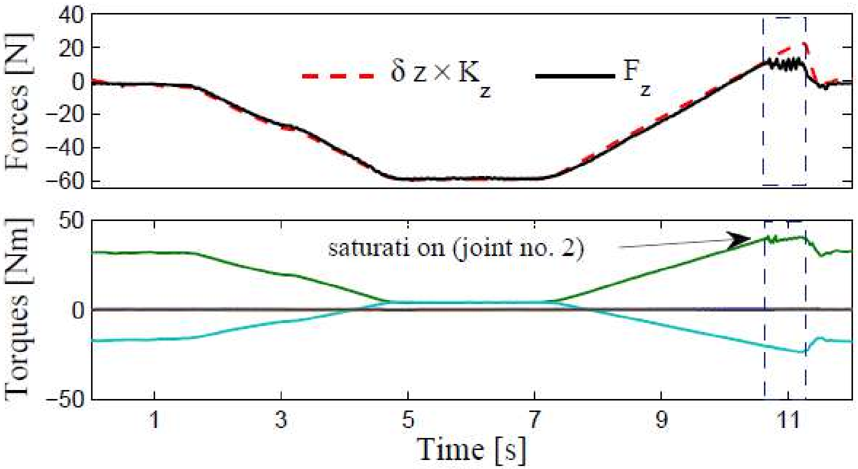
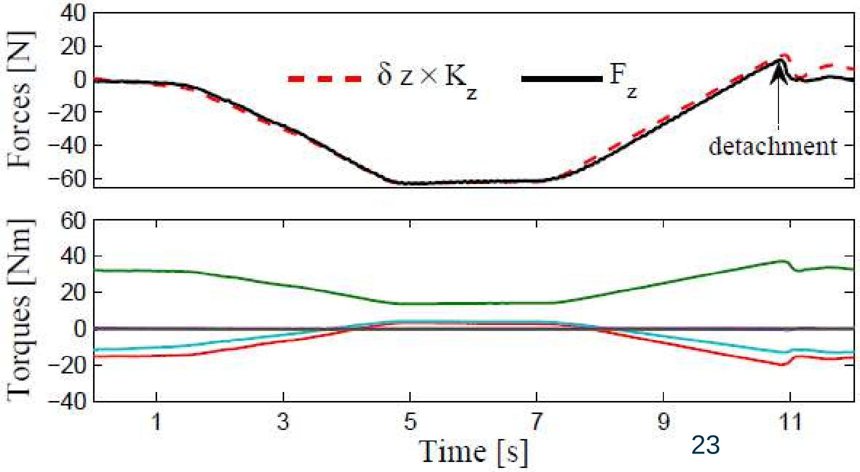




How to use Variable Impedance?

Soft Robots

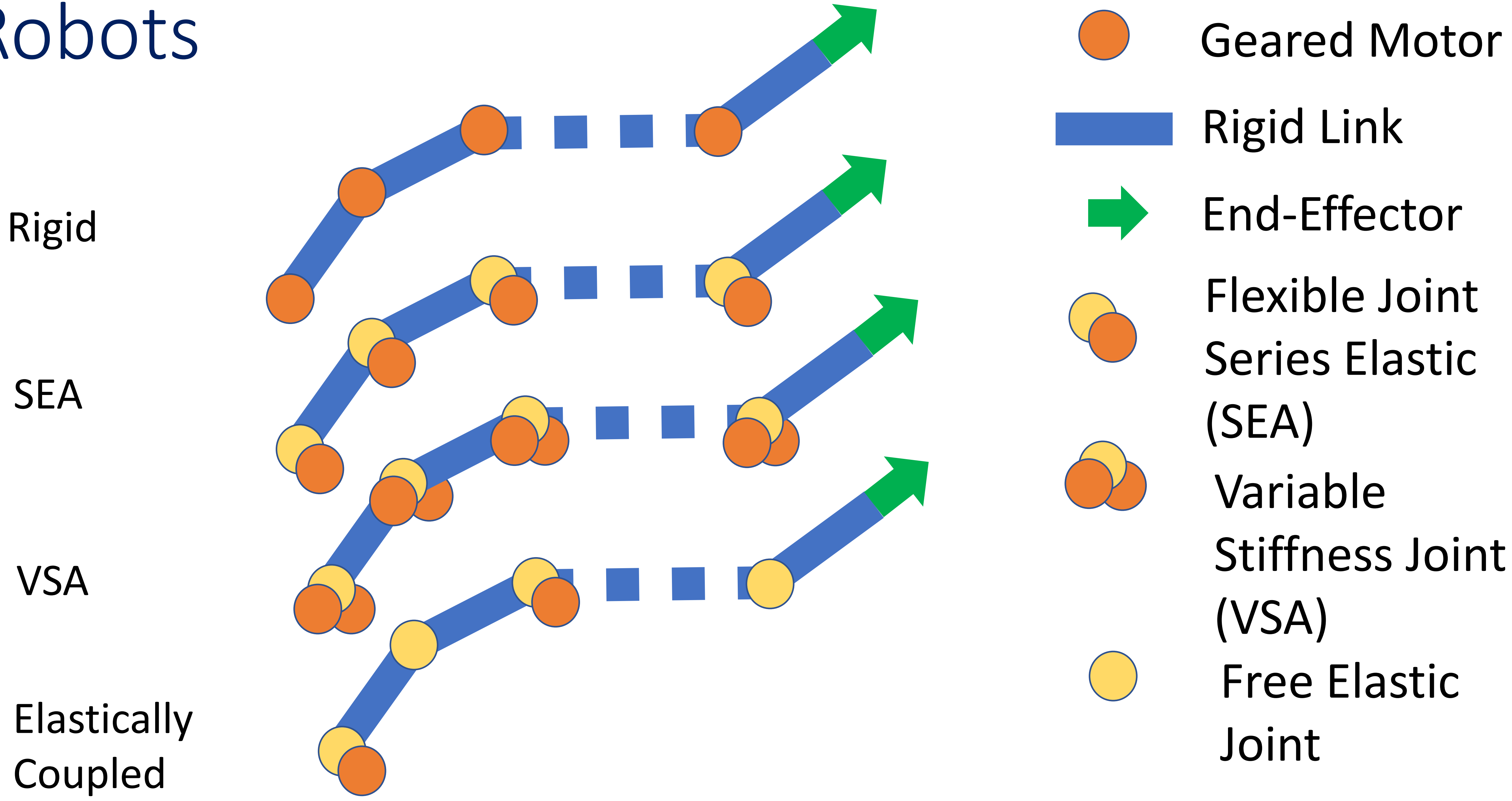
- Safer
- Faster
- More adaptable
- More robust

However

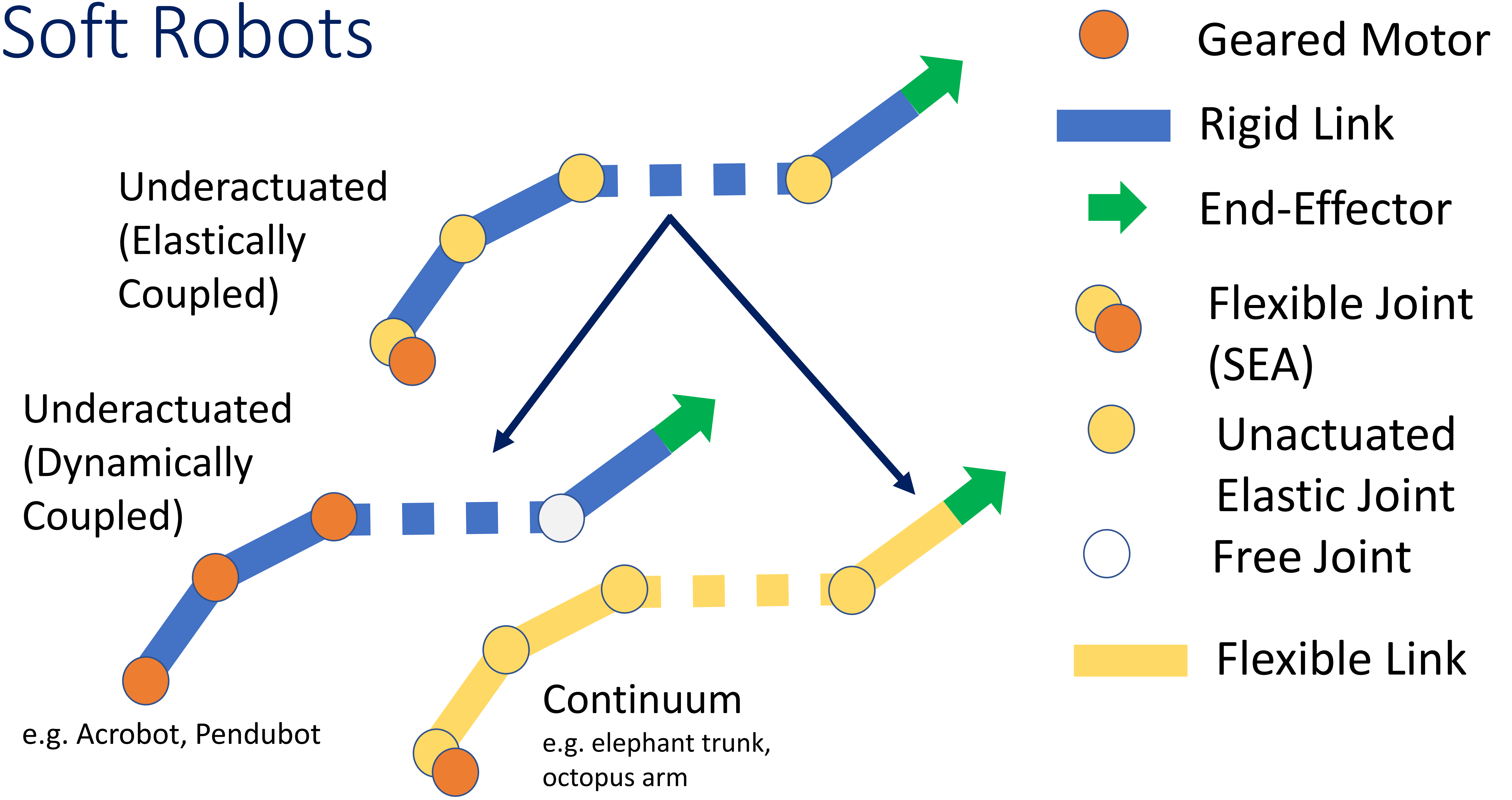
- Nonlinear
- Uneractuated
- Lower control authority
- Lower relative degree

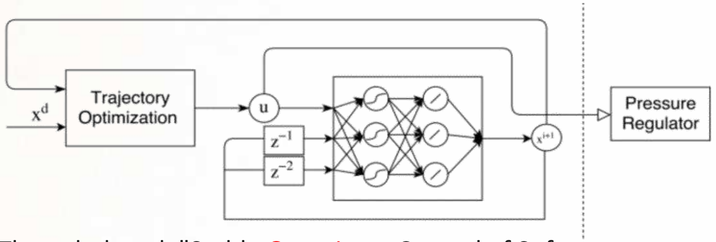
→ More difficult to control

Robots

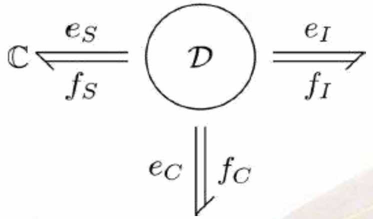

Rigid
SEA
VSA
Elastically Coupled
Geared Motor
Rigid Link
End-Effector
Flexible Joint Series Elastic (SEA)
Variable Stiffness Joint (VSA)
Free Elastic Joint

Soft Robots

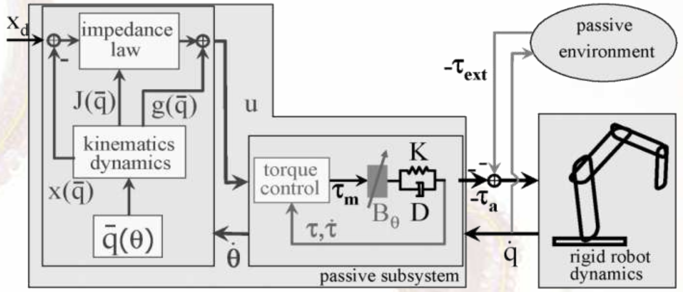

Underactuated
(Elastically
Coupled)
Underactuated
(Dynamically
Coupled)
e.g. Acrobot, Pendubot
Continuum
e.g. elephant trunk,
octopus arm
Geared Motor
Rigid Link
End-Effector
Flexible Joint
(SEA)
Unactuated
Elastic Joint
Free Joint
Flexible Link



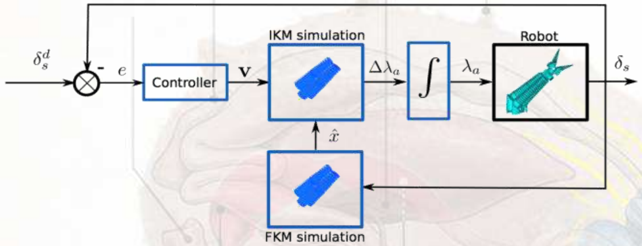
Thuruthel et al. "Stable Open Loop Control of Soft Robotic Manipulators." *RAL* (2018)



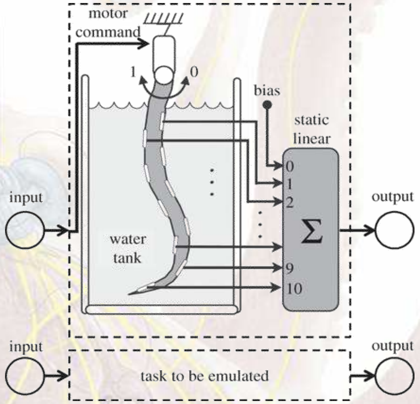
Carloni et al. "Variable stiffness actuators: A port-based power-flow analysis." *IEEE T-RO* (2012)



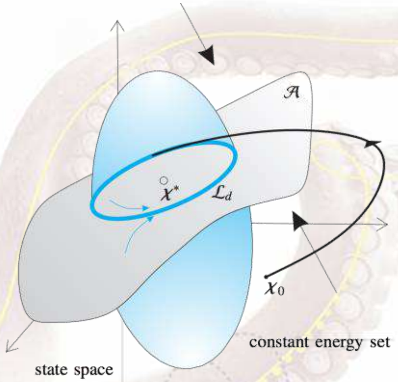
Albu-Schäffer et al. "A unified passivity-based control framework for position, torque and impedance control of flexible joint robots." *IJRR* (2007)



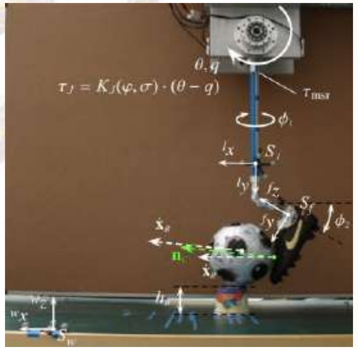
Bieze et al. "FEM-based kinematics and closed-loop control of soft, continuum manipulators." (2018).



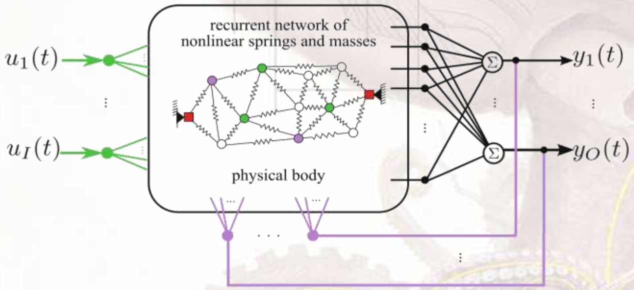
Nakajima et al. "Exploiting short-term memory in soft body dynamics as a computational resource." *Journal of The Royal Society Interface* (2014)



Garofalo and Ott. "Energy based limit cycle control of elastically actuated robots." *TAC* (2017)



Haddadin et al. "Kick it with elasticity: Safety and performance in human–robot soccer." *Robotics and Autonomous Systems* (2009)

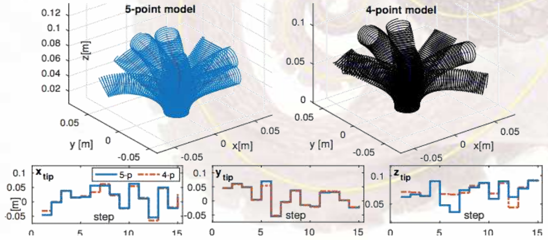


Hauser et al. "The role of feedback in morphological computation with compliant bodies." *Biological cybernetics* (2012)

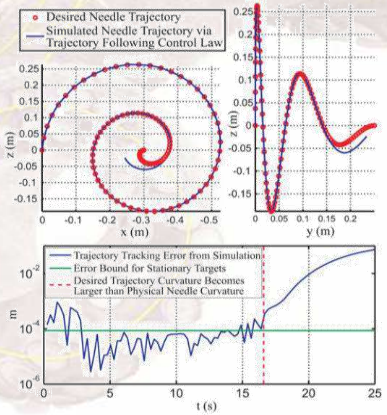
$$\ddot{q} = M^{-1}(q)\left[\tau_e - n(q,\dot{q})\right]$$

$$\dddot{q} = M^{-1}(q)\left[\dot{\tau}_e - \left(\dot{M}(q)\ddot{q} + \dot{n}(q,\dot{q})\right)\right]$$

Buondonno and De Luca. "Efficient computation of inverse dynamics and feedback linearization for VSA-based robots." *RAL* (2016)



Sadati et al. "Control Space Reduction and Real-Time Accurate Modeling of Continuum Manipulators Using Ritz and Ritz–Galerkin Methods." *IEEE RAL (2018)*



Rucker, D. Caleb, et al. "Sliding mode control of steerable needles." *IEEE T-RO* (2013)

Best et al. "A new soft robot control method: using model predictive control for a pneumatically actuated humanoid." *RAM* (2016)

Control Properties

$$\begin{cases} M\ddot{q} + C\dot{q} + G + \dfrac{\partial V(q,\theta)^T}{\partial q} = \tau_{ext} \\ J\ddot{\theta} + D\dot{\theta} + \dfrac{\partial V(q,\theta)^T}{\partial \theta} = \tau_m \end{cases}$$

with $q \in \mathbb{R}^n$ and $\theta \in \mathbb{R}^m$

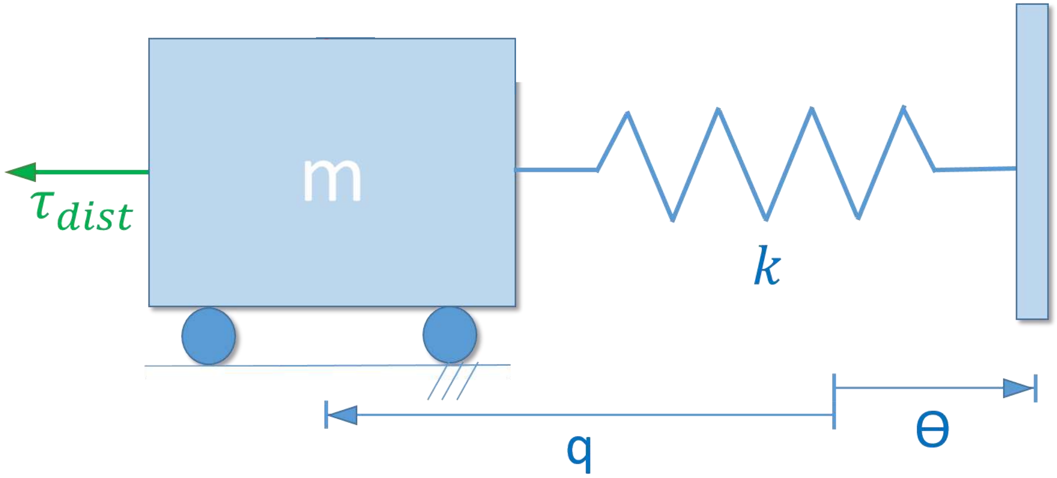
- All systems above are controllable in their linearization
- All are input/output feedback linearizable, with stable zero dynamics (except underactuated with dynamically coupled free joints)
- Collocated control easy, but low performance
- Non-collocated control not impossible in theory
- However…

Feedback control of Soft Robots
An Elementary Example

Consider the simplest soft robot, a cart connected through a spring to a moving element…

System dynamics

$$\underbrace{m}_{\text{mass}}\ddot{q} + \underbrace{\beta}_{\text{damping}}\dot{q} + \overbrace{k}^{\text{stiffness}}\underbrace{q}_{\text{position}} = k\underbrace{\theta}_{\text{input}} + \underbrace{\tau_{dist}}_{\text{External torque}}$$



Limits of feedback control in soft robots: An Elementary PD Example

…controlled with a simple proportional control

$$\theta = -K_P q$$

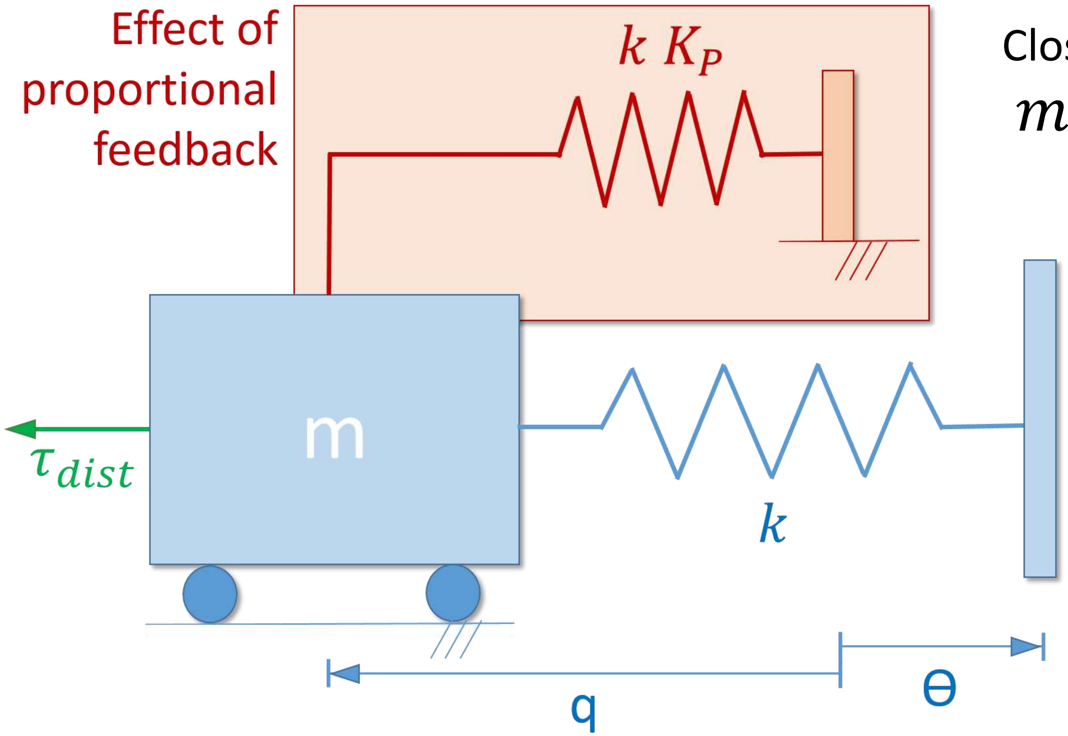
System dynamics

$$m\ddot{q} + \beta\dot{q} + kq = k\theta + \tau_{dist}$$

P controller
$\theta = -K_P q$

Closed loop dynamics

$$m\ddot{q} + \beta\dot{q} + k(1 + K_P)q = \tau_{dist}$$



The closed loop stiffness increases by a factor $(1 + K_P)$

Limits of feedback control in soft robots

Elastic field Stiffness input

$$B(q)\ddot{q} + C(q,\dot{q})\dot{q} + T(q-\theta,\sigma) = \tau_{dist}$$

Generic soft robot

Control input

Generic algebraic controller

$$\theta \; = \psi(q,\dot{q},\sigma,t,r)$$

Generic closed loop

$$B(q)\ddot{q} + C(q,\dot{q})\dot{q} + T(q \; - \; \psi(q,\dot{q},\sigma,t,r),\sigma) = \tau_{dist}$$

Define the stiffness variation as (q^* fixed point of ψ)

$$\nu = \left\| \left.\frac{dT(q \; - \; \psi(q,\dot{q},\sigma,t,r),d)}{dq}\right|_{q=q^*} - \left.\frac{dT(q \; - \theta,\sigma)}{dq}\right|_{q=\theta} \right\|$$

Closed loop stiffness

Open loop stiffness

Matrix norm

Limits of feedback control in soft robots

Elastic field

Stiffness input

$$B(q)\ddot{q} + C(q,\dot{q})\dot{q} + T(q - \theta, \sigma) = \tau_{dist}$$

Generic soft robot

Control input

Generic algebraic controller

$$\theta = \psi(q, \dot{q}, \sigma, t, r)$$

Generic closed loop

$$B(q)\ddot{q} + C(q,\dot{q})\dot{q} + T(q - \psi(q, \dot{q}, \sigma, t, r), \sigma) = \tau_{dist}$$

If

$$\left\| \left. \frac{\partial \psi(q, \dot{q}, d, t, r)}{\partial q} \right|_{q=q^*} \right\| \leq \delta \left\| \frac{\partial T}{\partial q}(0, \sigma) \right\|^{-1}$$

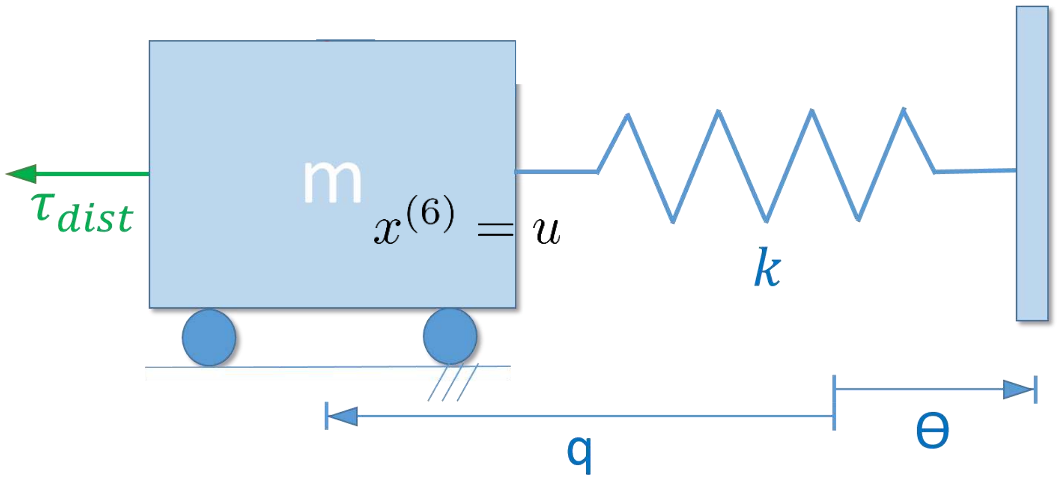
then $v \leq \delta$. Softness is completely preserved (i.e. $v = 0$) iff

$$\left\| \left. \frac{\partial \psi(q, \dot{q}, d, t, r)}{\partial q} \right|_{q=q^*} \right\| = 0$$

Stiffness variation due to closed loop

Proportional component of the feedback controller

Limits of feedback control in soft robots: Feedback Linearization



$$\ddot{q} = \tau_n$$

$$x_1^{(4)} = u_1$$

$$x_2^{(2)} = u_2$$

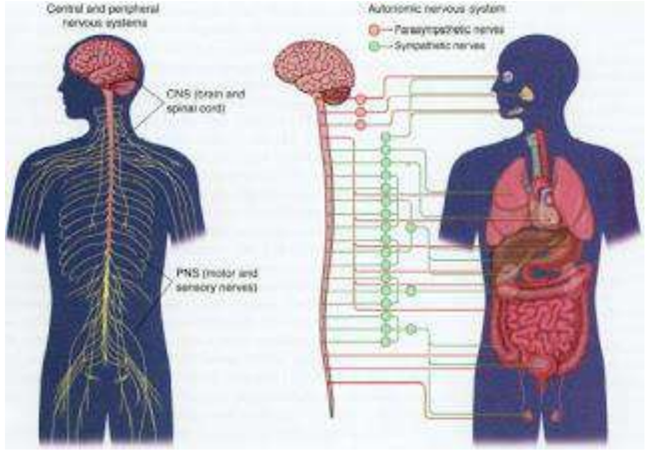
Learning to Control Soft Robots

In feedback control, performance is directly related to gain – i.e. stiffness

Now that we have soft robots, we don't want to fight softness by control

Need "minimally invasive" control

Ideas from humans



CNS loops ~100ms
PNS loops ~10ms

PREDICTIVE FEED-FORWARD SENSORY CONTROL DURING GRASPING AND MANIPULATION IN MAN

ROLAND S. JOHANSSON and BENONI B. EDIN
Department of Physiology, University of Umeå, S-091 87 Umeå, Sweden

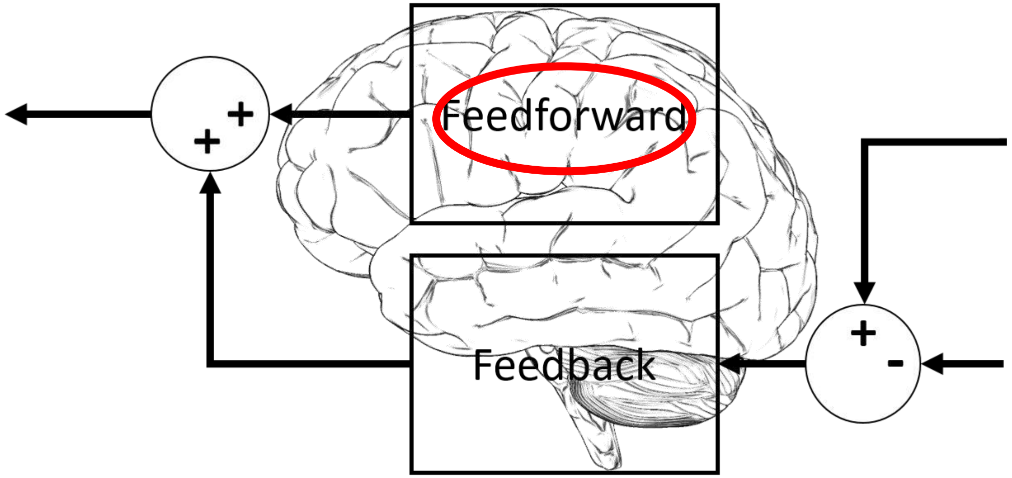
Exp. Brain Res., 1984

ABSTRACT

During dexterous manipulation the basal relationships expressed in the employed fundamental muscle synergies are tuned precisely not only to the manipulative intent, but also to the physical properties of the object. Recent findings indicate that the sensorimotor mechanisms involved depend largely on predictive rather than servo-control mechanisms. The CNS monitors specific, more-or-less expected, peripheral sensory events and use these to directly apply control signals that are appropriate for the current task and its phase. On a fast time scale, discrete mechanical events encoded in populations of somatosensory afferents trigger compensatory actions to task perturbations, and allow task progress to be monitored for timing the release of motor commands related to the serial manipulative phases. This type of predictive feed-forward sensory control is termed '*sensory discrete-event driven control*'. On an extended time scale, previous experience with the object at hand or similar objects is used to adjust the motor commands parametrically in advance of the movement, *e.g.* for the object's weight and surface friction. Through vision, for instance, common objects can be identified in terms of the grip and lifting forces necessary for a successful lift. This ability to directly parameterize the default motor commands is termed '*anticipatory parameter control*'.

Anticipatory control

Fast, powerful,accurate movements



Anticipatory behavior: the ability of CNS to anticipate the necessary control action relying on sensory-motor memory

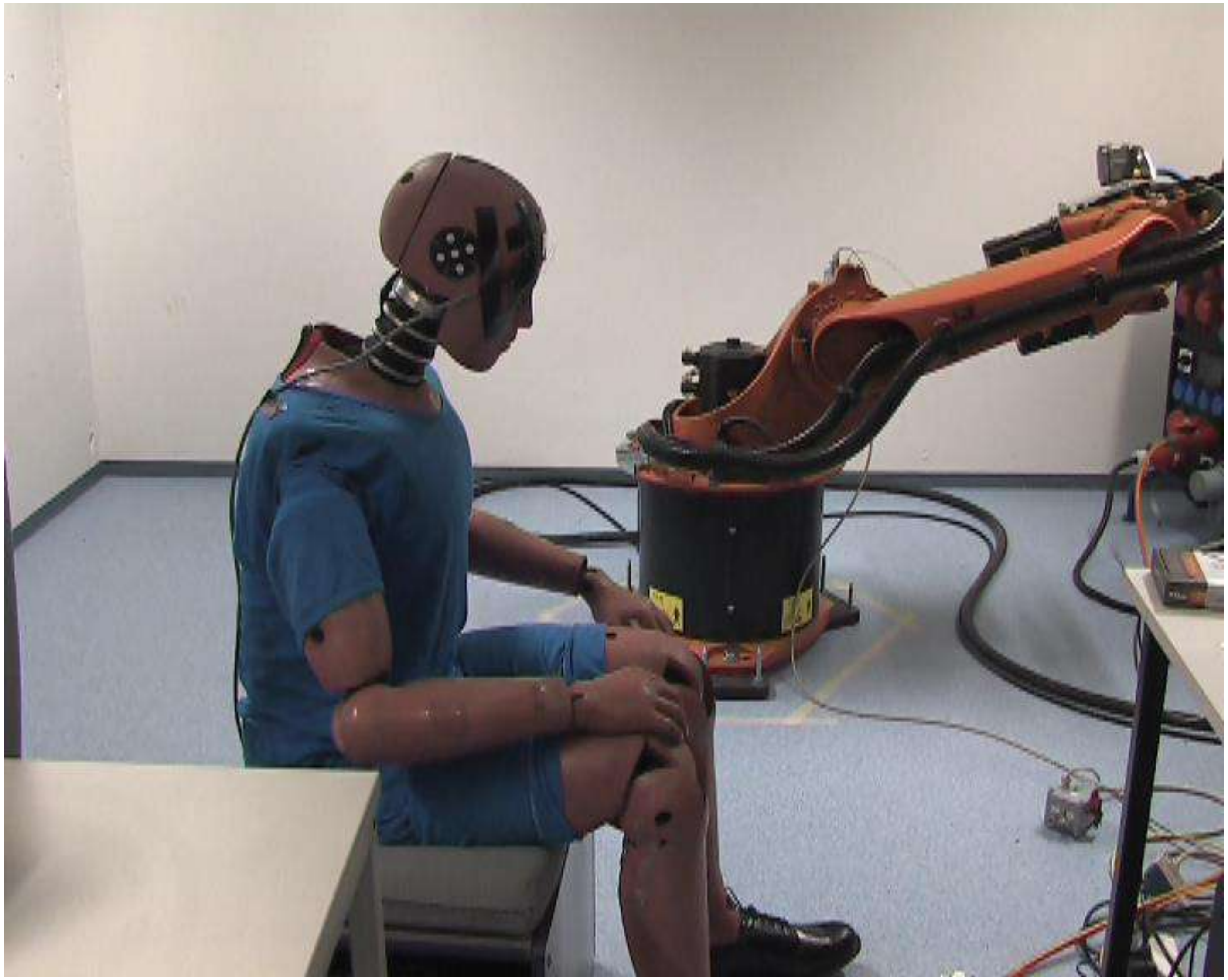
Anticipatory behavior permits to obtain high performance in presence of perception delays.

Model-based (optimal) Anticipatory Control

Data based (learning) Anticipatory Control

Planning Impedance

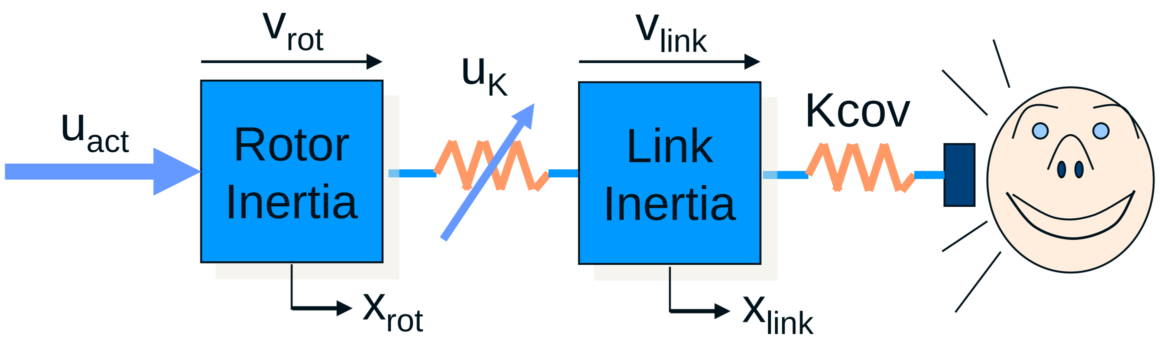
Optimal Control to Minimize Impact



On making robots understand safety: Embedding injury knowledge into control
S Haddadin, S Haddadin, **A Khoury**, T Rokahr, S Parusel, R Burgkart, A. Bicchi
The International Journal of Robotics Research 31 (13), 1578-1602

The Safe Brachistochrone

How to control velocity and compliance to optimize performance within guaranteed safety limits?



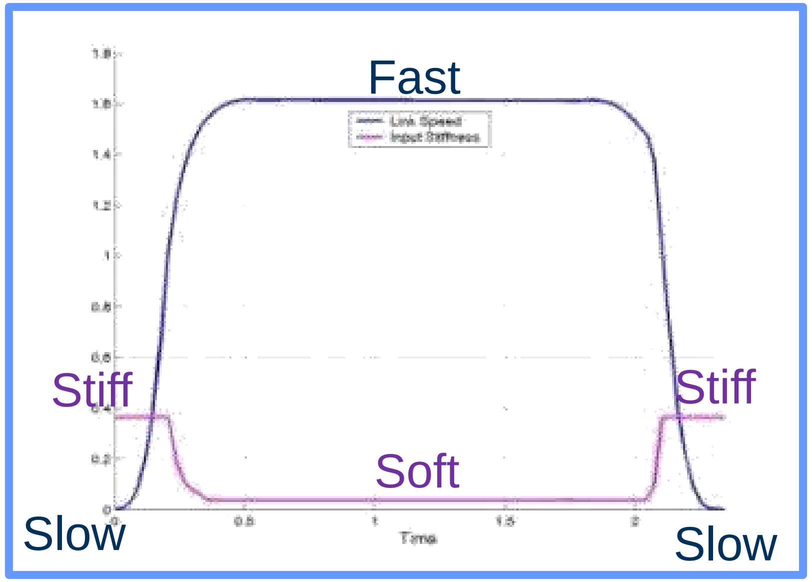
The **<u>Safe Brachistocrone problem</u>**

$$
\begin{cases}
\min_T \int_0^T 1\,dt \\
M_{rot}\ddot{x}_{rot} + u_K(x_{rot} - x_{link}) = u_{act} \\
M_{link}\ddot{x}_{link} + u_K(x_{link} - x_{rot}) = 0 \\
|\dot{x}_{link}| \leq \beta(u_K) HIC_{max}^{\frac{2}{5}} \\
|u_{act}| \leq U_{max} \\
u_{K,min} < u_K < u_{K,max} \\
(x_{link}, \dot{x}_{link})(0) = (X_{ini}, 0) \\
(x_{link}, \dot{x}_{link})(T) = (0, 0)
\end{cases}
$$

HIC: Safety & Control bounds

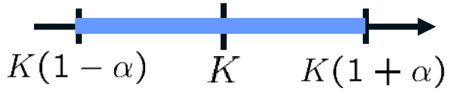
VSA Bounds

The Safe Brachistochrone



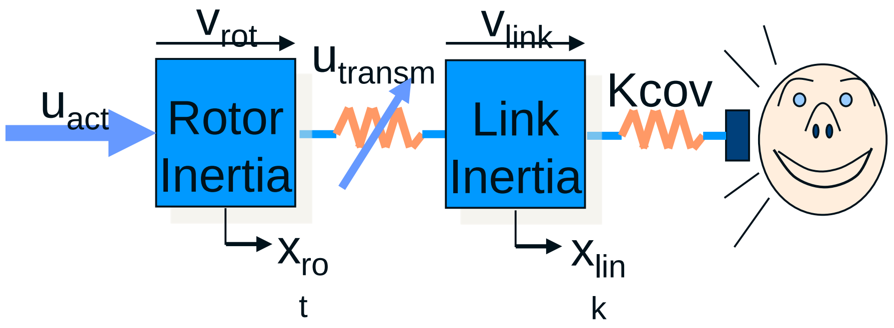
The intuitive policy of synchronizing joint stiffness and joint velocity is indeed consistent with the optimal solution for the safe brachistochrone

→ *Fast & Soft, Stiff & Slow*

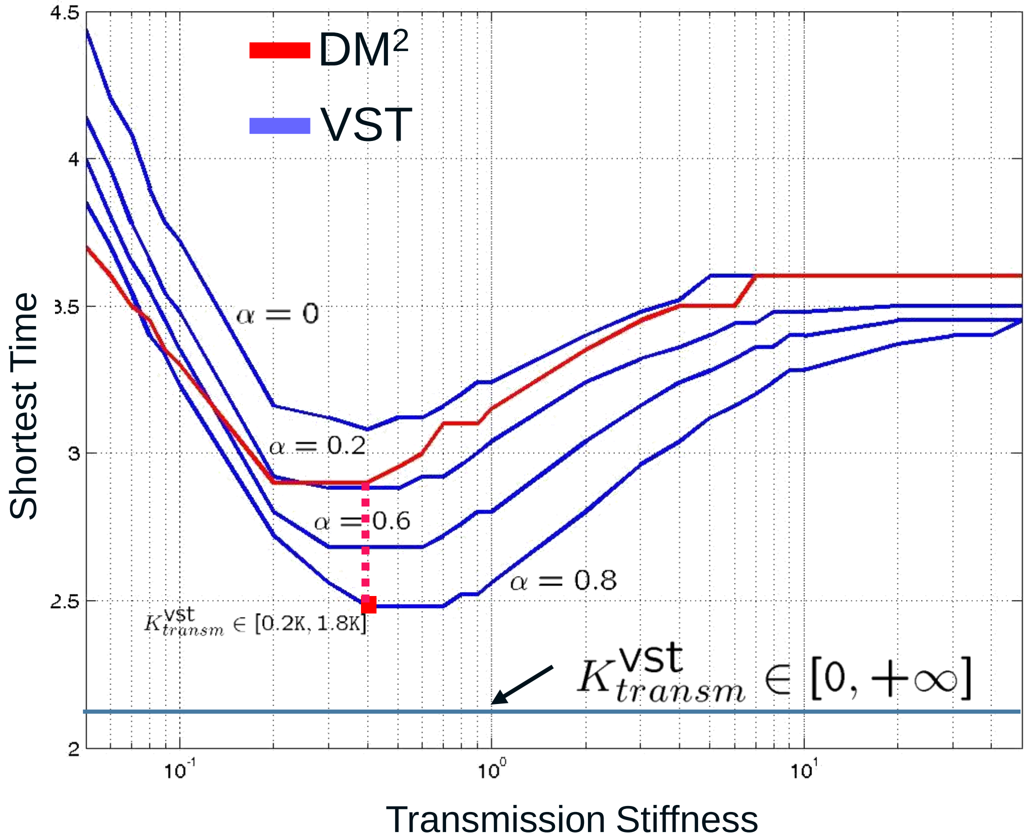


A. Bicchi and **G. Tonietti**,
Fast and Soft Arm Tactics
IEEE RAM 2004

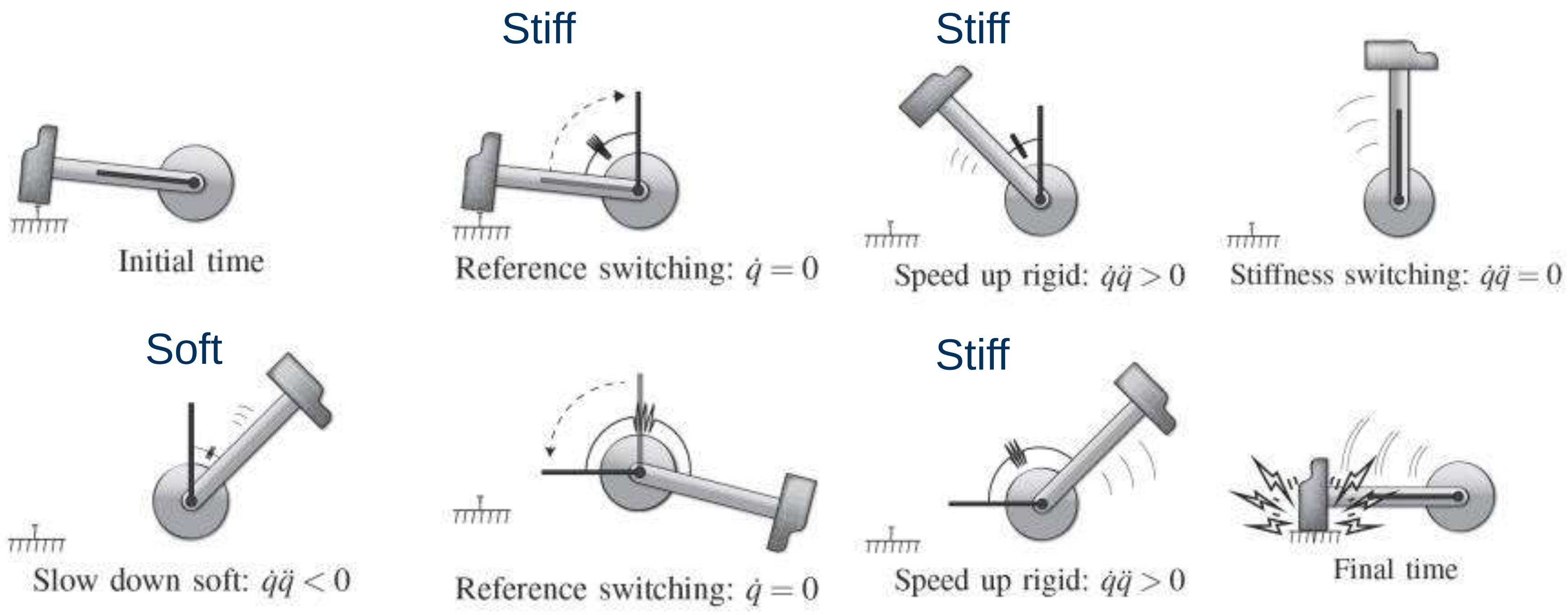
$$u_K = K^{vst}_{transm} \in [(1-\alpha)K, (1+\alpha)K]$$



VSA beats both Rigid, DM² and SEA



Optimal Control to Maximize Impact



Theorem 2: The stiffness optimal control is:

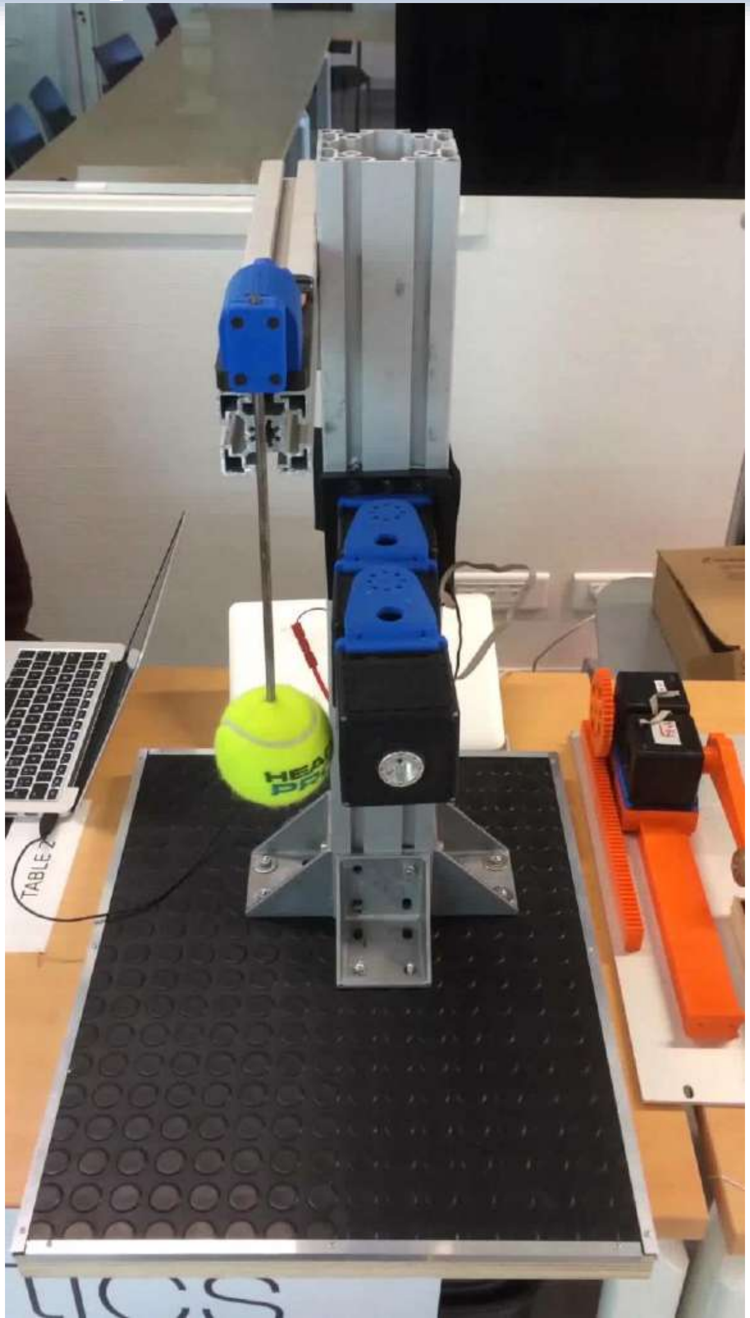
$$u_2 = \begin{cases} u_{2,\max} & \text{if } \dot{q}\ddot{q} > 0 \\ u_{2,\min} & \text{if } \dot{q}\ddot{q} < 0 \end{cases}$$

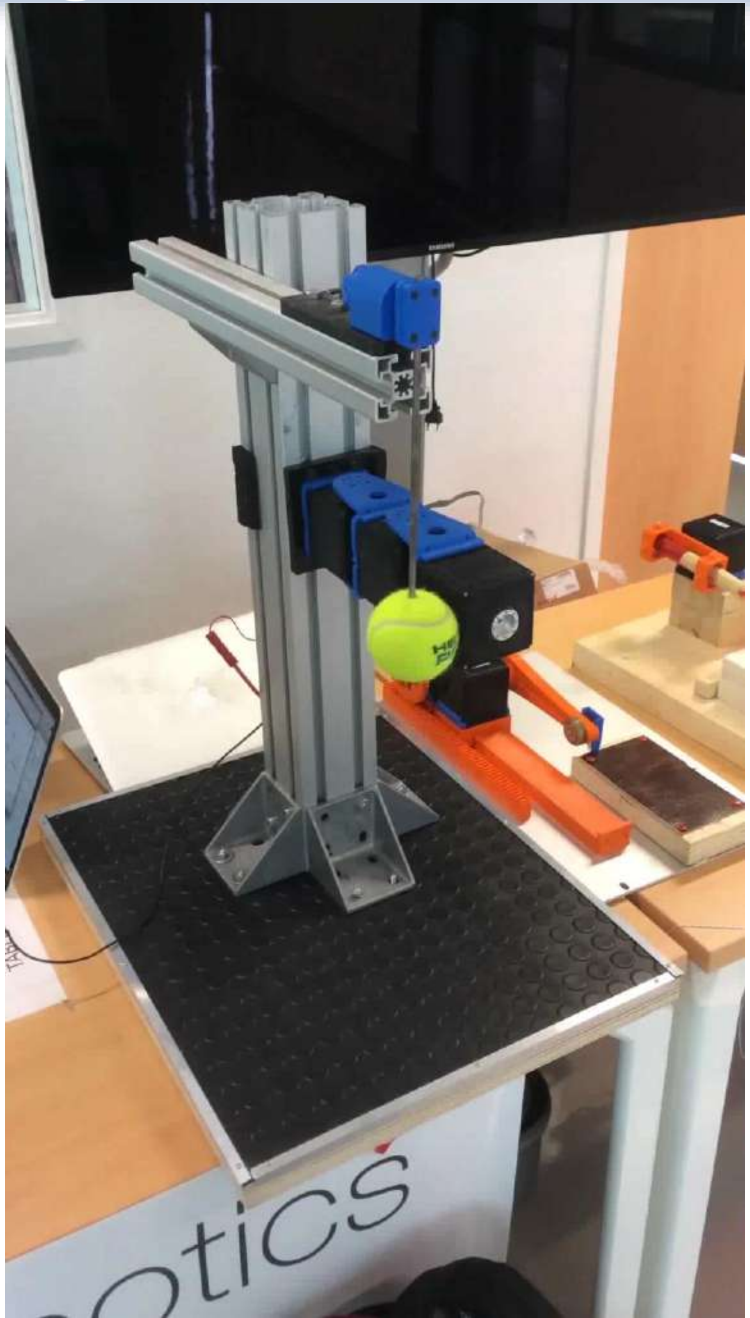
Max speed at free terminal time, bounded torque

Optimality principles in variable stiffness control: The VSA hammer
M Garabini, A Passaglia, F Belo, **P Salaris**, A Bicchi
2011 Ieee/Rsj International Conference on Intelligent Robots and Systems

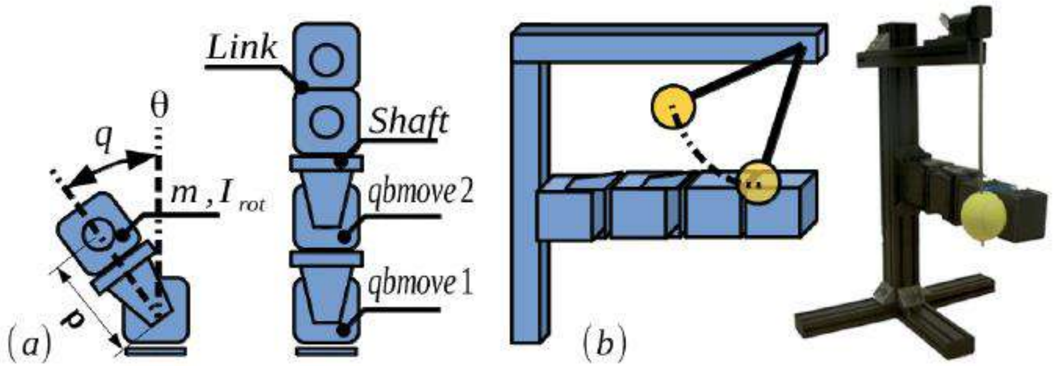
Stiff speed-up, soft slow-down

Maximize impact: 2DoF hitting





The other way around: Maximize Damping



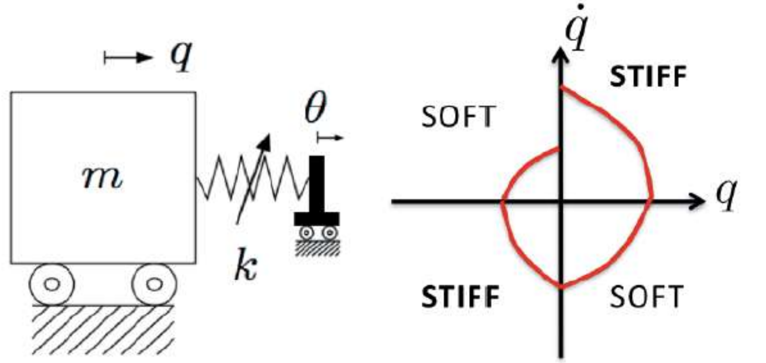
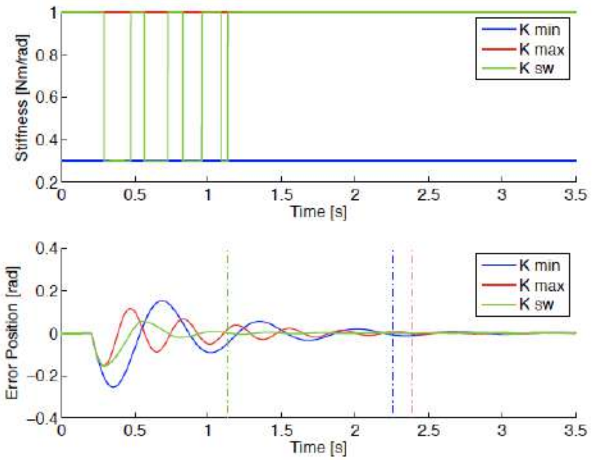
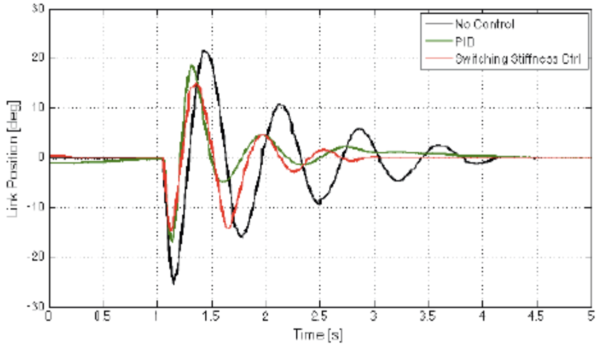


Fig. 1: Left: schematic of a 1 DoF soft actuator used for the optimal control problem. Right: Optimal stiffness switching control provided in this work.





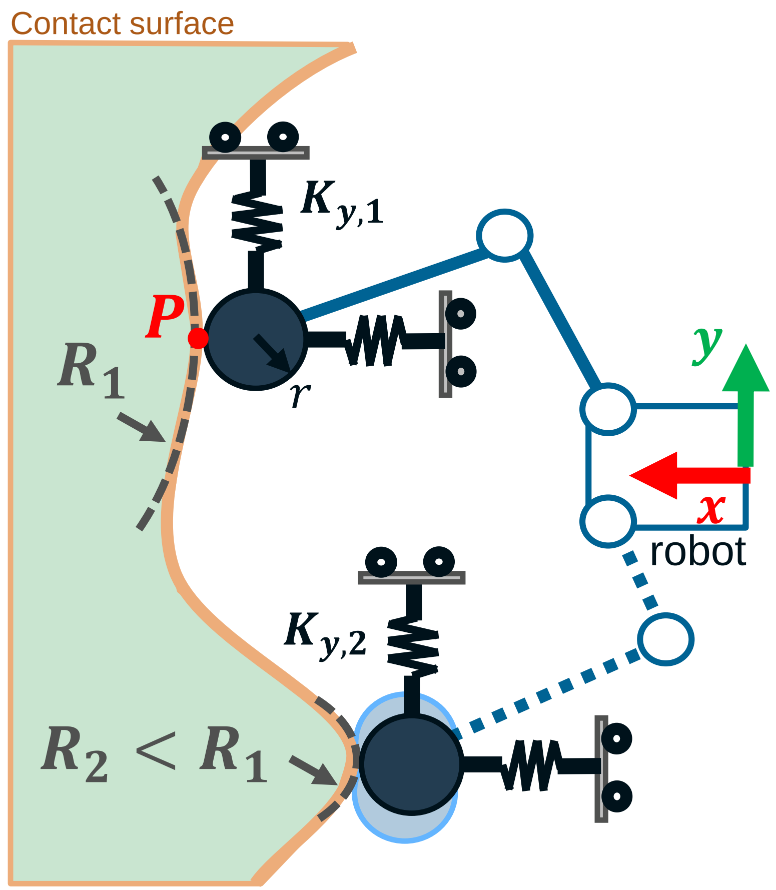
Min energy at
fixed terminal time,
bounded input

Variable stiffness control for oscillation damping
GM Gasparri, M Garabini, **L Pallottino**, L Malagia, M Catalano, G Grioli, A. Bicchi
2015 IEEE/RSJ International Conference on Intelligent Robots and Systems

Soft speed-up, stiff slow-down

Resilient and Stable Physical Interaction

<u>Goal:</u> perform an interaction task where the contact must be kept



<u>Issues:</u>

- Instability
- Resilience
- Minimum force to achieve the task
- Positioning errors

⇩

<u>Stiffness bounds</u> related to:

- uncertainties
- contact surface curvature
- interaction forces

Mengacci, R., **Angelini, F.**, Catalano, M. G., Grioli, G., Bicchi, A., & Garabini, M. (2019). "Stiffness Bounds for Resilient and Stable Physical Interaction of Articulated Soft Robots". IEEE Robotics and Automation Letters, 4(4), 4131-4138.

Resilient and Stable Physical Interaction

Theoretical result

$$\frac{F_{\mathrm{min}}}{|\bar{x}_{\mathrm{c}} + \Delta x - R\cos(\theta)|} < K_{\mathrm{x}} < \frac{F_{\mathrm{max}}}{|\bar{x}_{\mathrm{c}} - \Delta x - R\cos(\theta)|}$$

Bounded by the force required by the **task specifications**

Bounded by the interaction force to **avoid damages**

$$\frac{F_{\mathrm{x}}}{R} < K_{\mathrm{y}} < --$$

Bounded by the **stability** condition

No theoretical bound (if stable)

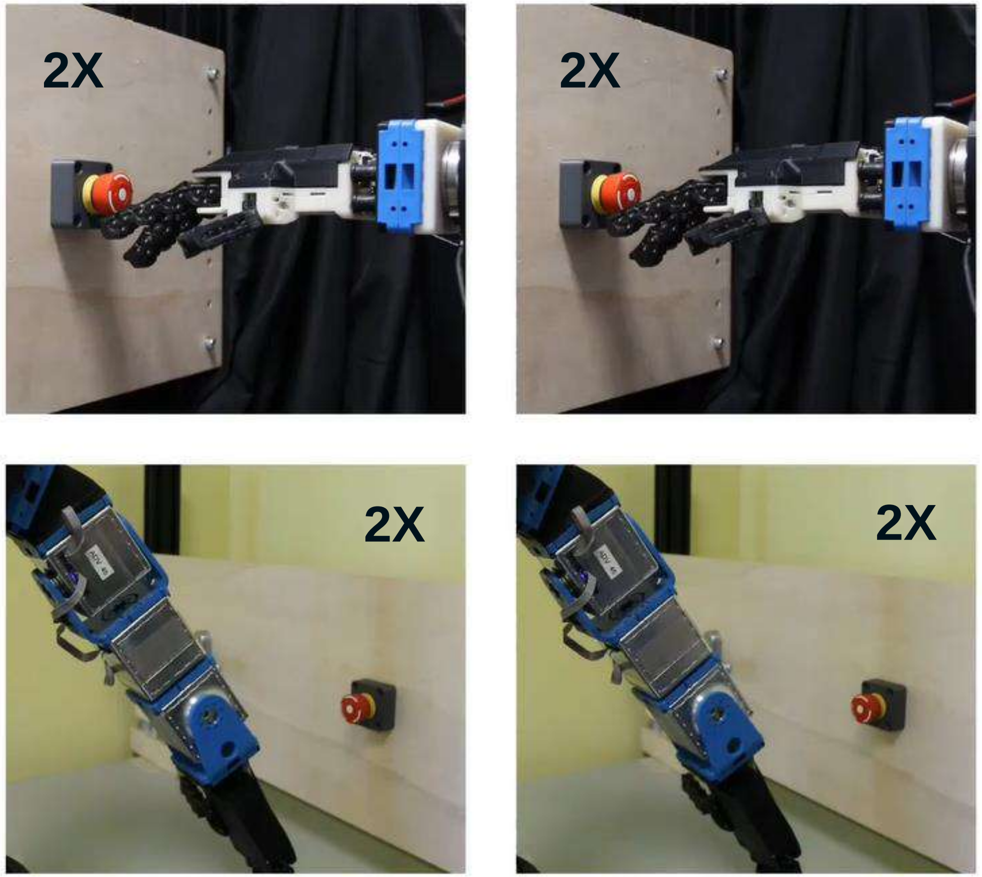
R	Curvature radius	F_{min}	Force to achive the task		
$\bar{x}_{\mathrm{c}}$	Reference EE position	F_{max}	Max. force	Δx	Uncertainty

Failure | Success

SW

Impedance Control

HW



Mengacci, R., Angelini, F., Catalano, M. G., Grioli, G., Bicchi, A., & Garabini, M. (2019). “Stiffness Bounds for Resilient and Stable Physical Interaction of Articulated Soft Robots”. IEEE Robotics and Automation Letters, 4(4), 4131-4138.

Model-based (optimal) Anticipatory Control

Data based (learning) Anticipatory Control

Learning by Repetition

$$u_i : [0, t) \rightarrow Rm$$

In motor control [Emken et al. 2007]:

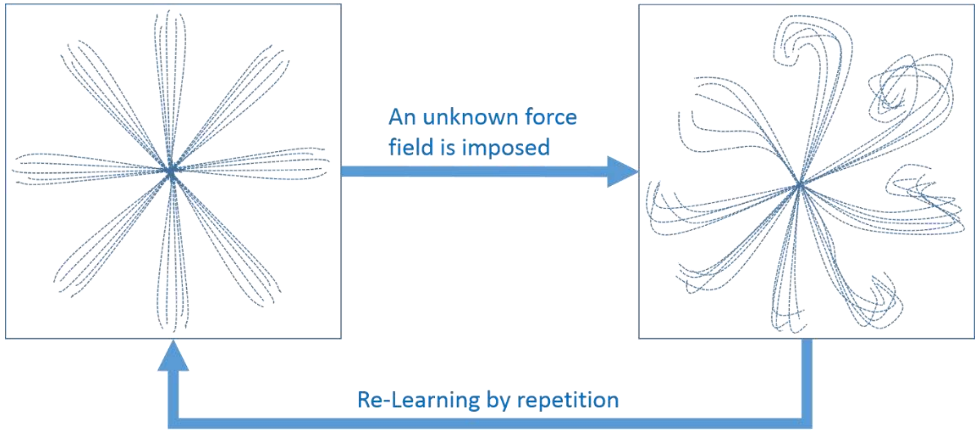
$$u_{i+1} = f u_i + \alpha e_i$$

i → trial

u_i → i-th motor action

e_i → i-th percept error

f, α → constant



Learning by Repetition

$$u_i : [0,t) \rightarrow Rm$$

Motor Control [Emken et al. 2007]:

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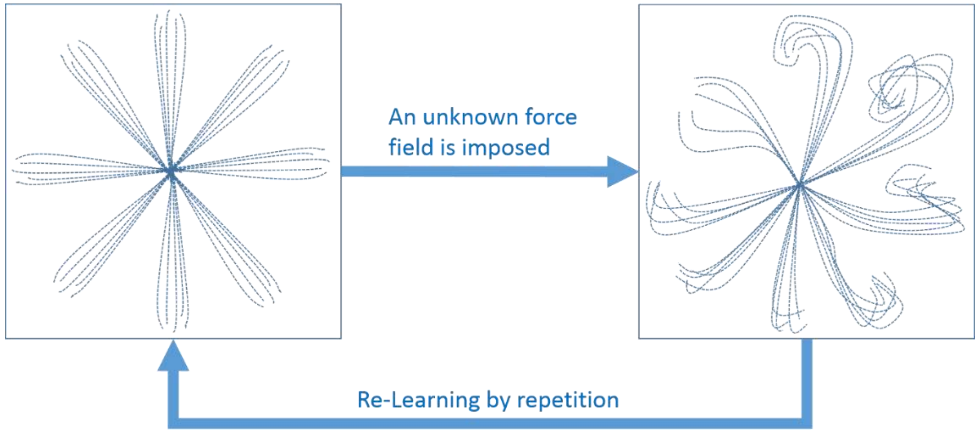

Iterative Learning Control

$$u_{i+1} = Q(u_i) + r(e_i)$$

Q → forgetting factor

r → updating law

Learning by Repetition

$$u_i : [0, t) \rightarrow Rm$$

Motor control [Emken et al. 2007]:

$$u_{i+1} = f u_i + \alpha e_i$$

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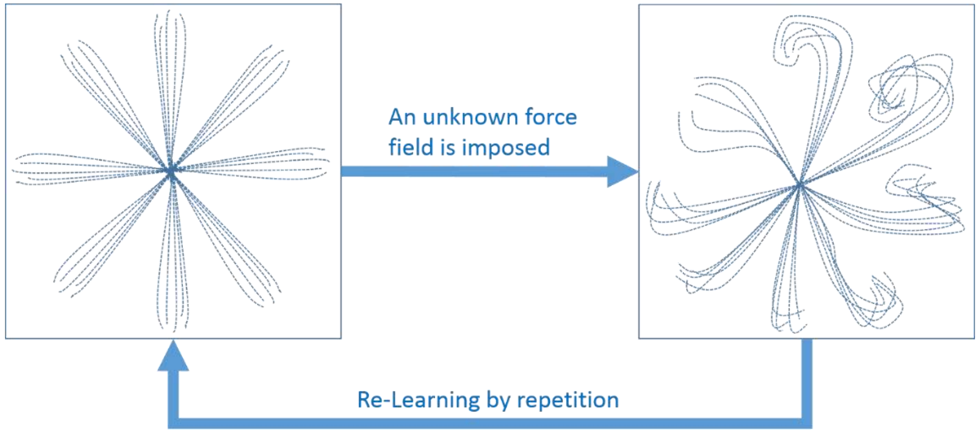
f, α → constant



Iterative Learning Control

$$u_{i+1} = Q(u_i) + r(e_i)$$

Q → forgetting factor

r → updating law

Contribution of feedback error in future motor actions [Kawato et al. 1996]

$$u_{i+1} = Q(u_i) + r(e_i, e_{i+1})$$

e_{i+1} → feedback error

Softness Preservation - decentralized approach

Requirement

$$\left\| \frac{\partial T(q-r,d)}{\partial q}\Big|_{q\equiv r} - \frac{\partial T(q-\psi(q,\dot{q},t,d),d)}{\partial q}\Big|_{q\equiv q_*} \right\| \leq \delta$$

Hypothesis

- Symmetry
- Diagonal dominance

$$\left\| \frac{\partial \psi_i(q)}{\partial q_i}\Big|_{q\equiv q_*} \right\| \leq \frac{\delta}{2||\overline{\sigma}_i||}$$

$$\overline{\sigma}_i \triangleq \frac{\partial \tau_i}{\partial q_i}\Big|_{q\equiv r}$$

Feedback action must be low

Softness Preservation - decentralized approach

$$P \triangleq \left.\frac{\partial T(q-r,d)}{\partial q}\right|_{q\equiv r} - \left.\frac{\partial T(q-\psi(q,\dot{q},t,d),d)}{\partial q}\right|_{q\equiv q_*}$$

$$\boxed{|p_{i,i}| < \tfrac{\delta}{2}\ \forall i \in \{1\ldots N\} \Rightarrow \|P\|_2 \leq \delta}$$

First Gershgorin Theorem and reverse triangular inequality $\left|||x|| - ||y||\right| \leq ||x-y||$

$$\max_i\{|\lambda_i|\} \leq \max_i\{|p_{i,i}| + \textstyle\sum_{i\neq j} |p_{i,j}|\}$$

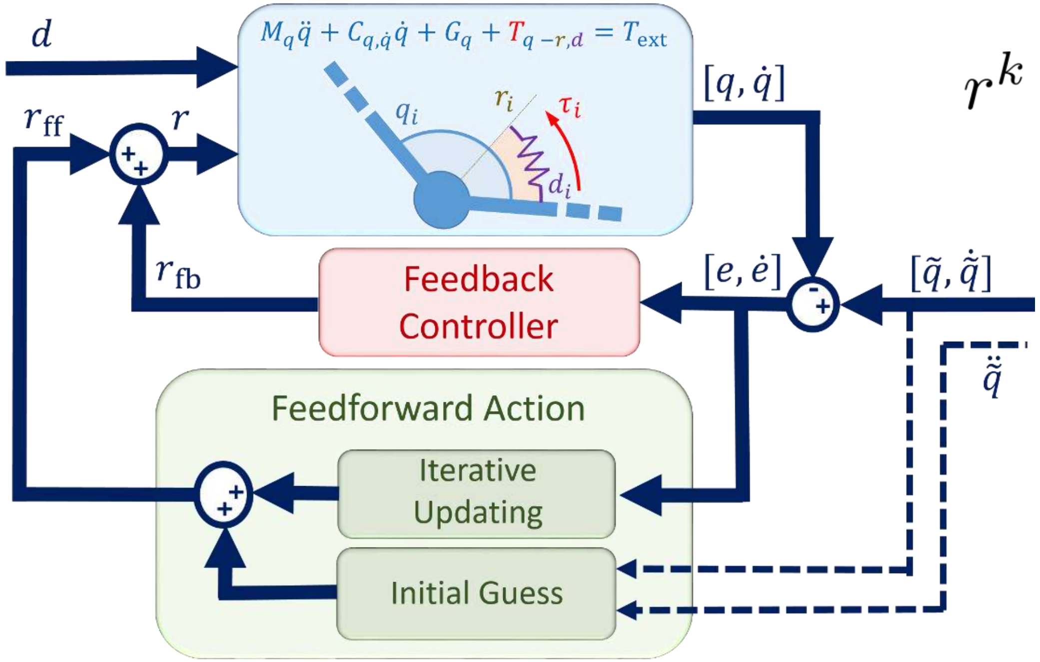
$\lambda_i = \mathrm{eig}(P)$

$\sum_{i\neq j} |p_{i,j}| \leq |p_{i,i}|$ Diagonal dominance

$$\max_i\{|\lambda_i|\} \leq \max_i\{|p_{i,i}| + \textstyle\sum_{i\neq j} |p_{i,j}|\} \leq \max_i\{2|p_{i,i}|\}$$

P symmetric $\|P\|_2 = \max_i |\lambda_i|$ $\max_i\{2|p_{i,i}|\} < \delta$

Control Architecture



$$r^k = r^{k-1} + K_{\text{on}} e^k + K_{\text{off}} e^{k-1}$$

Given the system

$$\dot{\xi} = f(\xi) + H(t)\nu$$

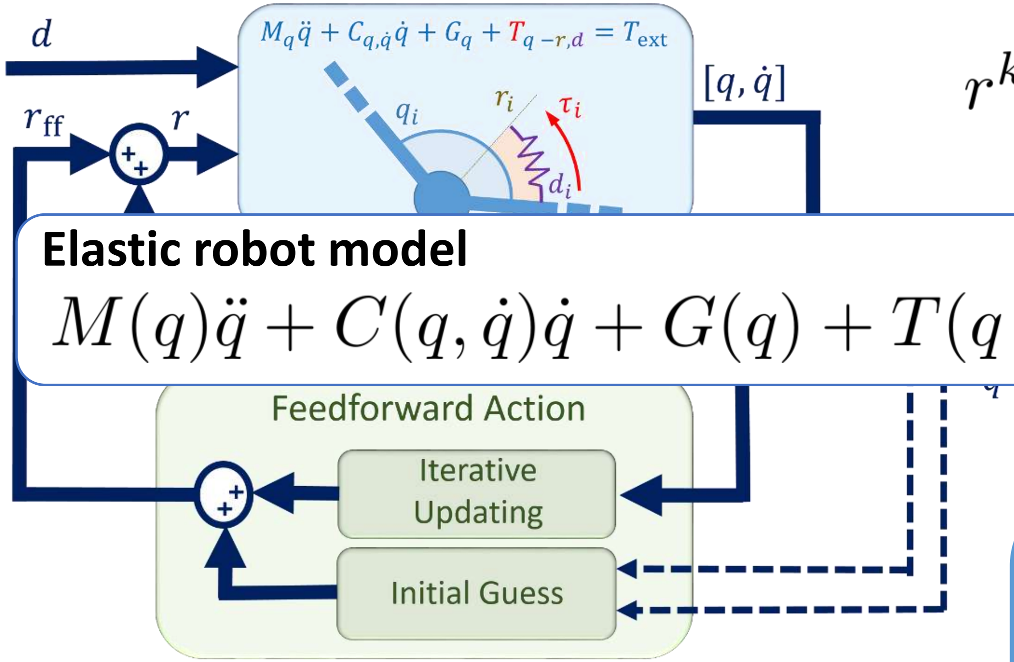
Convergence condition

$$\left\|(I + K_{\text{on}}(t)H(t))^{-1}\right\| < 1$$

$$\|I - K_{\text{off}}(t)H(t)\| < 1$$

C Della Santina, M Bianchi, G Grioli, F Angelini, M Catalano, M Garabini, A. Bicchi: “Controlling soft robots: balancing feedback and feedforward elements” IEEE Robotics & Automation Magazine 24 (3), 75-83

Control Architecture



$$r^k = r^{k-1} + K_{\text{on}} e^k + K_{\text{off}} e^{k-1}$$

Elastic robot model

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) + T(q-r,d) = T_{\text{ext}}(q,\dot{q})$$

Given the system

$$\dot{\xi} = f(\xi) + H(t)\nu$$

Convergence condition

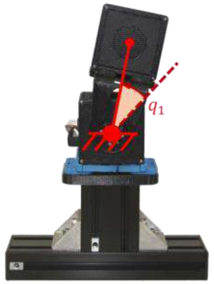
$$\left\|(I + K_{\text{on}}(t)H(t))^{-1}\right\| < 1$$

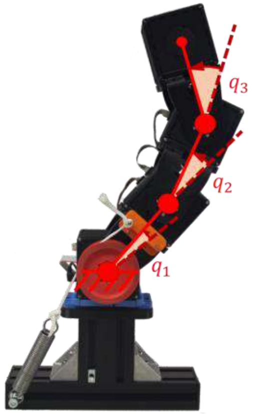
$$\|I - K_{\text{off}}(t)H(t)\| < 1$$

Convergence does not depend on the drift term.
Thus an algorithm verifying this condition is robust to external uncertainties.

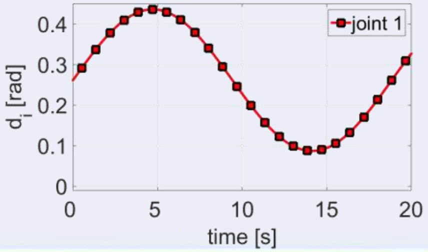
Learning to control soft robots

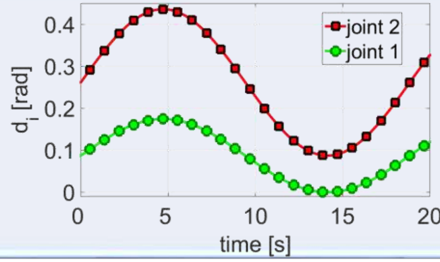
Note: no information is given to the algorithm about the kinematic structure and the external fields

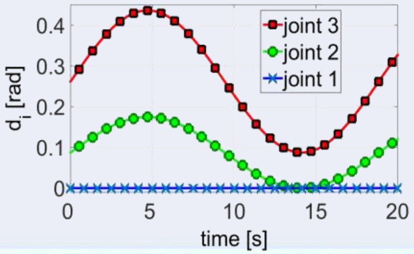




Stiffness Variation (exogenous)







Trajectories

$$q_1(t) = -\frac{\pi}{12}\cos(2t)$$

$$q_1(t) = -\frac{\pi}{12}\cos(2t)$$
$$q_2(t) = \frac{\pi}{12}\cos(2t)$$

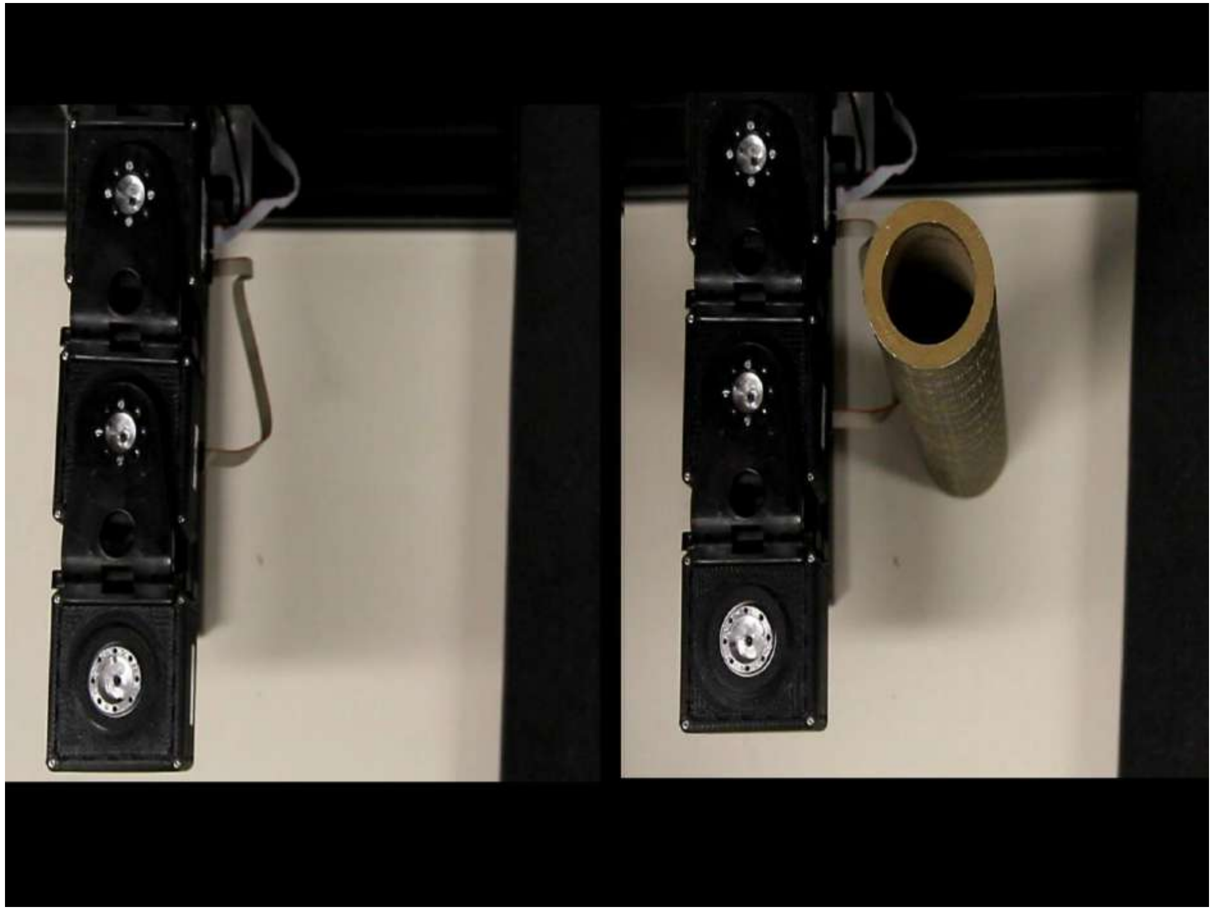
$$q_1(t) = q_3(t) = -\frac{\pi}{12}\cos(2t)$$
$$q_2(t) = \frac{\pi}{12}\cos(2t)$$

F Angelini, C Della Santina, M Garabini, M Bianchi, GM Gasparri, G Grioli, A.Bicchi, 2 Decentralized trajectory tracking control for soft robots interacting with the environment, Transactions on Robotics, 2018

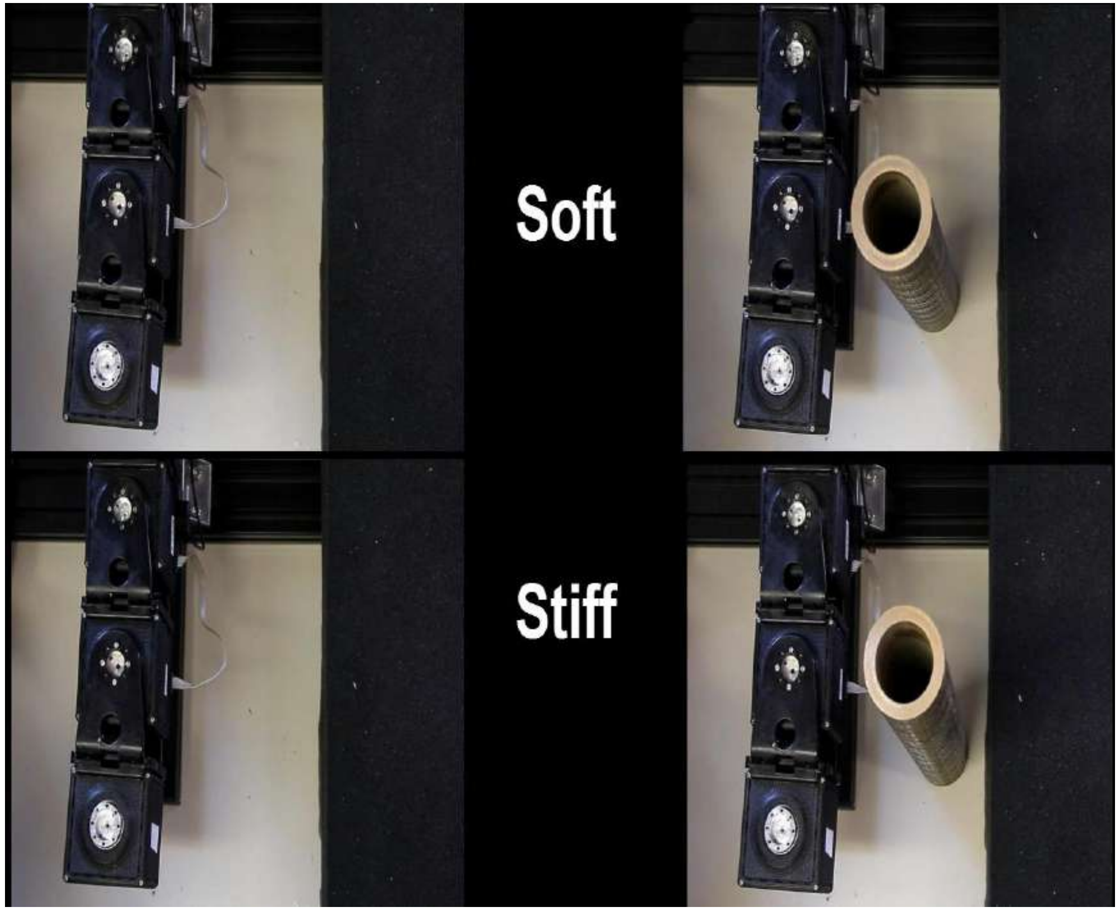
G. Averta, V. Arapi, A. Bicchi, C. Della Santina, M. Bianchi, **Modeling Human Motor Skills to Enhance Robots' Physical Interaction,** Human-Friendly Robotics 2020

Preserving Softness

PID control
makes a physically soft robot stiff



ILC algorithm
preserves physical softness



Decreasing Brockett's "Attention Functional"

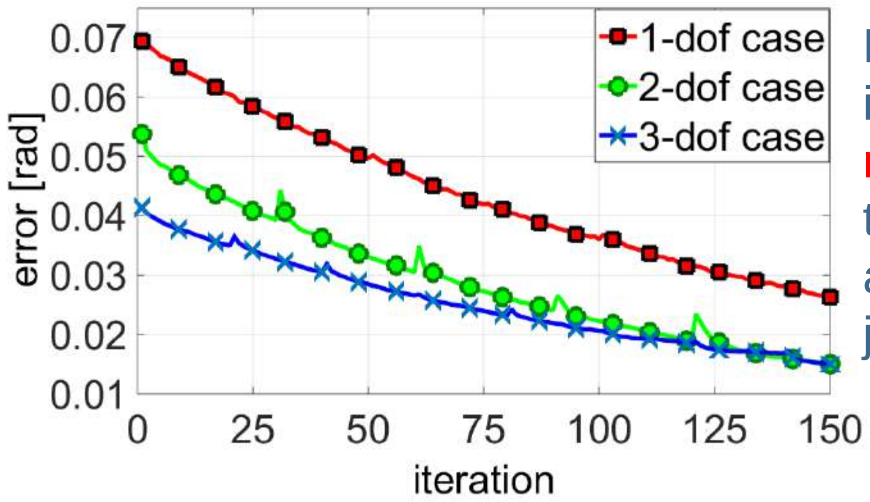
Proceedings of the 36th
Conference on Decision & Control
San Diego, California USA • December 1997

Minimum Attention Control

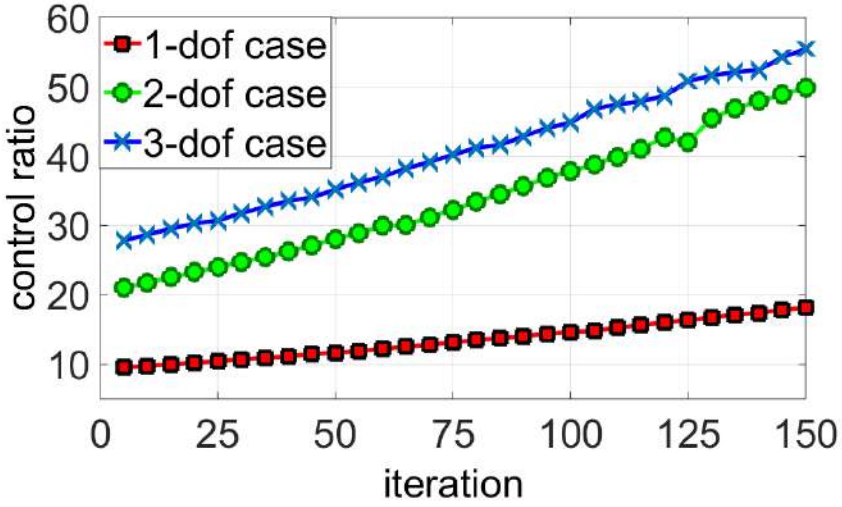
R. W. Brockett [1]

$$\eta_a = \int_\Omega \phi\left(x, t, \frac{\partial u}{\partial x}, \frac{\partial u}{\partial t}\right) dx dt$$

Textbooks on optimal control discuss the difference between open-loop and closed-loop control however the classification is rather informal and in many cases (e.g., fixed end-point linear-quadratic optimal control on finite time intervals) it is unclear what might be meant by a closed-loop solution. This makes it difficult for researchers in other fields to discuss the distinction in a precise way. At an intuitive level, it seems that biological motor control involves not only "pure" open-loop control but also a gradation of modalities spanning a range between open-loop and closed-loop operation. Intuitively, one thinks that large values of $||\partial u/\partial x||$ indicate closed-loop control and that large values of $||\partial u/\partial t||$ indicate open-loop control. By modifying the attention functional we can change the ratio of the penality put on the closed-loop $||\partial u/\partial x||$ terms relative to the penality put on the open-loop $||\partial u/\partial t||$ terms. In this way we create a continiuum and arrive at a characterization which makes possible a quantitative study of the trade-offs between open-loop and closed-loop control.



Evolution of the integral of the error normalized by the terminal time and the number of joints.



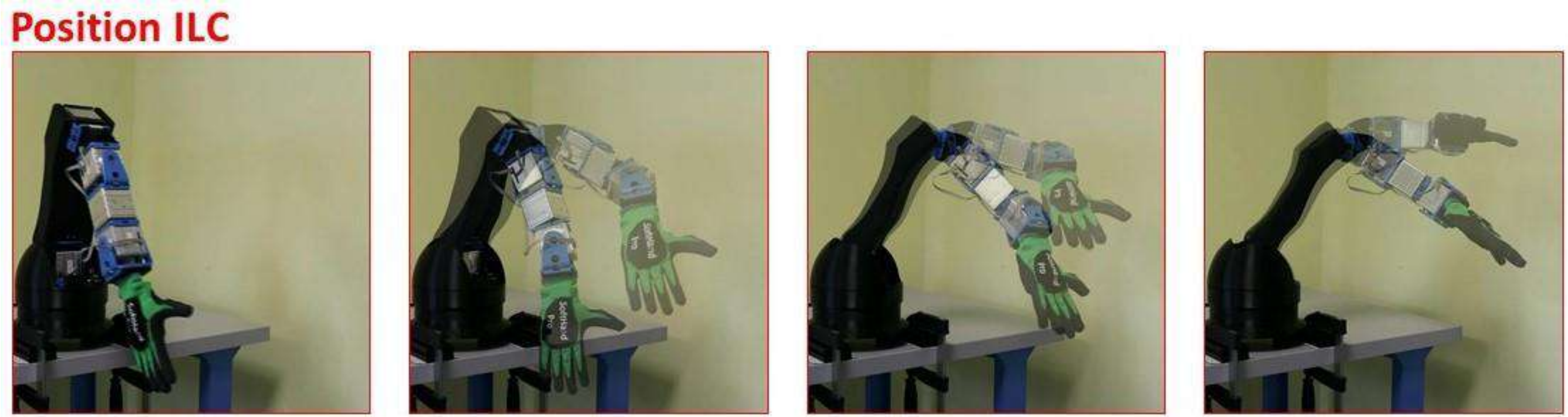
Ratio between the integrals of the feedforward and feedback actions during the task for the three setups.

Experiments

6-DOFs system with elastic VSAs.

Learn the torque control input τ_{eq} in soft (or stiff) behavior that allows to track the position reference then, change θ_{sr} to stiff (or soft) to prove the decoupling.

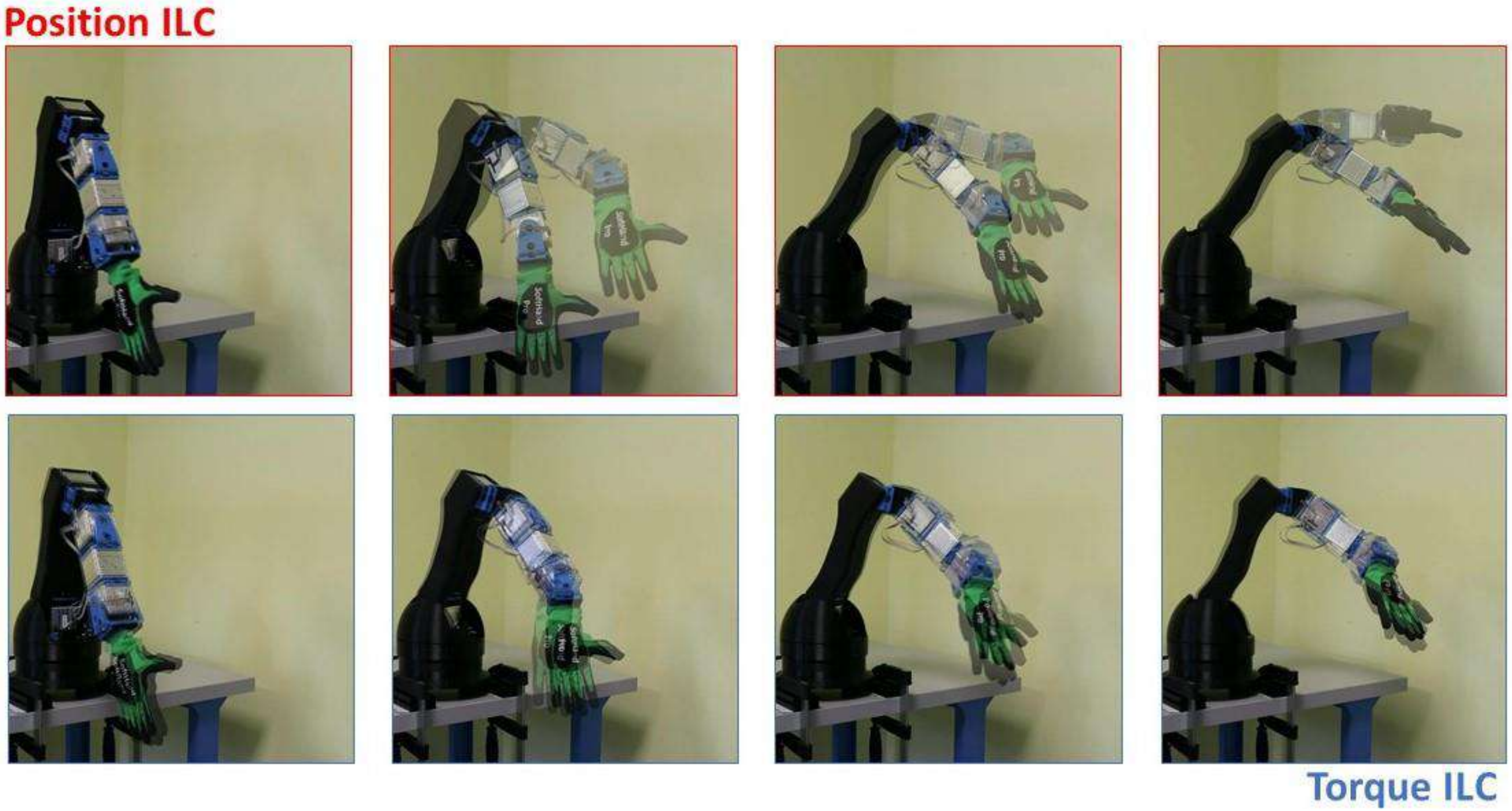
ILC with Unknown Stiffness Changes



Results
(Soft to Stiff transition)

Torque ILC

Results
(comparison)



R Mengacci, F Angelini, MG Catalano, G Grioli, A Bicchi, M Garabini, “On the motion/stiffness decoupling property of articulated soft robots with application to model-free torque iterative learning control”, The International Journal of Robotics Research 40 (1), 348-374 2021

Data-Based Anticipatory Control: Take-Home Messages

How can variable physical impedance of soft robots be usefully exploited?

- Data-based control tools use experimental data to build an “empirical” model of the system
- High-robustness (until the system is changed)
- Little insight

Open Problems:

- Many data needed, Long learning time, robot wear etc.
- How do we generalize what was learned to new cases?
- Assess/Increase robustness of data-based approaches to robot/environment changes
- Merge Model-Based and Data-Based approaches?

Sim2Real

Can we learn iterative control from simulation and translate it to reality?

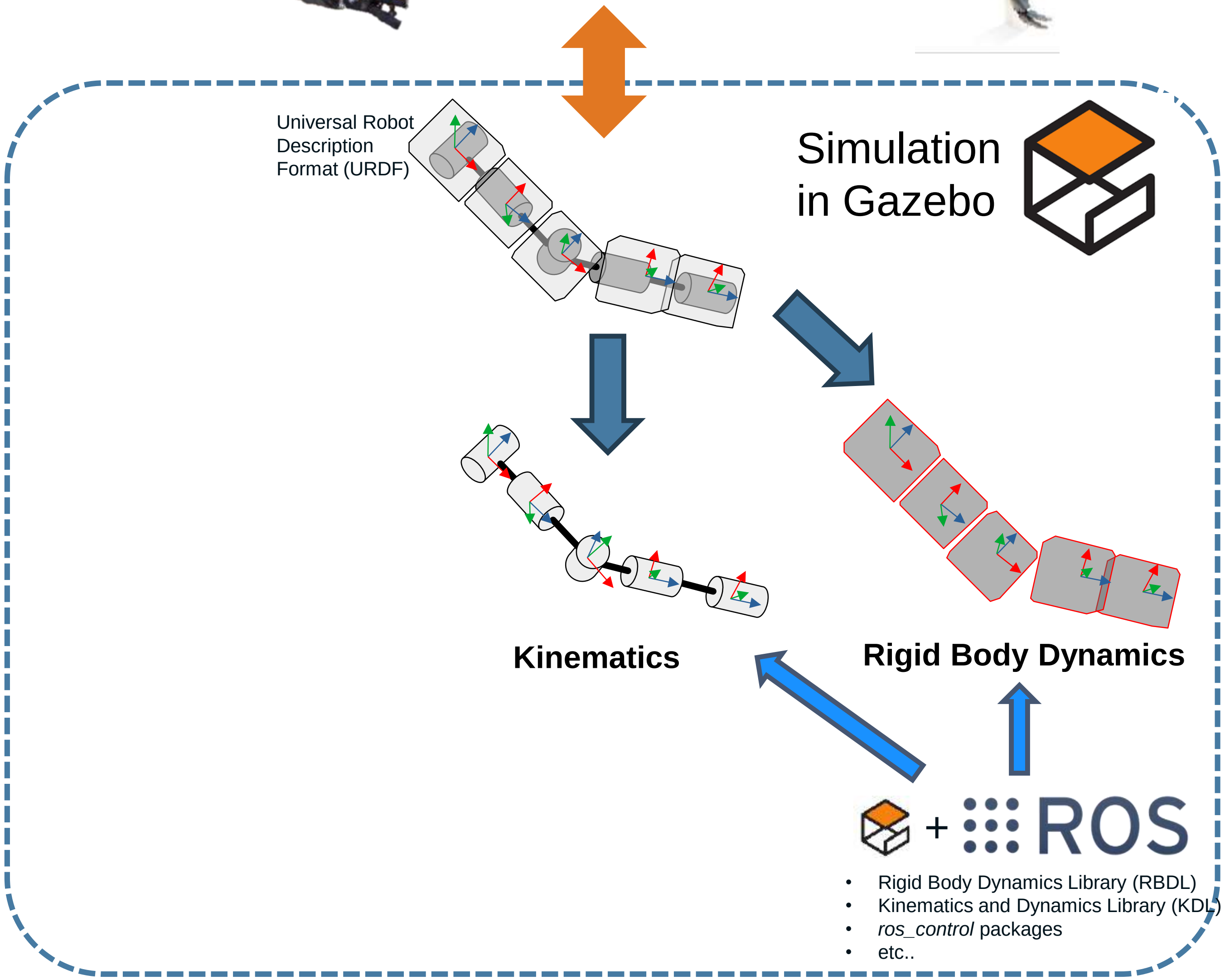
Articulated
Soft Robots

...

Articulated Soft Robots are usually made of compliant actuators at the joints.

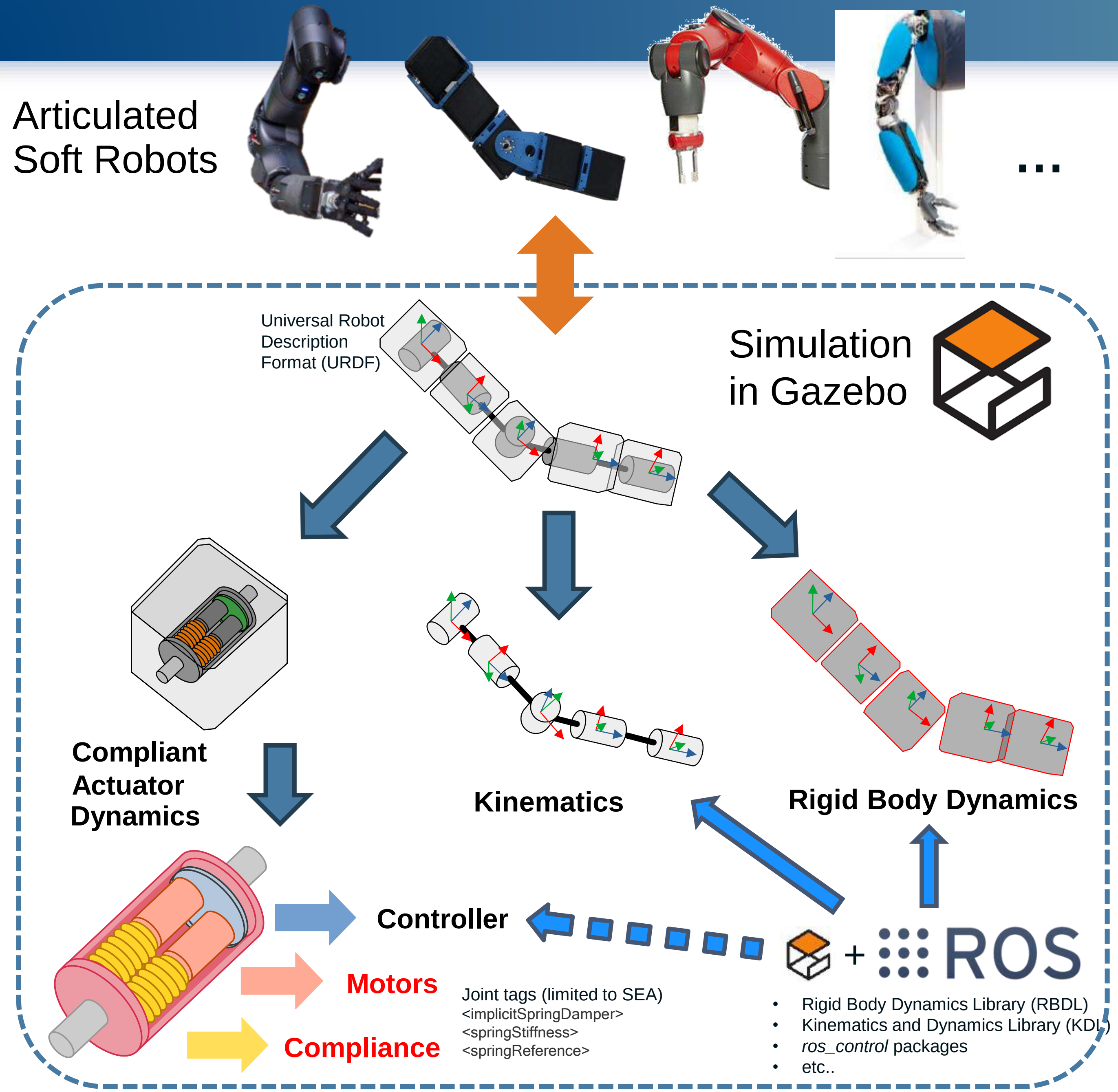
Articulated
Soft Robots

...



Articulated Soft Robots are usually made of compliant actuators at the joints.

To simulated them in Gazebo, we can exploit Robot Operating System (ROS) C++ libraries of kinematics and dynamics.

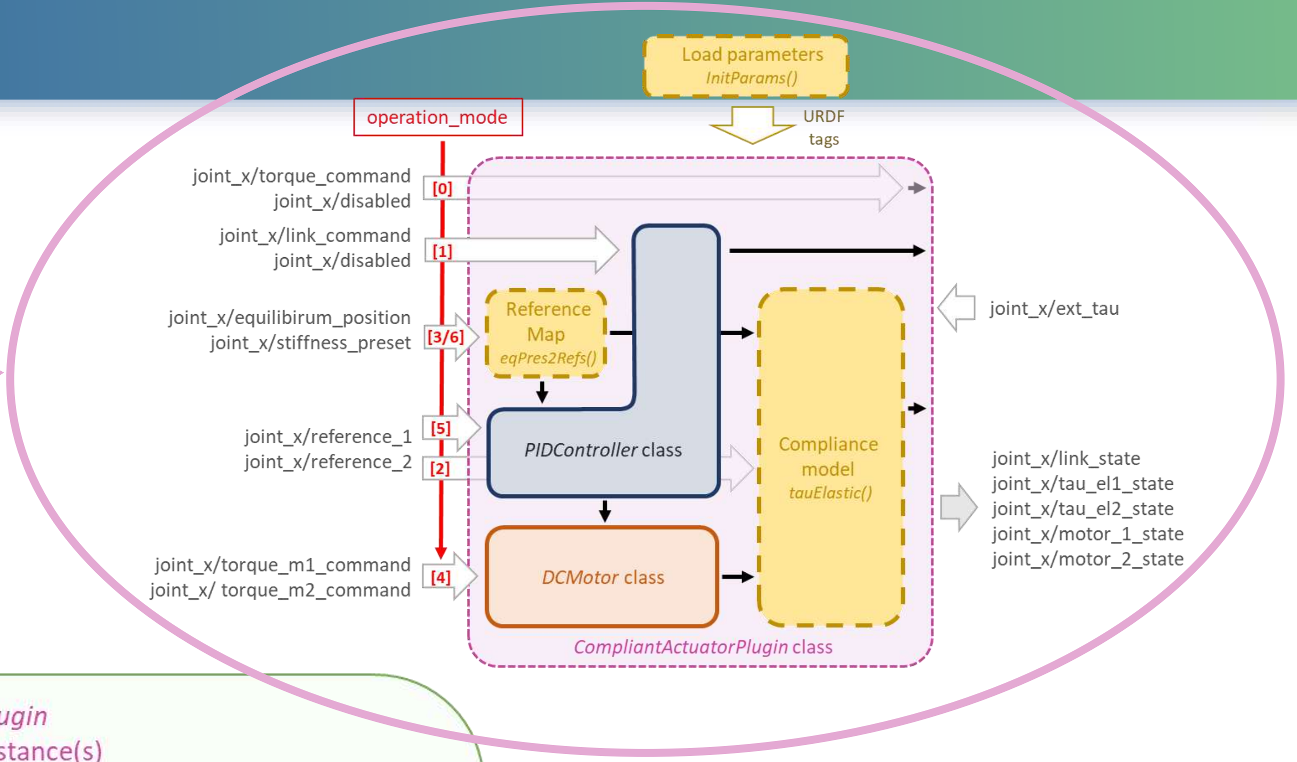


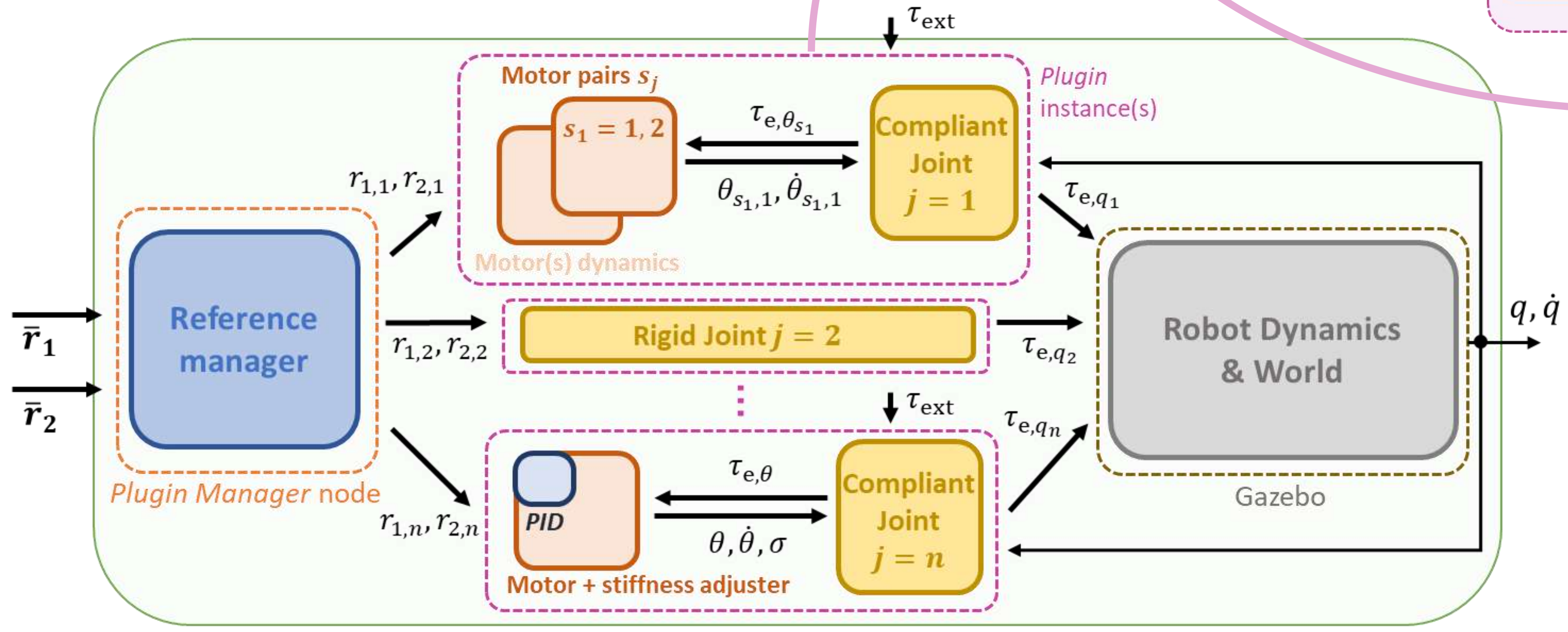
Articulated Soft Robots are usually made of compliant actuators at the joints.

To simulated them in Gazebo, we can exploit Robot Operating System (ROS) C++ libraries of kinematics and dynamics.

However, only the SEA dynamics can be handled by Gazebo right now.

A new ROS-GAZEBO toolbox allows simulating different compliant actuators, easily and reliably.

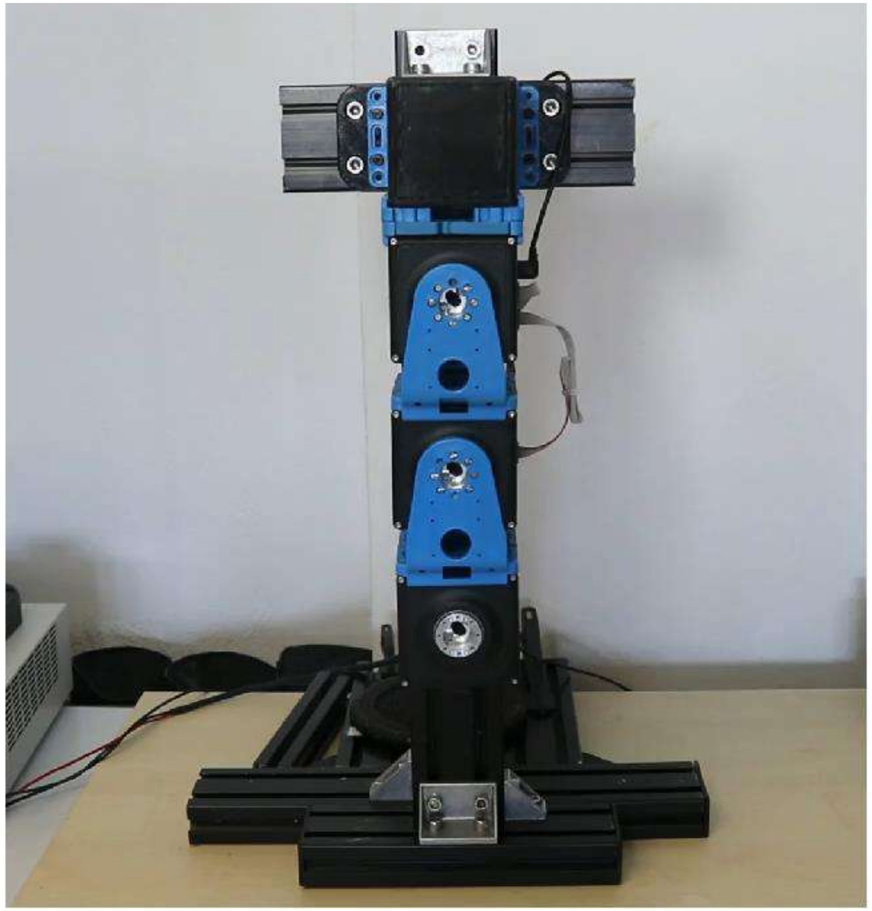


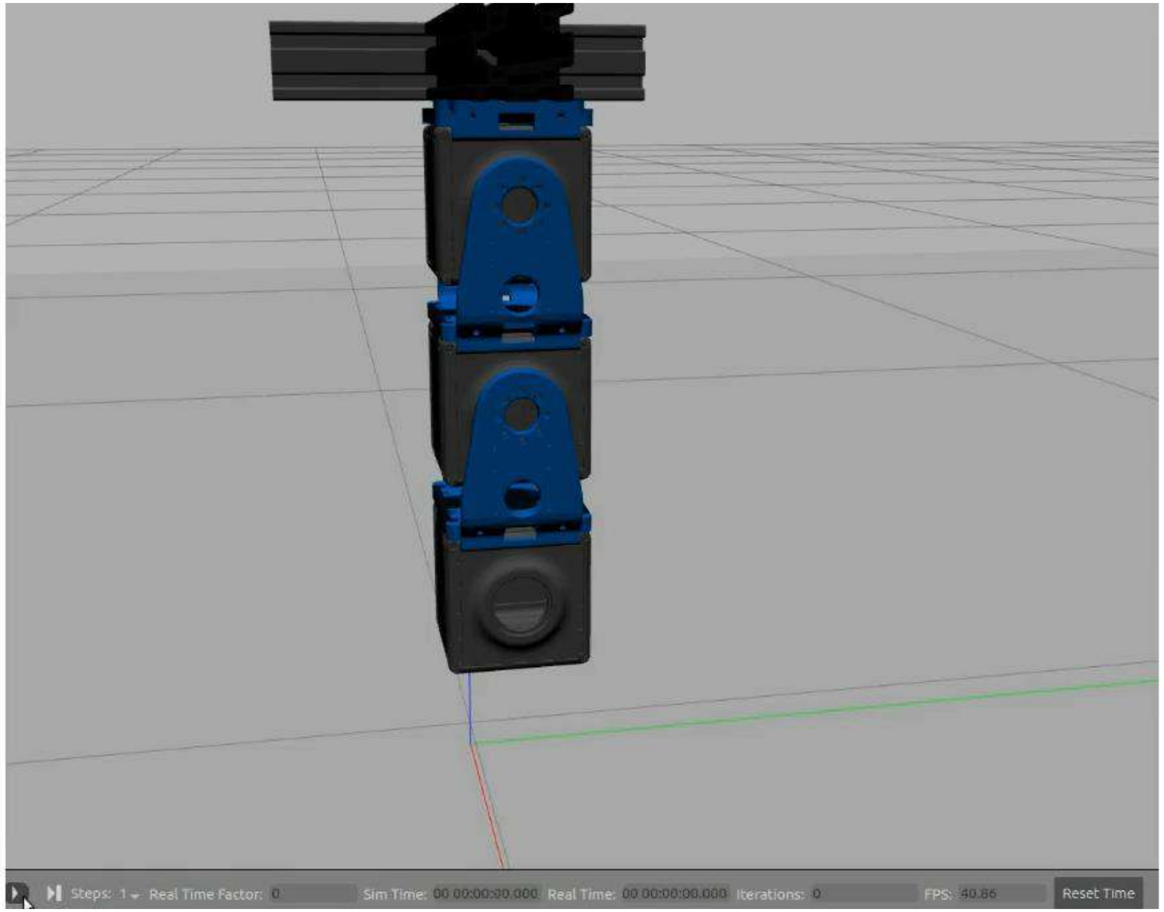


URDF + ROS-Gazebo-compliant-actuators-plugin

R. Mengacci, G. Zambella, G. Grioli, **D. Caporale**, M. G. Catalano and A. Bicchi

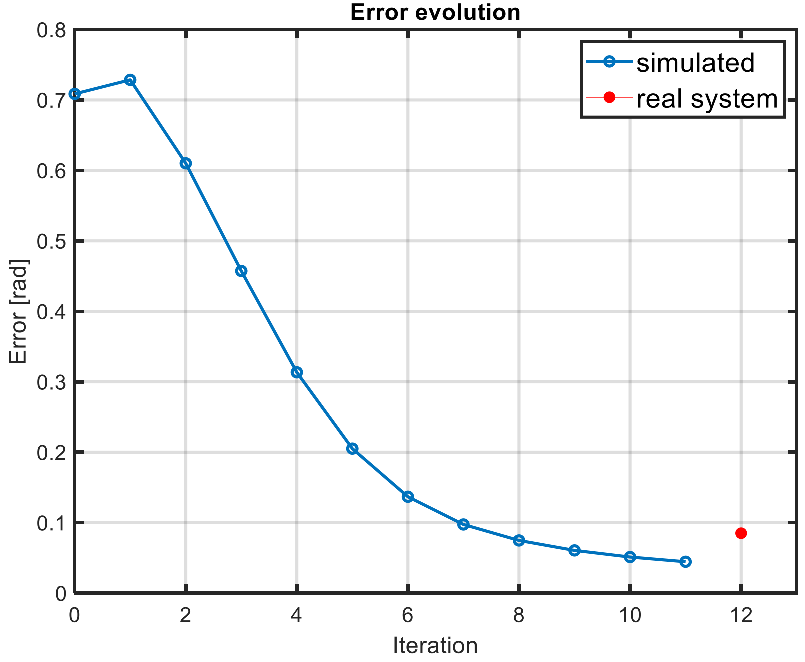
Trajectory Tracking Test

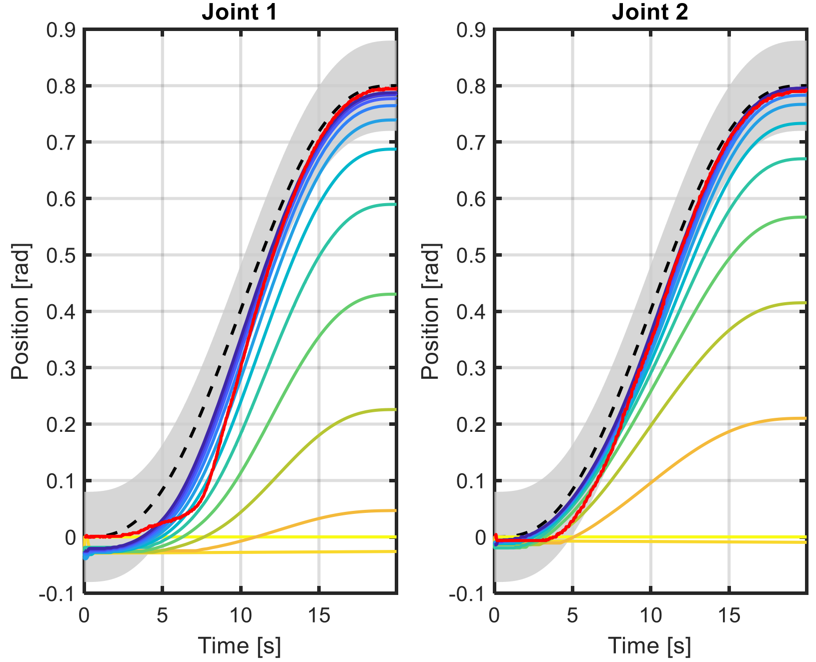


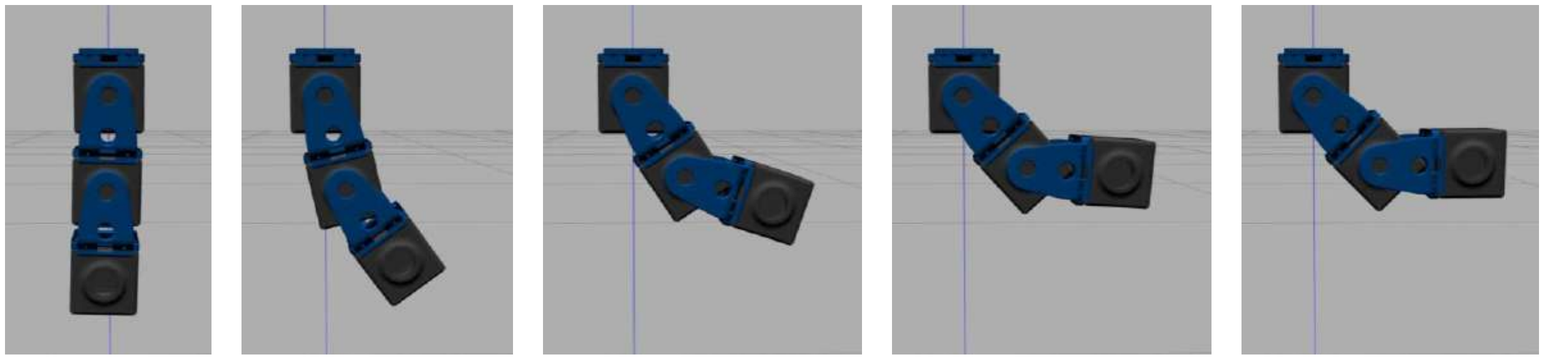


R. Mengacci, G. Zambella, G. Grioli, D. Caporale, M. G. Catalano and A. Bicchi

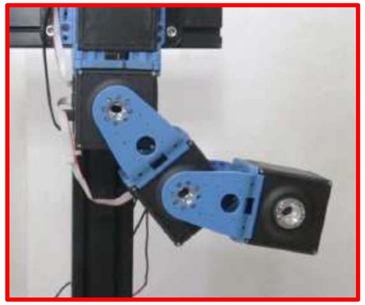
Iterative Learning Control Application - Results







$n = 0$ $n = 3$ $n = 6$ $n = 9$ $n = 11$

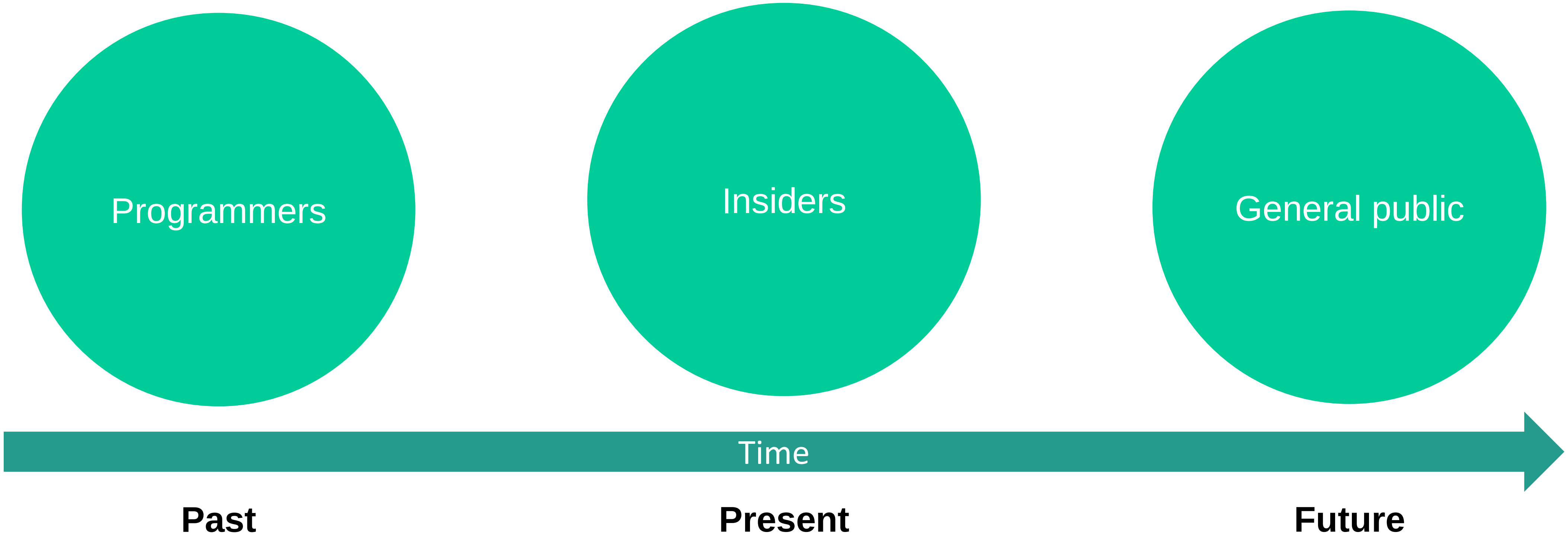


Learning more complex tasks

Toward Robot Programming Without Coding

Motivation

What skills do people need in order to use a robot?



Learning to Grasp

Teaching

Learning

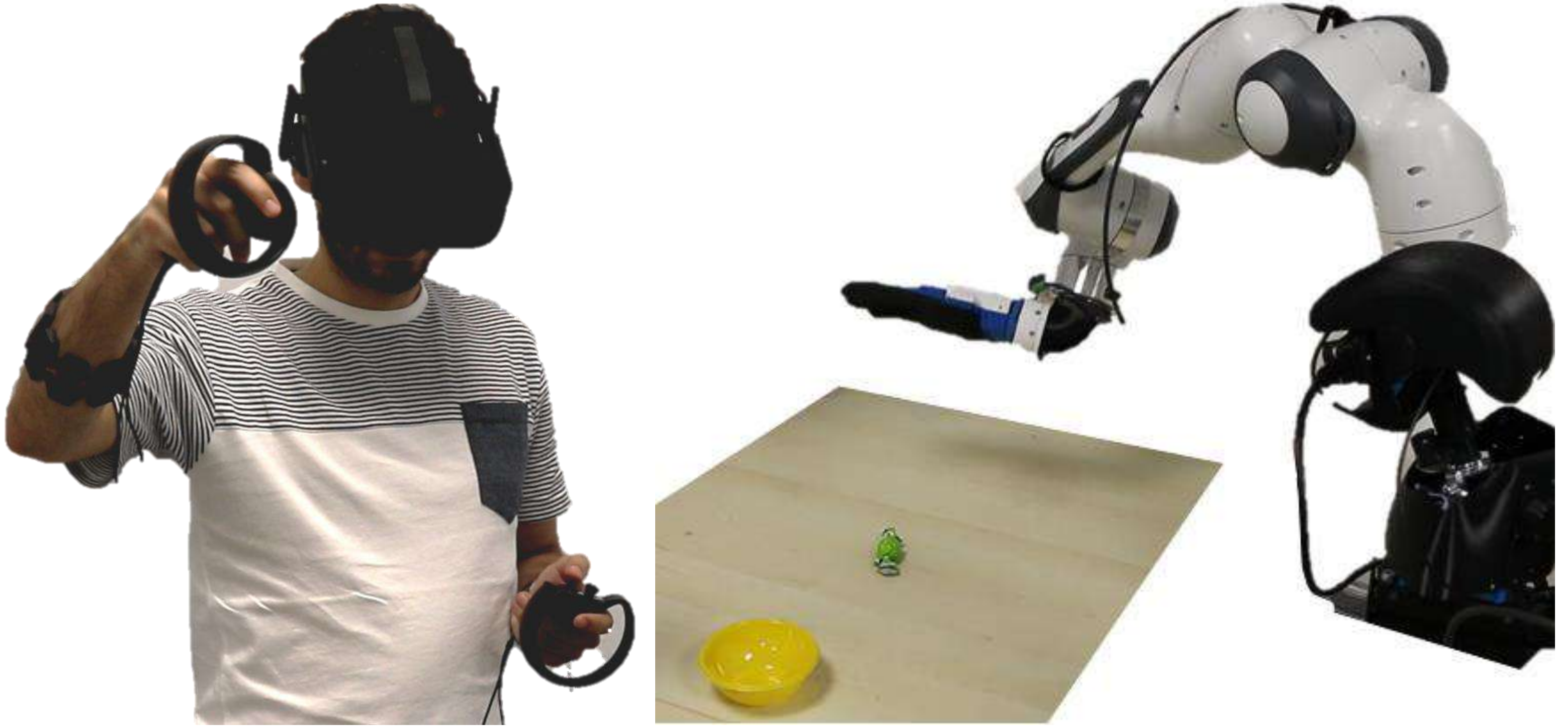
Execution

Learning from Demonstration

Teaching

Learning

Execution



Robot Programming without Coding
G Lentini, **G Grioli**, MG Catalano, A Bicchi
2020 IEEE International Conference on Robotics and Automation (ICRA), 7576-7582

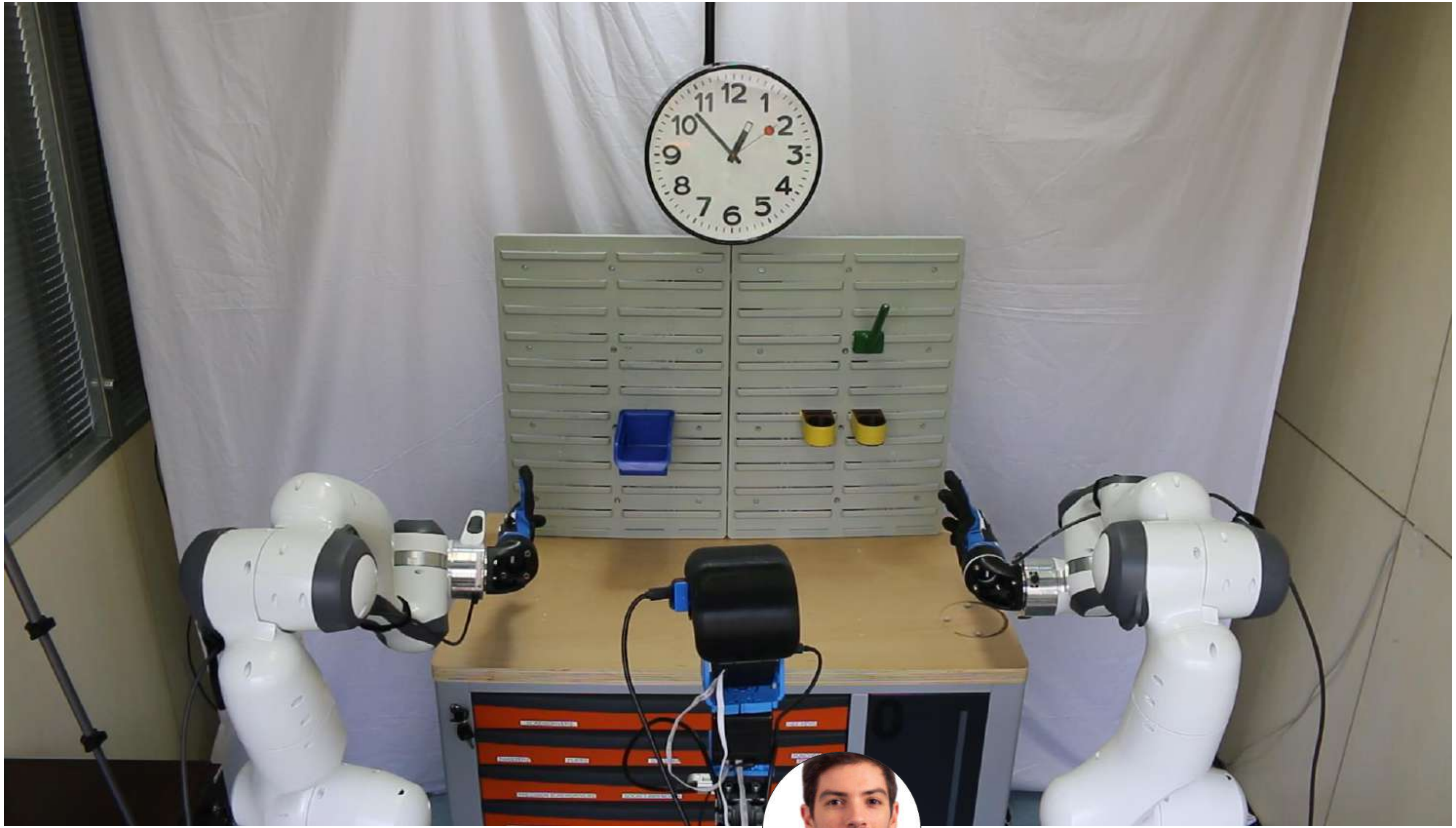
Should it really take so long?

When teaching a child, you do not need to give thousand examples

Mirroring mechanisms in our neural control system enormously facilitate learning

Leveraging on
human robot integration
and anthropomorphism may be a way to make teaching by demonstration easier

Experimental Setup

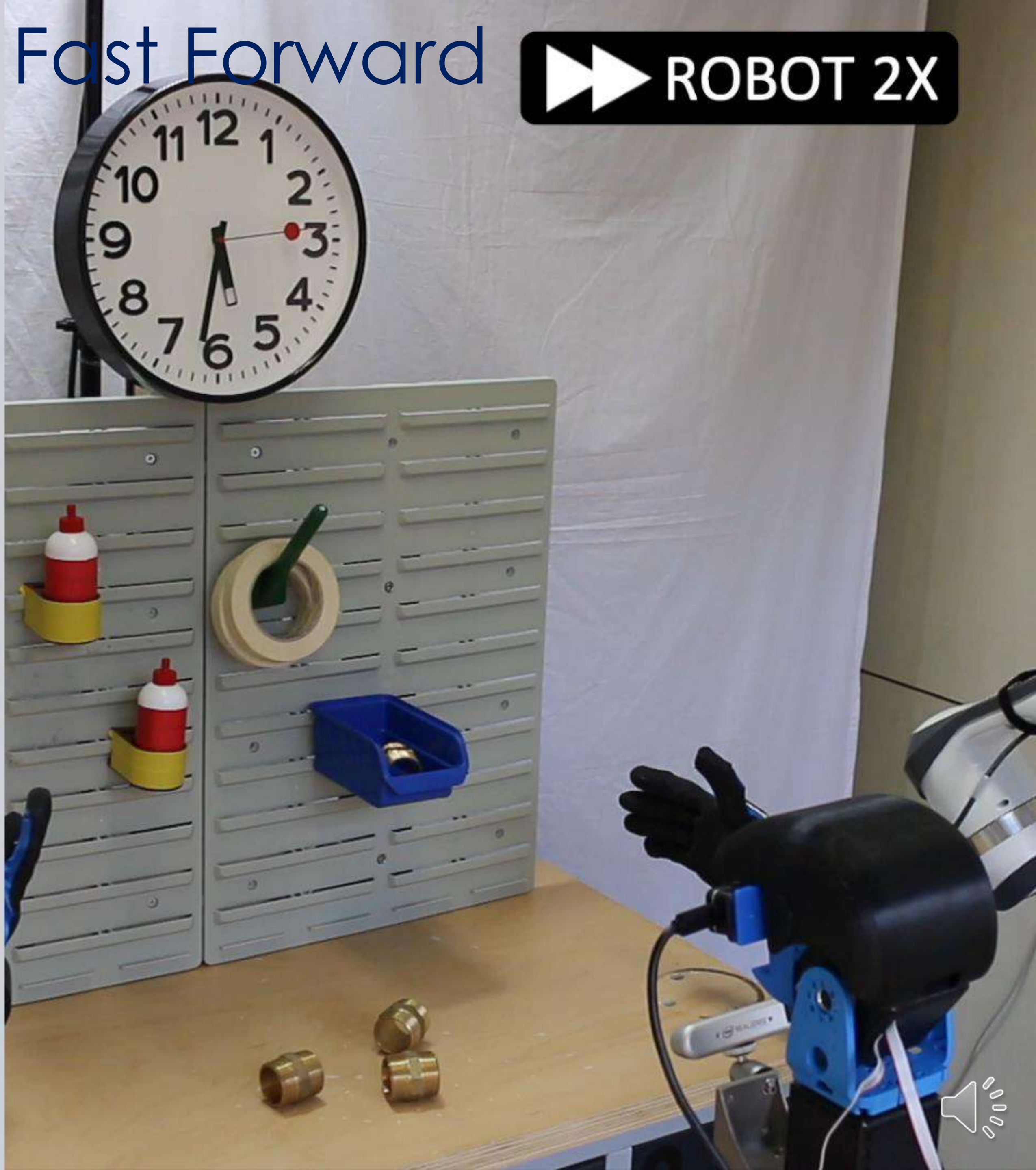


Robot Programming without Coding, **G Lentini**, G Grioli, MG Catalano, A Bicchi
2020 IEEE International Conference on Robotics and Automation (ICRA), 7576-7582

Object Sorting

Replay

Fast Forward



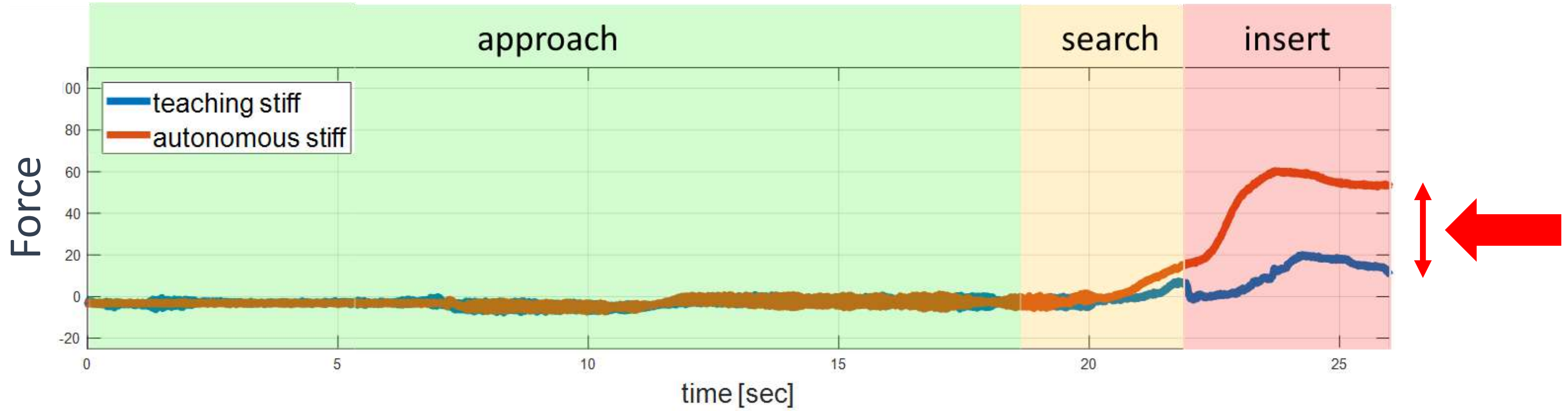
Teaching Interaction can be too hard

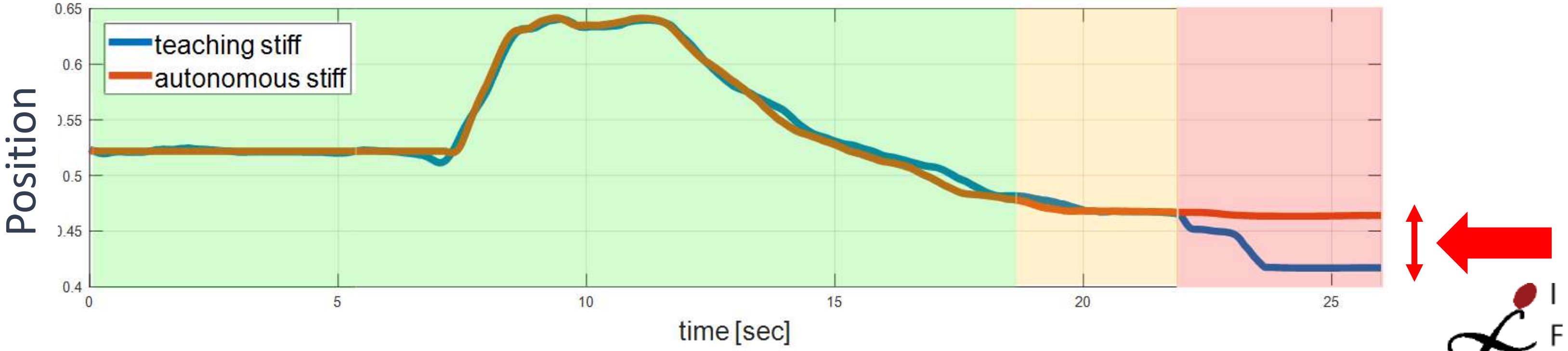
Stiff Robot

Teaching

Teaching a Rigid Robot:

- Successful demonstration
- Autonomous execution fails (too large interaction forces)





I
F
R
R

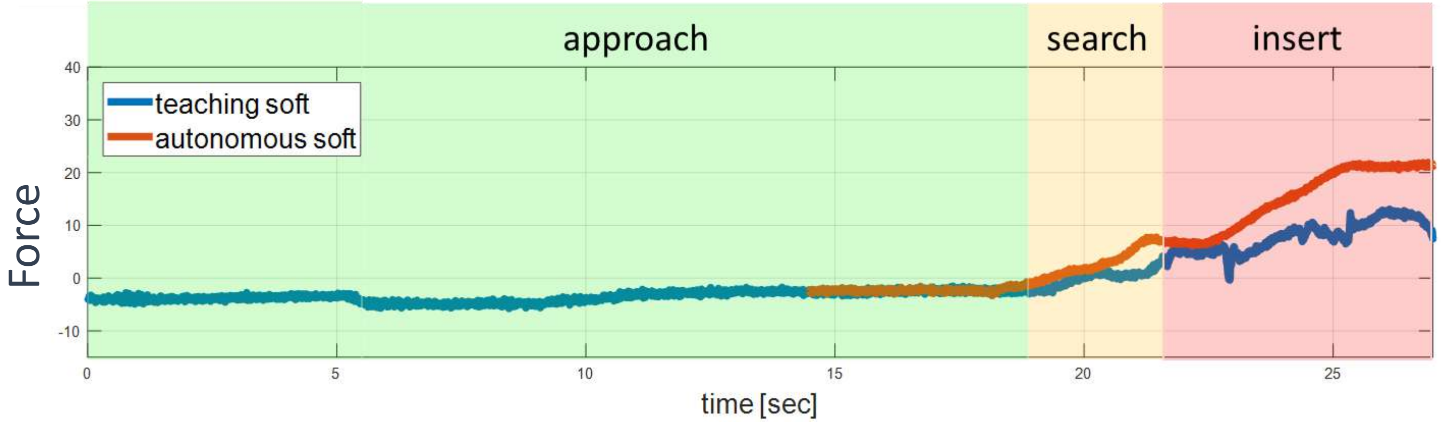
...or too soft

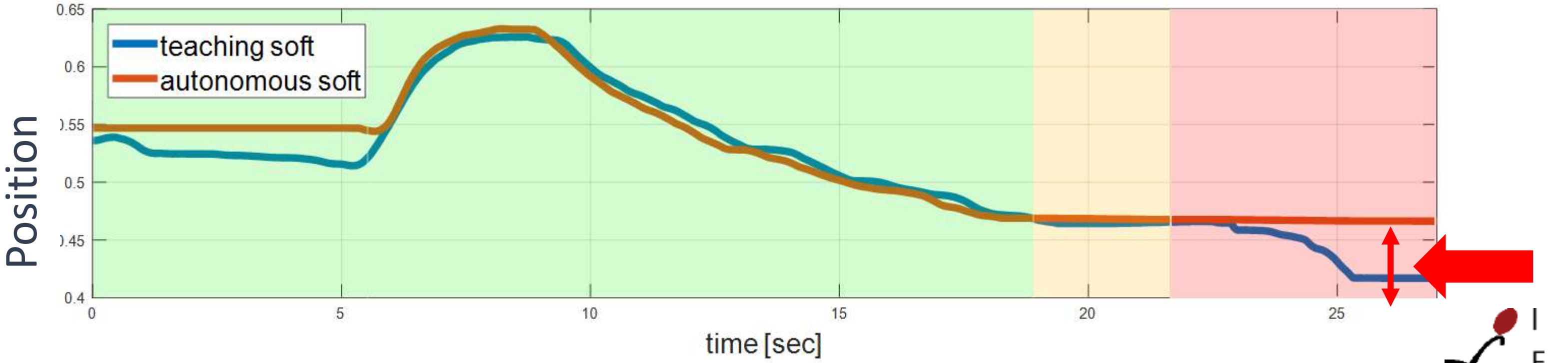
Soft Robot

Teaching

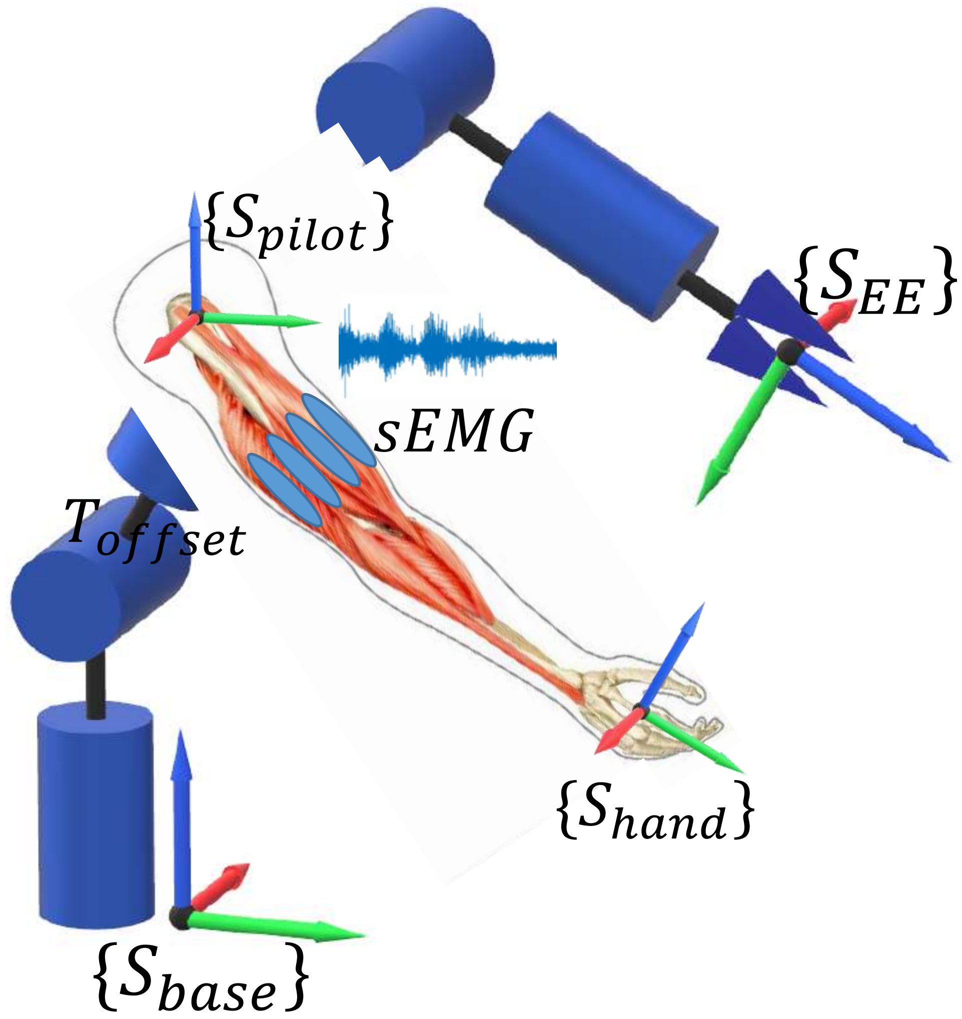
Teaching a Soft Robot:

- Successful demonstration
- Autonomous execution fails (too large tracking errors)

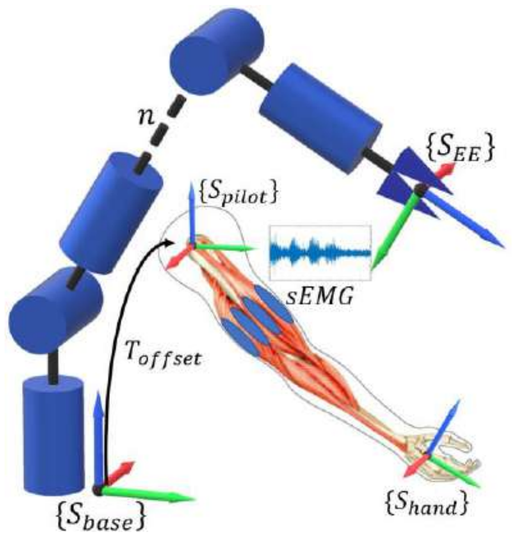


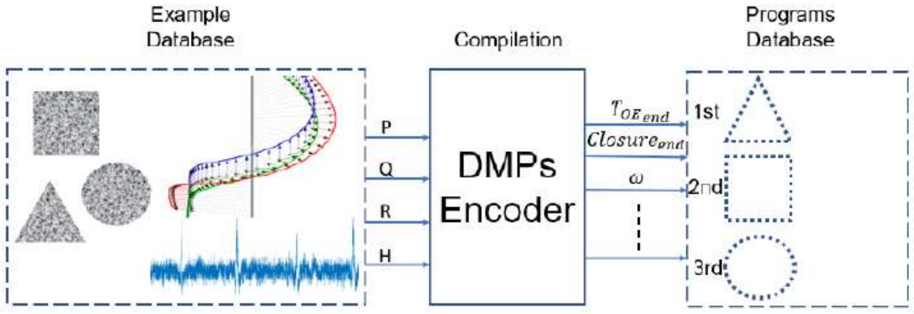


Teaching Impedance

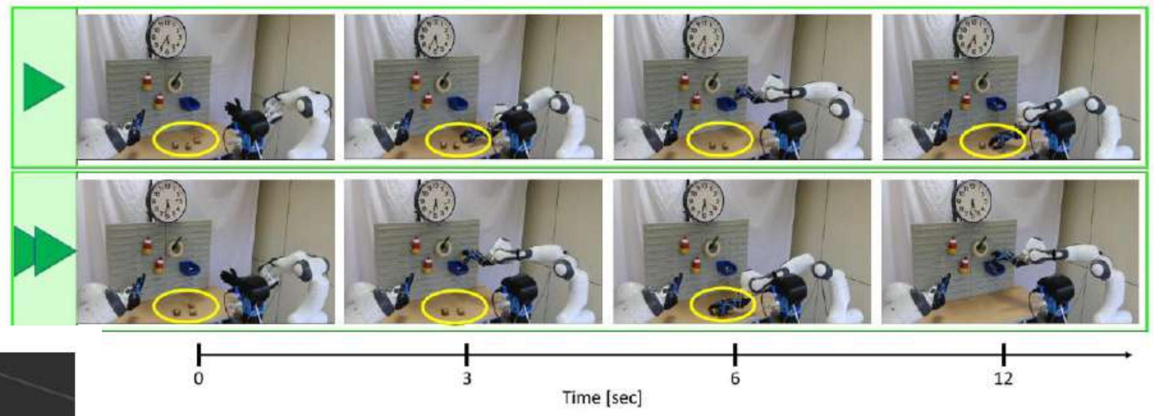


Putting Natural and Artificial Intelligence at work together





REC, PLAY, FF



Perceptual alignment

Demonstrating postures and impedance

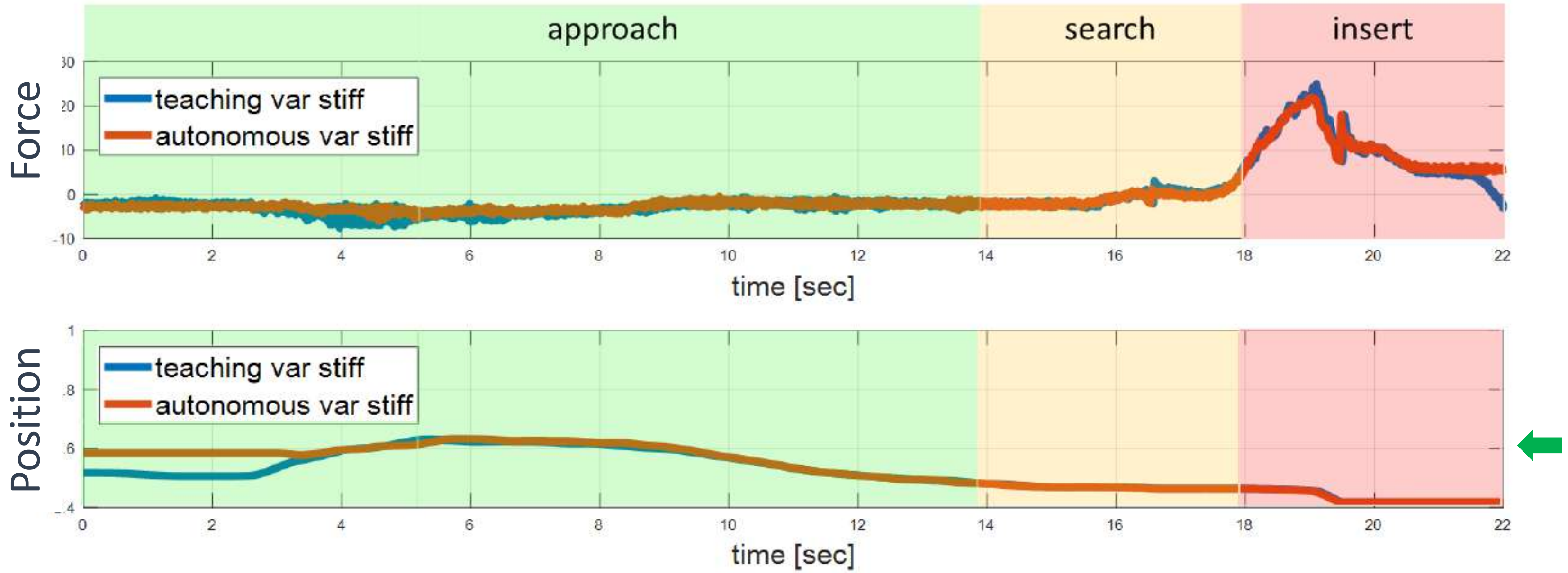
(a) (b) (c)

Saliency from gestures

Teaching Impedance

Variable Impedance

Teaching



I
F
R
R

Take-Home messages

Take-Home messages

Human impedance is variable inter- and intra-tasks

Part of the variability is intentional

Impedance variations are controlled by both muscle co-activation and arm posture

Robot Impedance can be varied by both SW and HW means

Impedance can be controlled by both varying gains/hw stiffness and arm posture

Planning of variable impedance can use insight from optimization

Humans can **control** variable impedance of robots through tele-impedance

Recent work shows that robots can **learn impedance behavior** from few human examples

Open questions

Variable impedance control comes at a cost

- in hardware (double actuators)
- In software (force sensors, open architectures)

When is it really worthwhle?

How do humans use their variable impedance?
Is it there "on purpose" or "by accident"?

How do we measure impedance in humans without perturbing it?

Thanks!