

Human-inspired strategies for grasping with SoftHands

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UNIVERSITÀ DI PISA



Centro E. Piaggio
bioengineering and robotics research center



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Freiburg im Breisgau - Germany



ROBOTICS
SCIENCE AND SYSTEMS

Where is the Intelligence?



Where is the Intelligence?

It is in the *body*



Anaxagoras [500 bC]

- *“The man is the most intelligent animal because of the hands”*

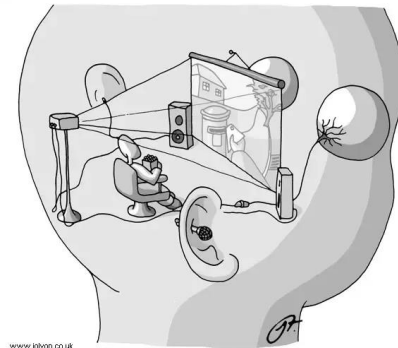
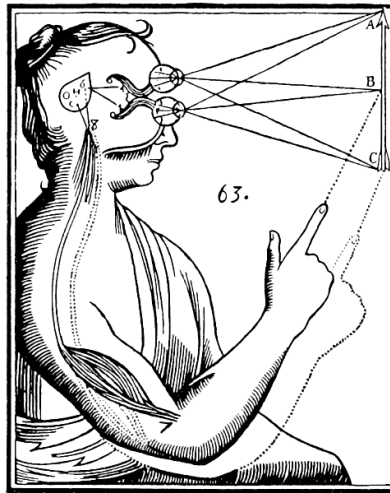
Where is the Intelligence?

It is in the *mind*

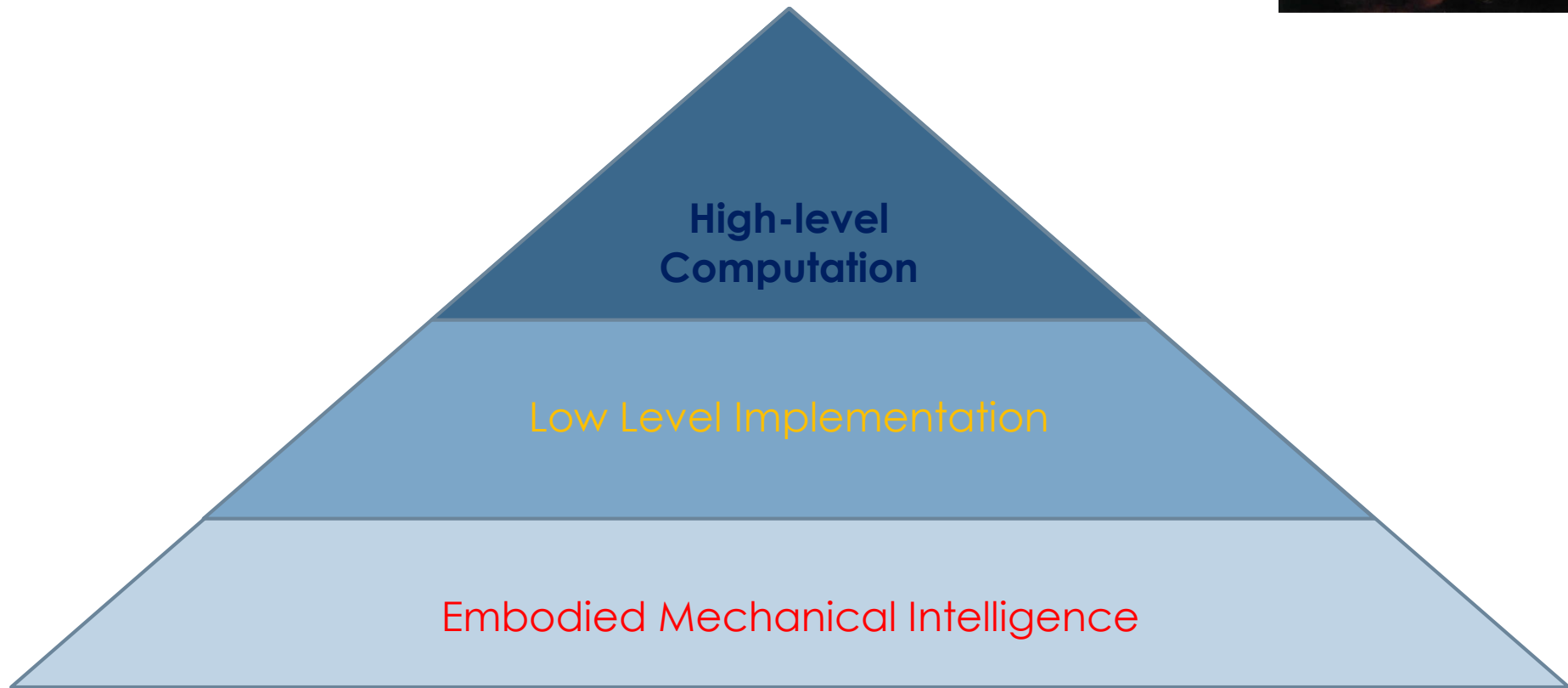
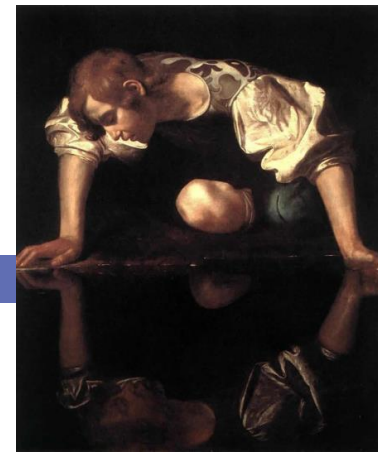


Descartes [1600 aC]

- The Cartesian mind-body dualism

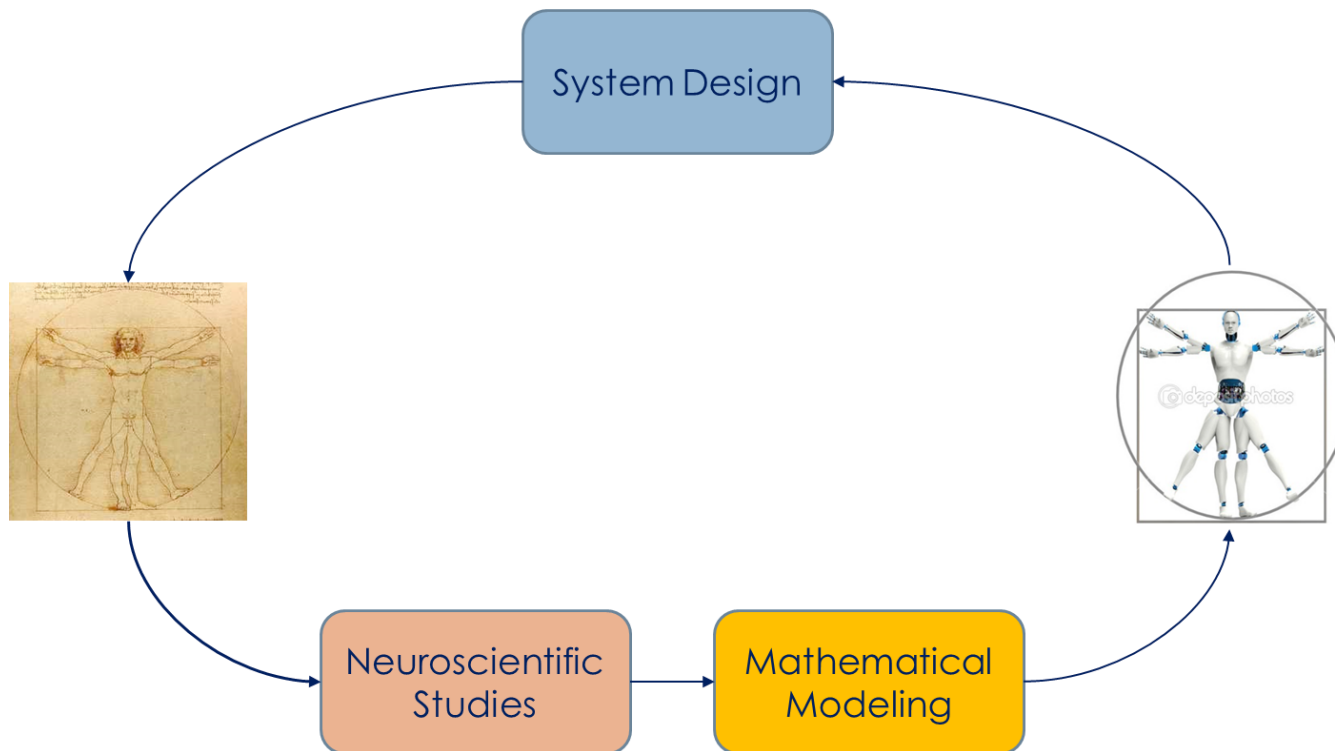


Distributed Intelligence for Grasping and Manipulation

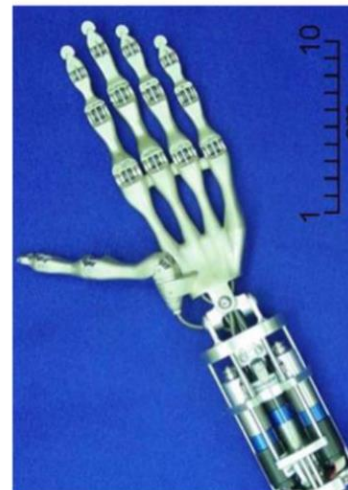
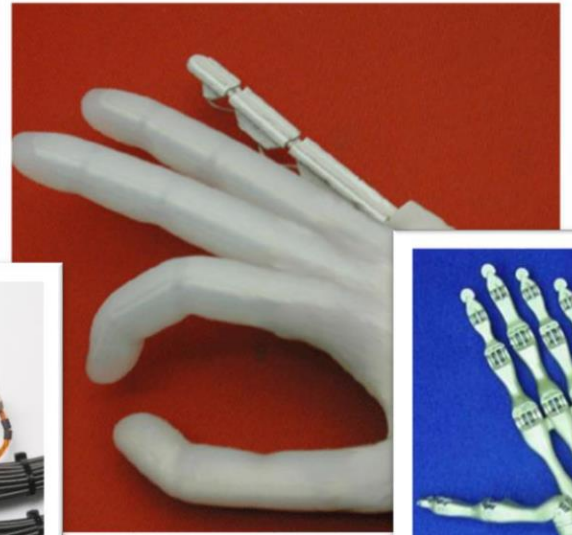
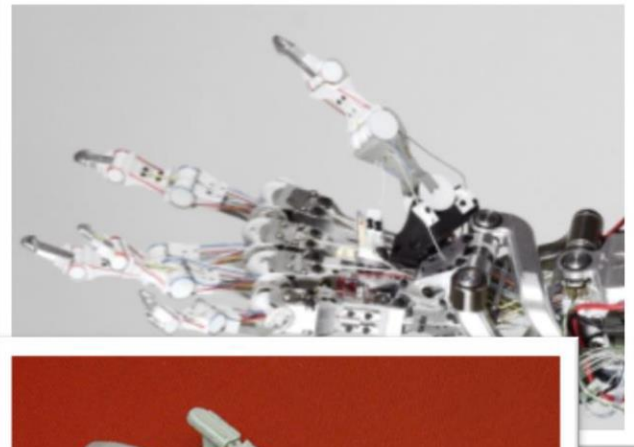
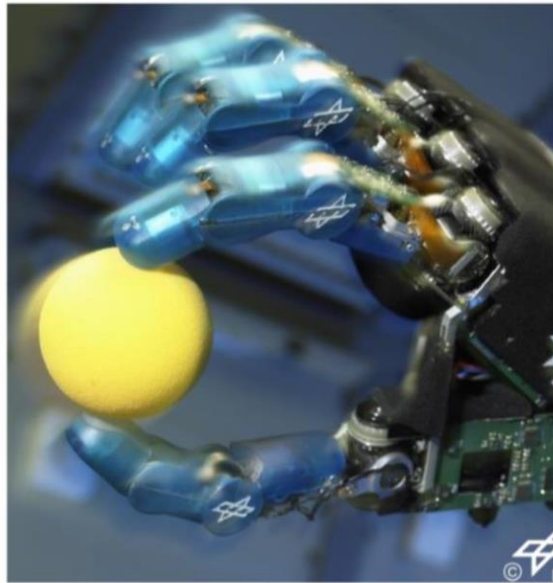


The Human Example

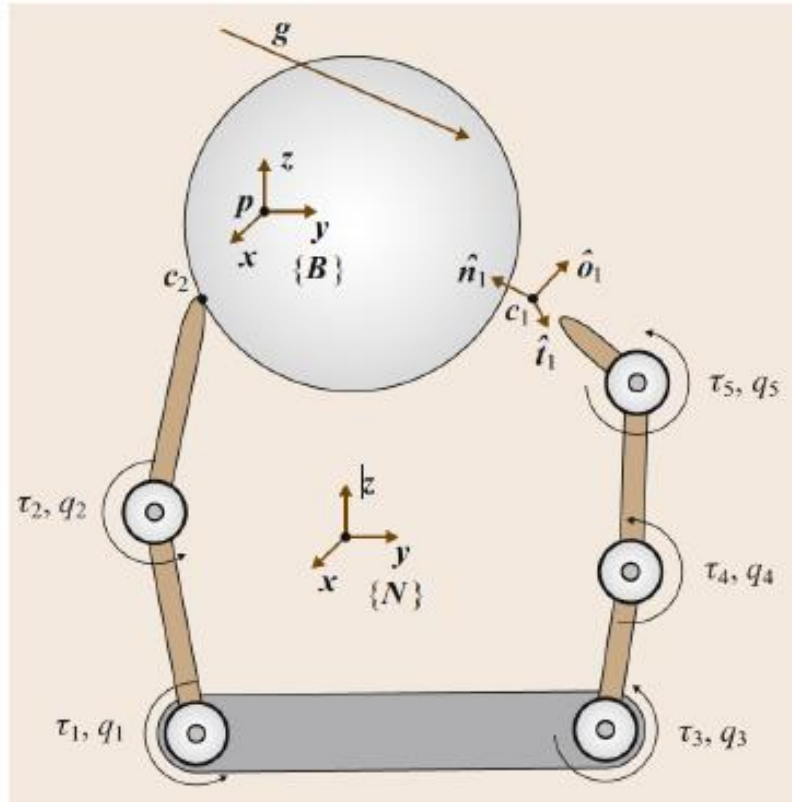
Human behavior is an **extraordinary source of inspiration**



Which Implications for the Design of Robot Hands?



Classical Approach for Robotic Grasping



[Handbook of Robotics, 2018]

Human Manipulation with the Environment



A Scene From
The French Chef - Julia Child
The Potato Show
Season 1, Episode 22, 1963

Julia Child's cooking show "The French Chef"
from 1963 (season 1, episode 22, entitled "The Potato Show")

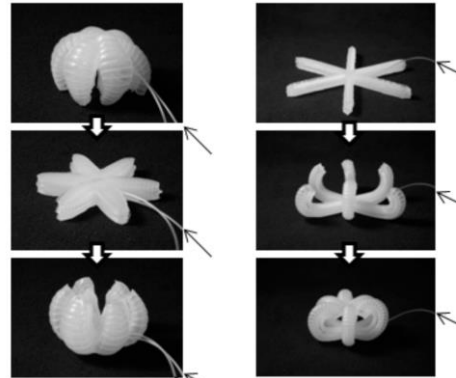
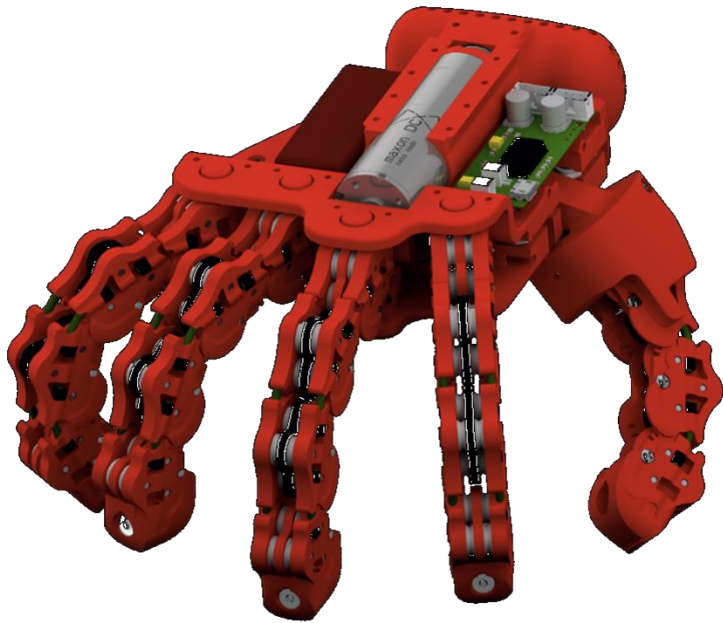
From Human Manipulation...



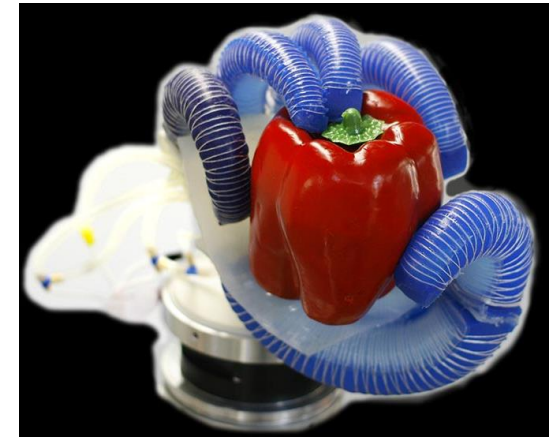
Julia Child's cooking show "The French Chef"
(1963, entitled "The Potato Show")

- Exploiting the **environment** to enhance manipulation skills
- Relying on hand **compliance**

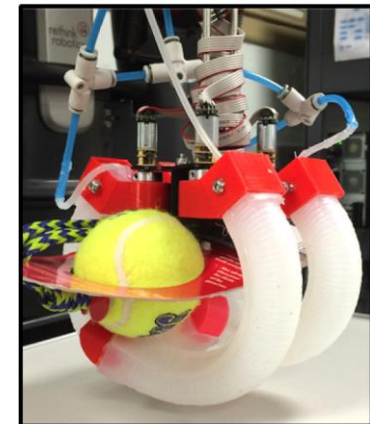
...To Soft Robotic Manipulation



Chemical Robots
[Ilievski et al. 2011]



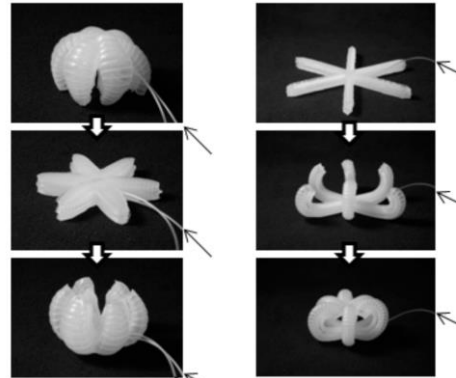
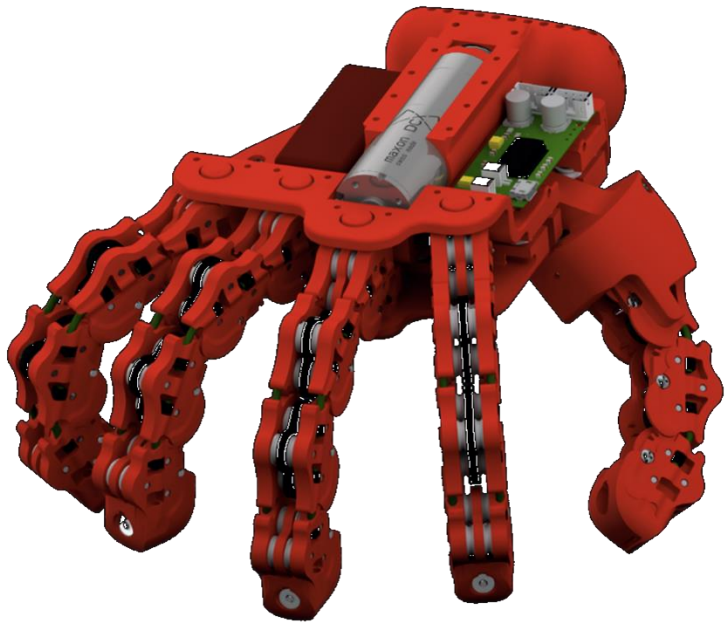
RBO-2 HAND
[Deimel et al. 2015]



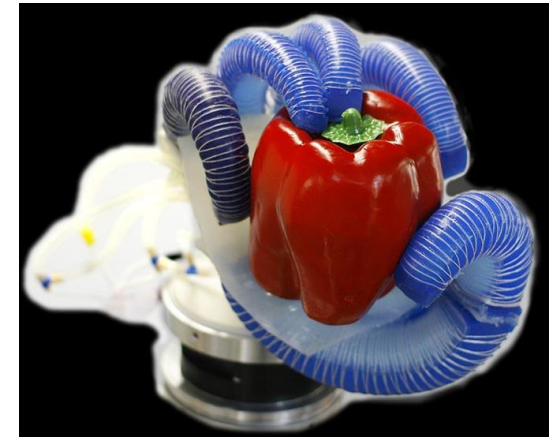
SPA HAND
[Morrow et al. 2016]

Robot embodied ability to comply and adapt to features of the environment

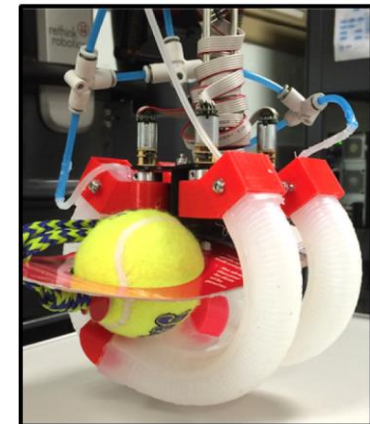
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Distributed Intelligence

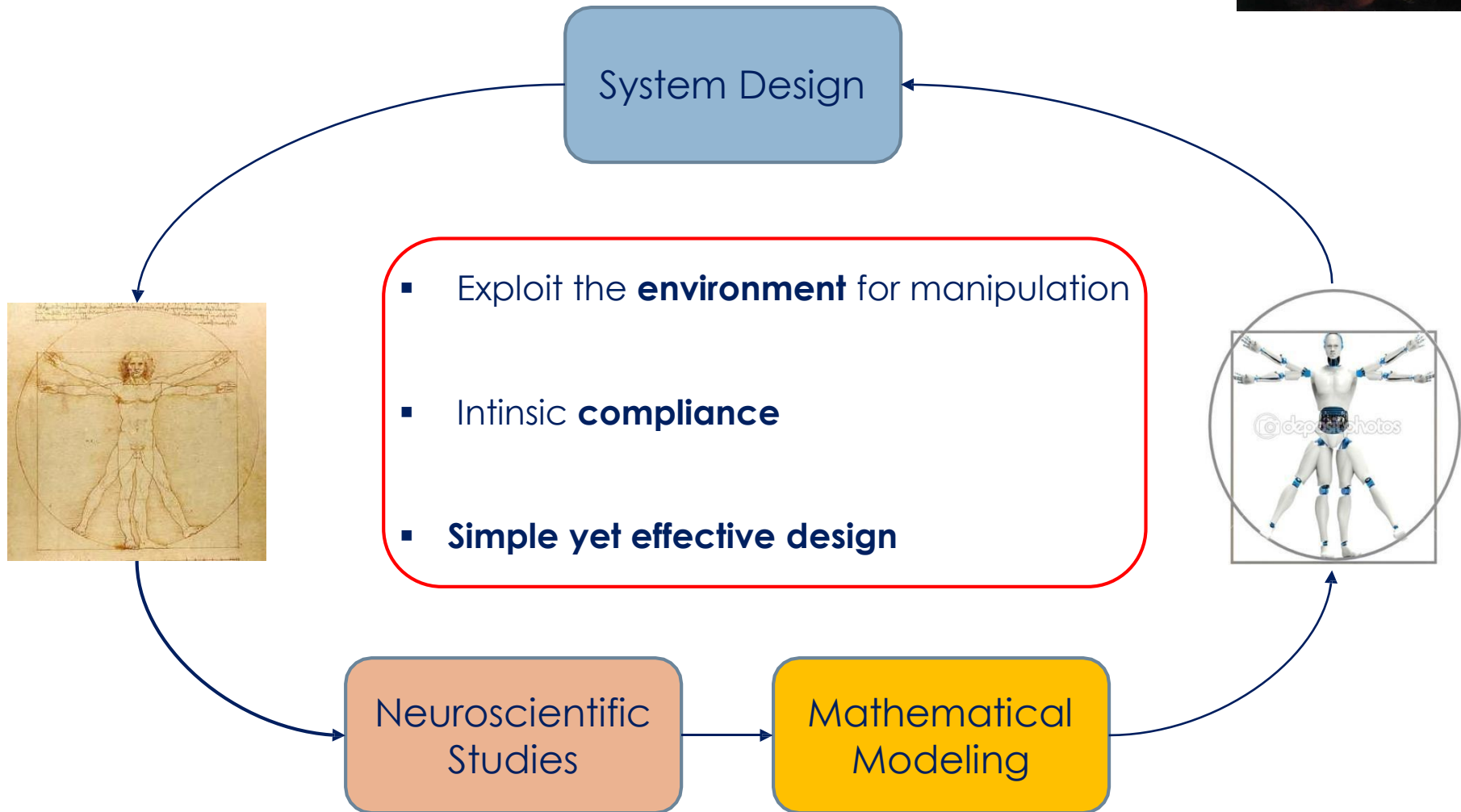
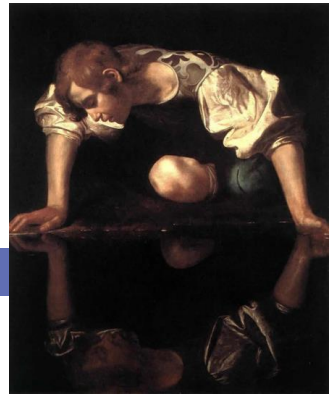


Embodied Mechanical Intelligence

How to design soft robotic hands?

- Exploit the **environment** for manipulation
- Intrinsic **compliance**
- **Simple yet effective design**

How to design soft robotic hands?



Motor Hand Synergies



Extensive neuroscientific studies have demonstrated that human central nervous system controls movements in a **synergistic manner** (Babinski (1914!), Bernstein, Latash, Bizzi, Soechting, D'Avella, Feldman...)



- **Synergies** can be defined as *“a collection of relatively independent degrees of freedom that behave as a single functional unit”* [Turvey et al. 2007]
- With special focus on **human hand**, synergies denote patterns of voluntary muscular activity and multi joints activation, and can be defined at different levels [Santello et al. 2013]

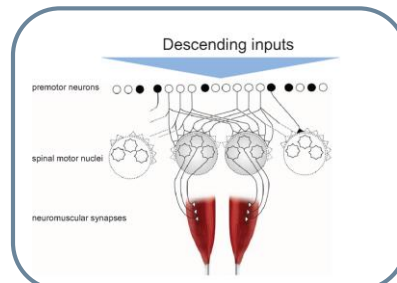
Kinematic



[Santello et al. 1998]

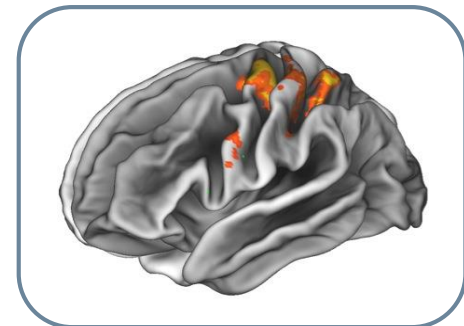


Muscular



[Ting and McKay 2007]

Neural



[Leo et al. 2016]
[Gentner et al. 2006]

The Dataset of Kinematic Motor Hand Synergies in Grasping

- ❑ 57 imagined objects – **Grasping**
- ❑ PCA (Principal Component Analysis)
- ❑ Few linear combinations of hand DoFs explain most of the variance



[Santello et al., 1998]

$$P_o = U_{P_o} \Sigma_{P_o} U_{P_o}^T \longrightarrow u_i(P_o)$$

A Priori Covariance

i-th EigenPosture

The Shape of Postural Synergies or Eigenpostures

Glossary: “Eigenpostures” = Principal Components of Grasp A Priori Covariance Matrix $S_i = u_i(Po)$

(1-st PC)



First two eigenpostures explain ~84%, first three ~90% of the covariance

First eigenposture alone more than 50%

The Shape of Postural Synergies or Eigenpostures

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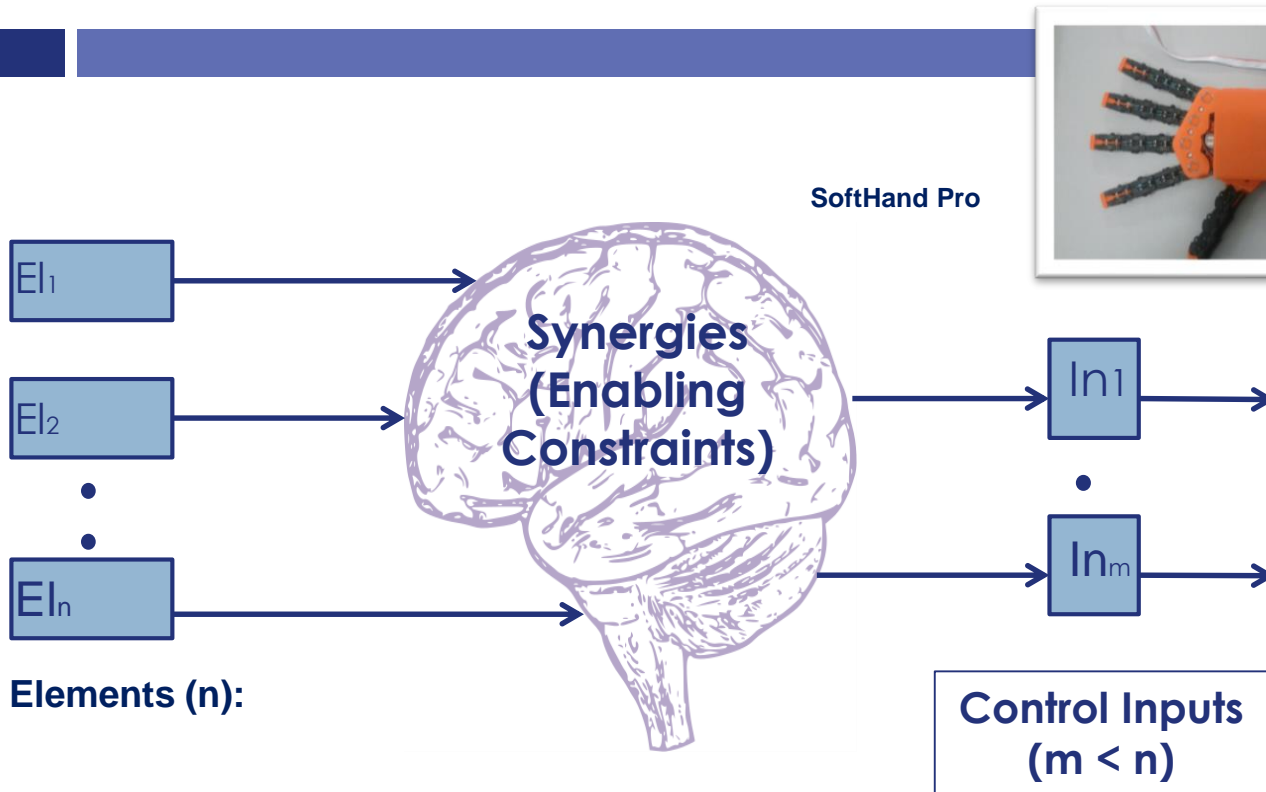
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Implication for Robotics: A Road Towards Simplification



To design (and control) robotic devices with a reduced number of control inputs, actuators

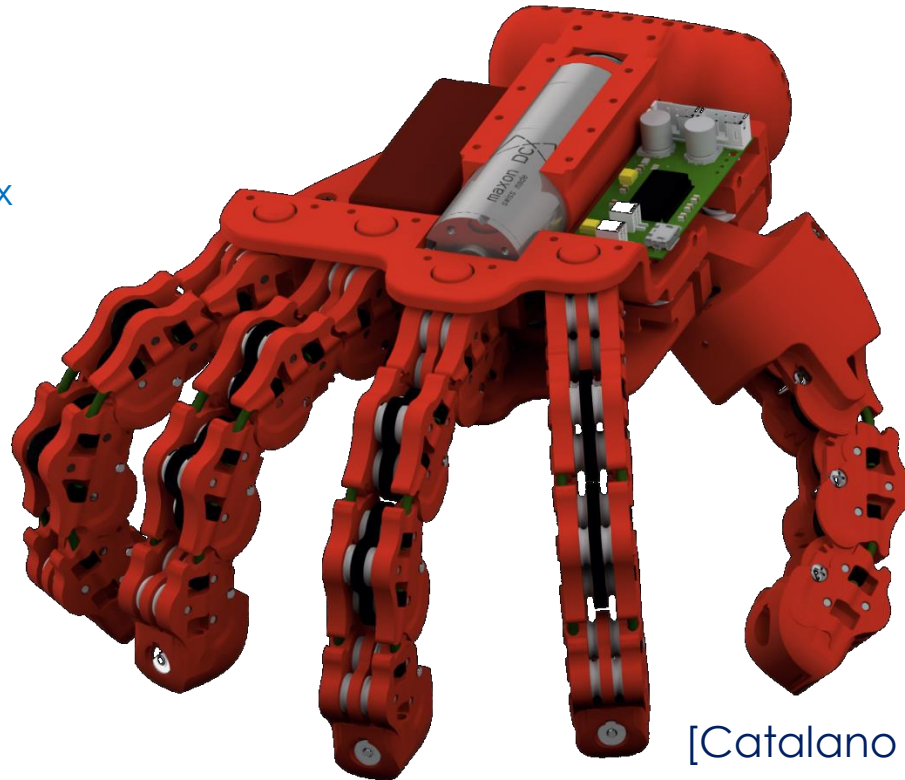
[Catalano et al. 2014]
[Brown and Asada, 2007]

The PISA/IIT SoftHand

19 degrees of freedom

1 Motor to move

MAXON DC-X 22s (24V, 15W of continuous power) - 86:1 gearbox



[Catalano et al. 2014]

Embodied Intelligence

Simple mechanics
Easy to control

Robust
Adaptive

Affordable
Modular

Under-Actuation and Adaptive Synergies

- Self (adaptive) motions

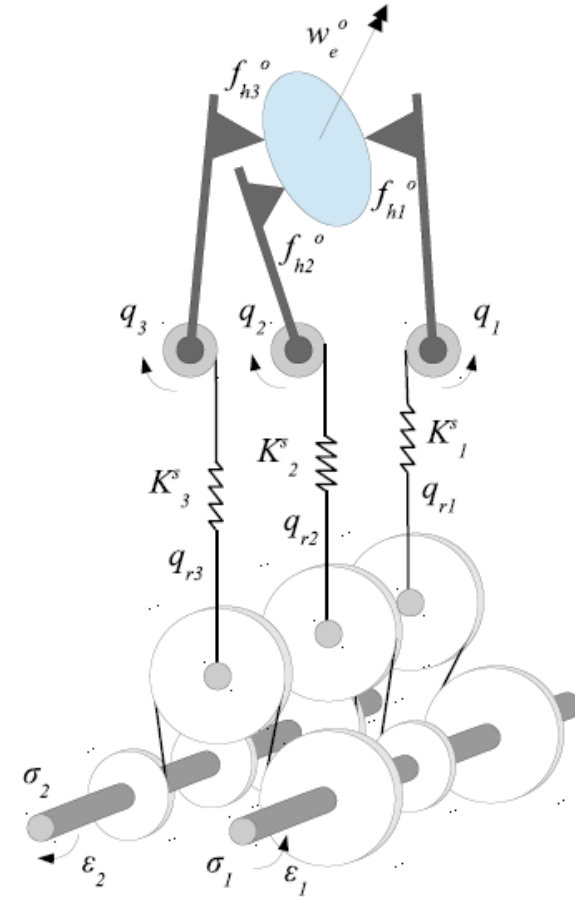
$$q = S^{(k)} \sigma^{(k)} + N^{(k)} \lambda$$

- Balance of actuator, recoil springs and contact forces

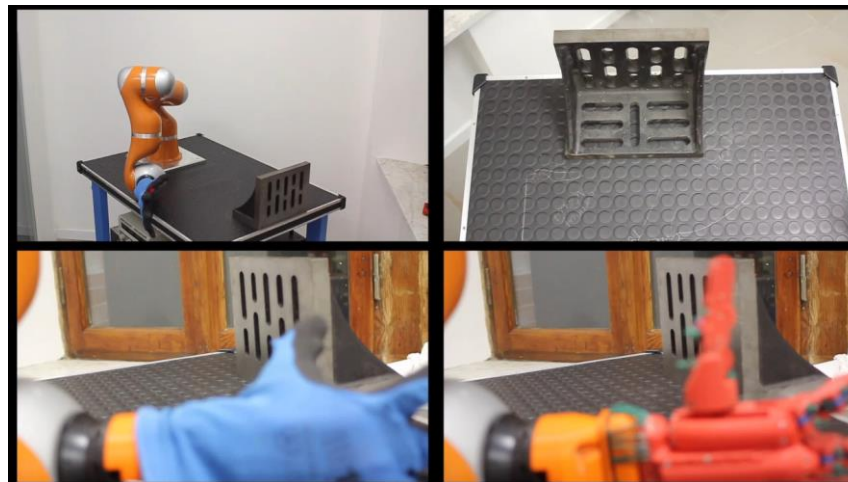
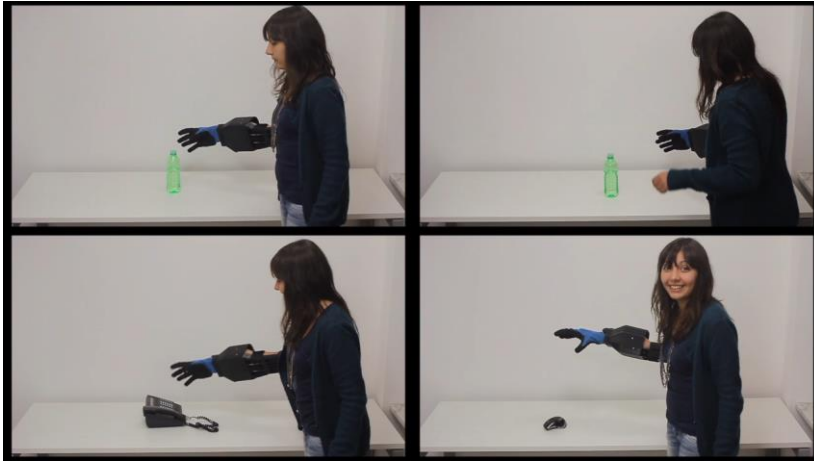
$$J^T f = R^T f - E q$$

- Design **springs** (E) and **pulley trains** (R) to achieve desired behavior

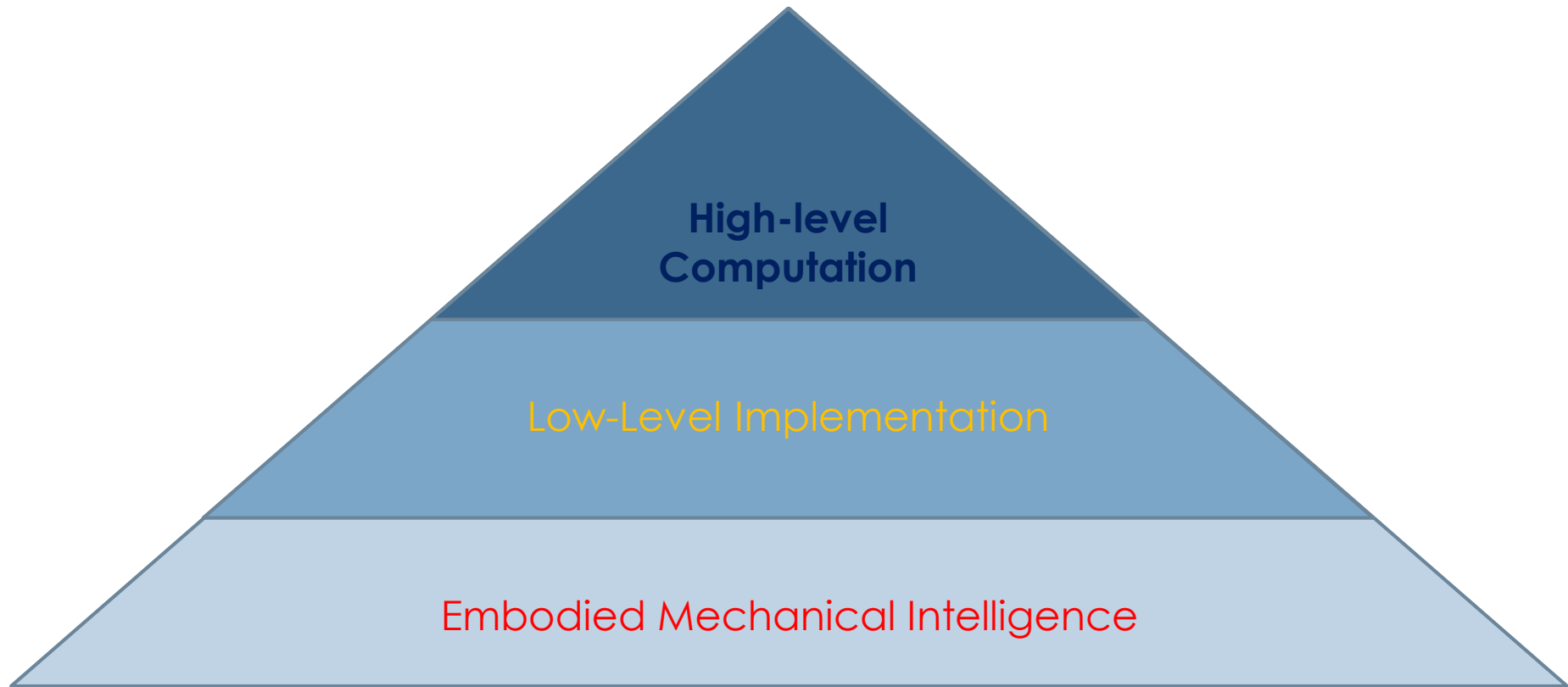
$$S^{(k)} = E^{-1} R^T (R E^{-1} R^T)^{-1}$$



Gentle, Robust, Adaptable: *Embodied Mechanical Intelligence*

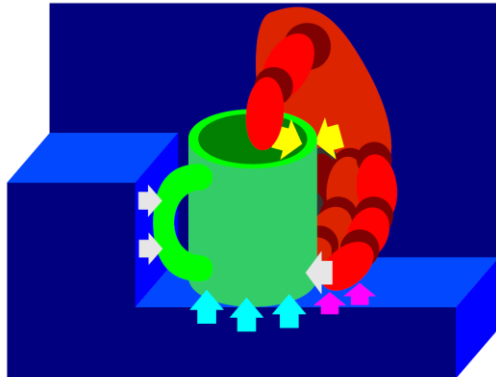


Distributed Intelligence



Key Features for Successful Soft Robotic Grasping

Thanks to the **intrinsic adaptability** of soft end effectors, an **approximation of object properties** and **hand pose definition** can be enough to generate successful grasps



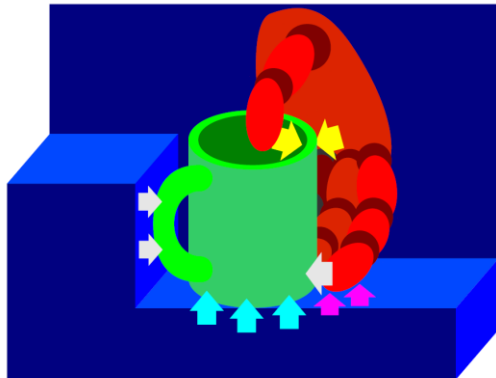
[Bonilla et al. 2014]

The **compliance** of the hand enables a successful interaction with the environment that acts as a **degree of freedom multiplier**



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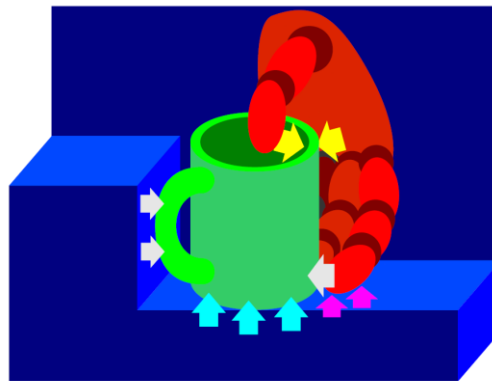
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Key Features

An effective design of **robotic wrist** is essential to simplify the grasp planning phase

Thanks to the *intrinsic adaptability* of soft end effectors, an approximation of object properties and **hand pose definition**, which is ultimately determined by the **wrist**, can be enough to generate successful grasps



[Bonilla et al. 2014]

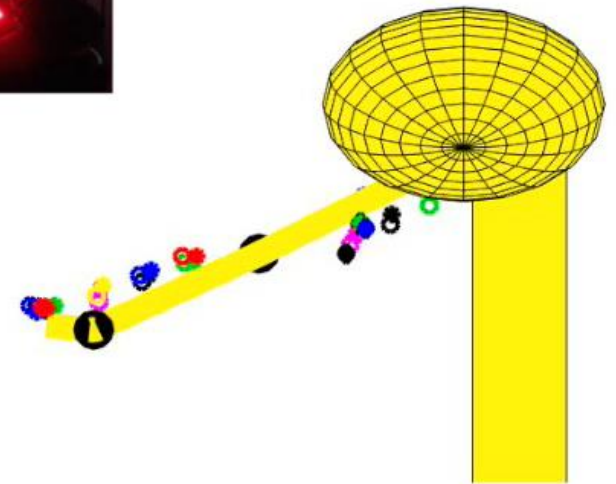
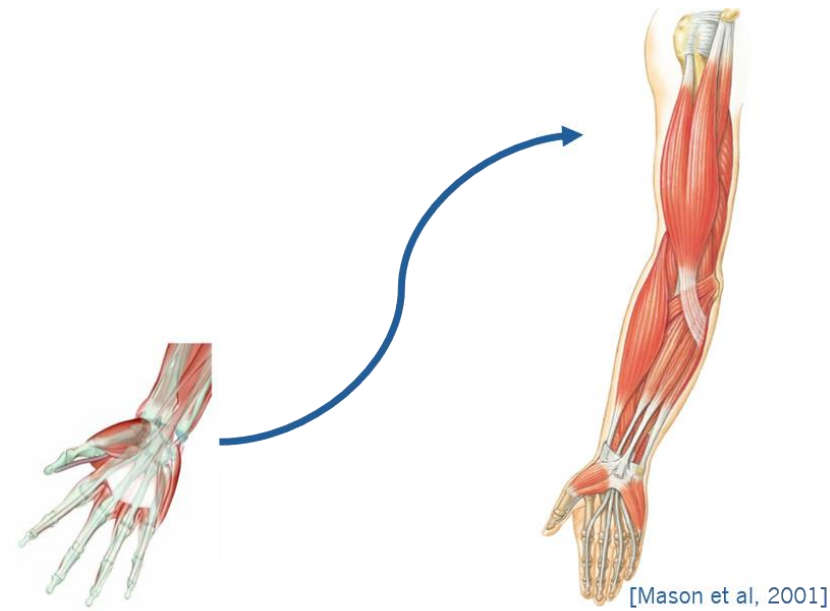
Observing Humans...



The wrist is crucial for manipulation:

- modulation of hand impedance with the environment
- approaching direction
- directionality of forces

From Hand to Upper Limb Synergies



Human-Inspired Robotic Wrist for an Under-Actuated SoftHand

[Casini, Simona, et al. Design of an under-actuated wrist based on adaptive synergies. In: Robotics and Automation (ICRA), 2017 IEEE International Conference on. IEEE, 2017. p. 6679-6686]

Use Adaptive Synergy Concept and Human Inspiration to realize an Under-Actuated Soft Wrist

Experiments with Humans for the extraction of wrist synergies



Mechanical Design of a modular two DoF system

The main purpose is to investigate:

- different DOFs configurations
- Wrist compliance
- Wrist adaptivity



Results

- **Principal component analysis** on pre-grasp wrist poses (6 subjects)
- 3 Wrist DOFs
- According to PC1, F-E plays the most important role



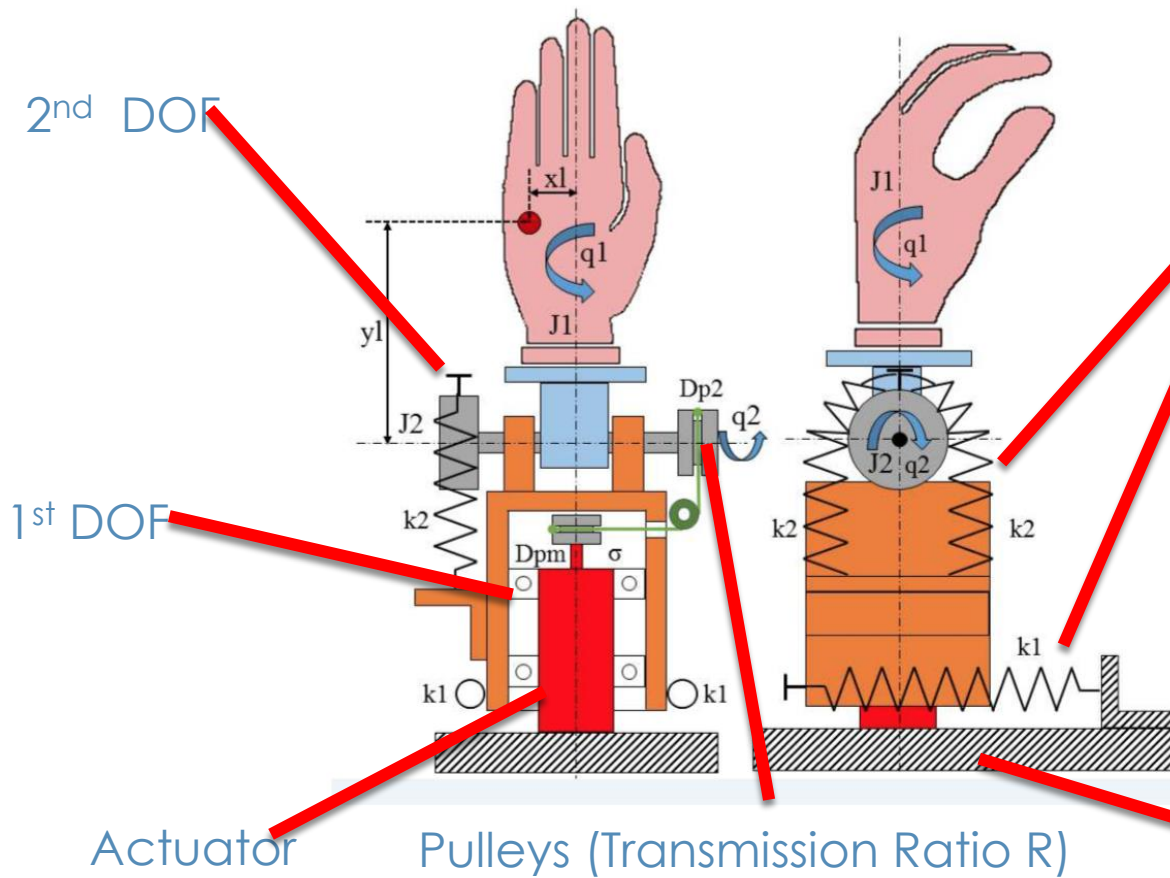
	P-S	A-A	F-E	variance
PC1	0.36	$4 \cdot 10^{-3}$	0.93	74%
PC2	0.93	0.013	-0.36	21%
PC3	-0.013	~ 1	$9.3 \cdot 10^{-4}$	5%

P-S: Prono-Supination; A-A: Abduction-Adduction; F-E: Flexo-Extension

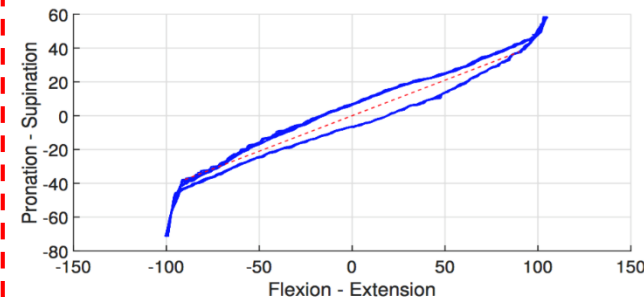
Mechanical Design

Soft Synergies = Differential + Elasticity

$$q = S\sigma - CJ^T f_{\text{ext}} \Rightarrow \begin{cases} J^T f_{\text{ext}} = R^T f - Eq \\ Rq = \sigma \end{cases} \Rightarrow \begin{aligned} S &= E^{-1} R^T (RE^{-1} R^T)^{-1} \\ C &= E^{-1} - E^{-1} R^T (RE^{-1} R^T)^{-1} RE^{-1} \end{aligned}$$

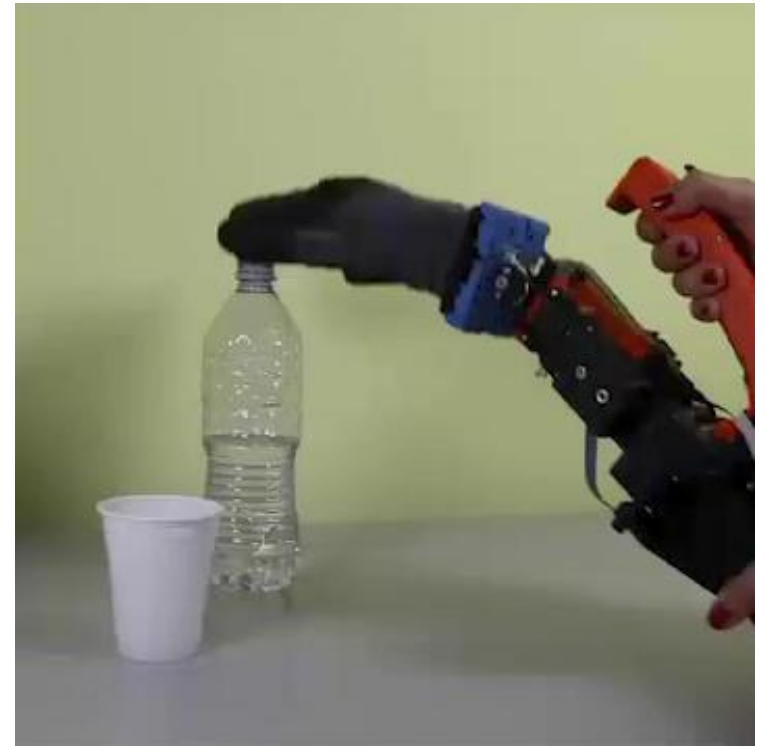


Springs
(Elastic Field E)



Ideal ratio between F-E and P-S movements (red line) vs. experimental ratio, 10 cycles, (blue lines)

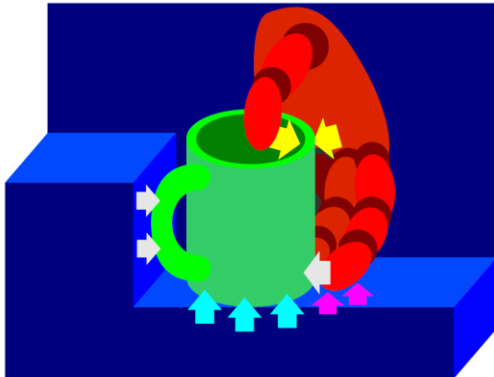
Mechanical Design



Adaptation Trough Under-actuation

Key Features for Successful Soft Robotic Grasping

Thanks to the **intrinsic adaptability** of soft end effectors, an **approximation of object properties** and **hand pose definition** can be enough to generate successful grasps



[Bonilla et al. 2014]

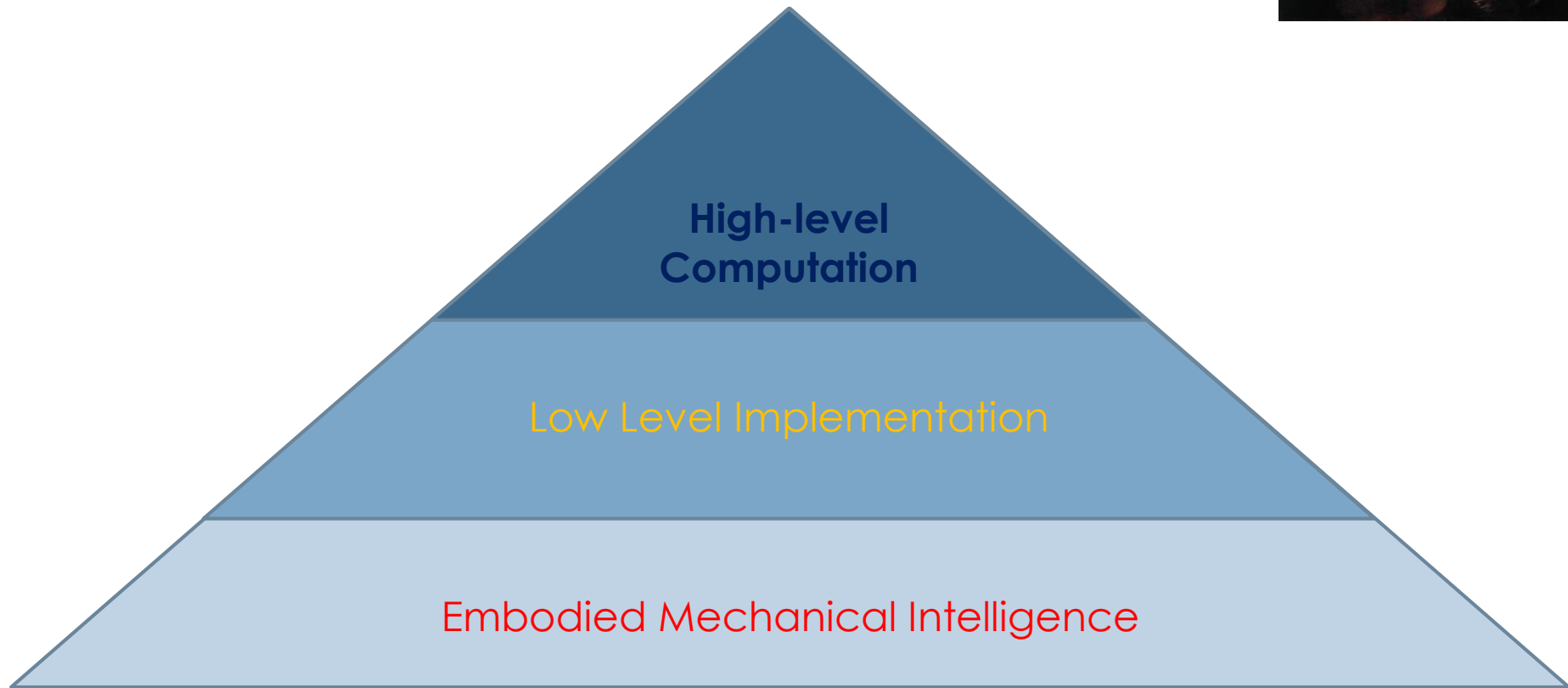
The **compliance** of the hand enables a successful interaction with the environment that acts as a **degree of freedom multiplier**



Key Features for Successful Soft Robotic Grasping

- Leverage on **hand embodied intelligence**
- Allow for **minimal sensing**
- Integrate **Computation**

Distributed Intelligence for Grasping and Manipulation



Human Inspiration for **Autonomous Soft Robotic Grasping**

The **Central Nervous System** 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

[R. S. Johansson and B. B. Edin, 1993]



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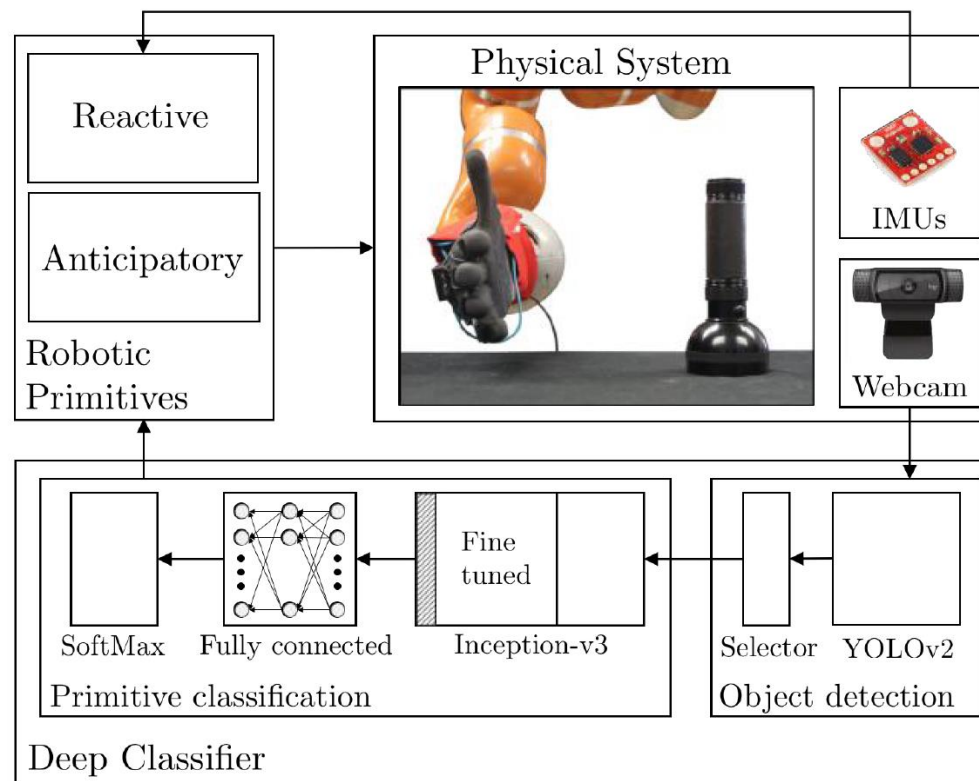
Feedforward components with sensory-triggered reactive actions



[C. Della Santina, V. Arapi, G. Averta, F. Damiani, G. Fiore, A. Settini, M. G. Catalano, D. Bacciu, A. Bicchi and M. Bianchi. Learning from humans how to grasp: a data-driven architecture for autonomous grasping with an anthropomorphic soft hand. ICRA + RAL 2019]

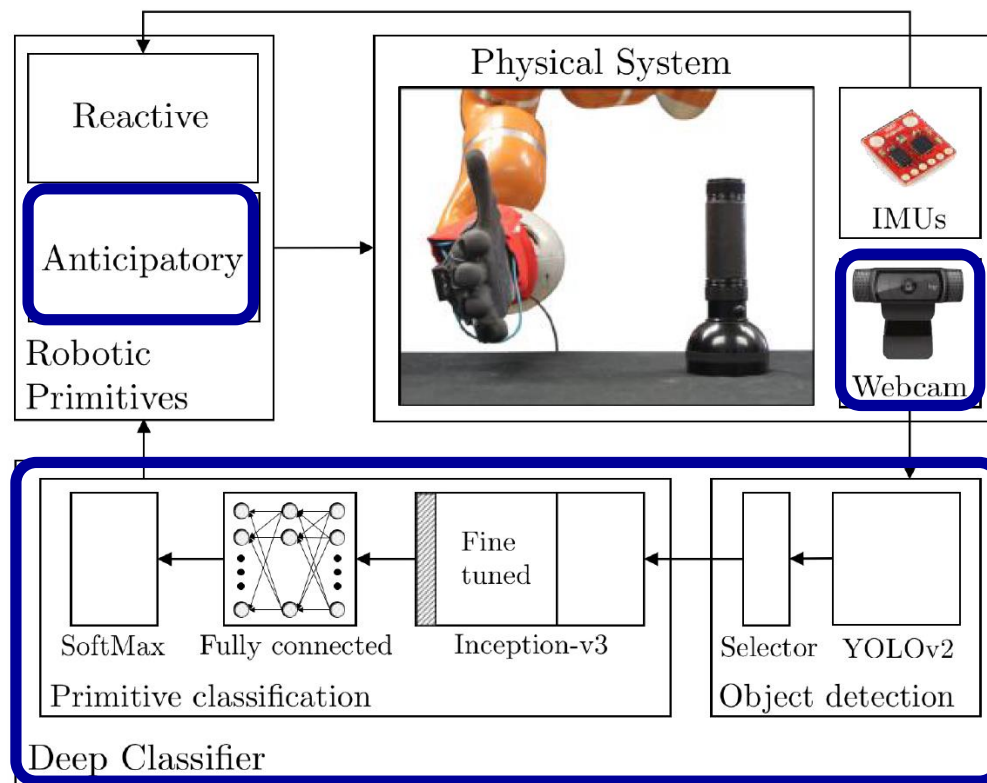
Human Inspiration for Autonomous Soft Robotic Grasping

**Feedforward components with
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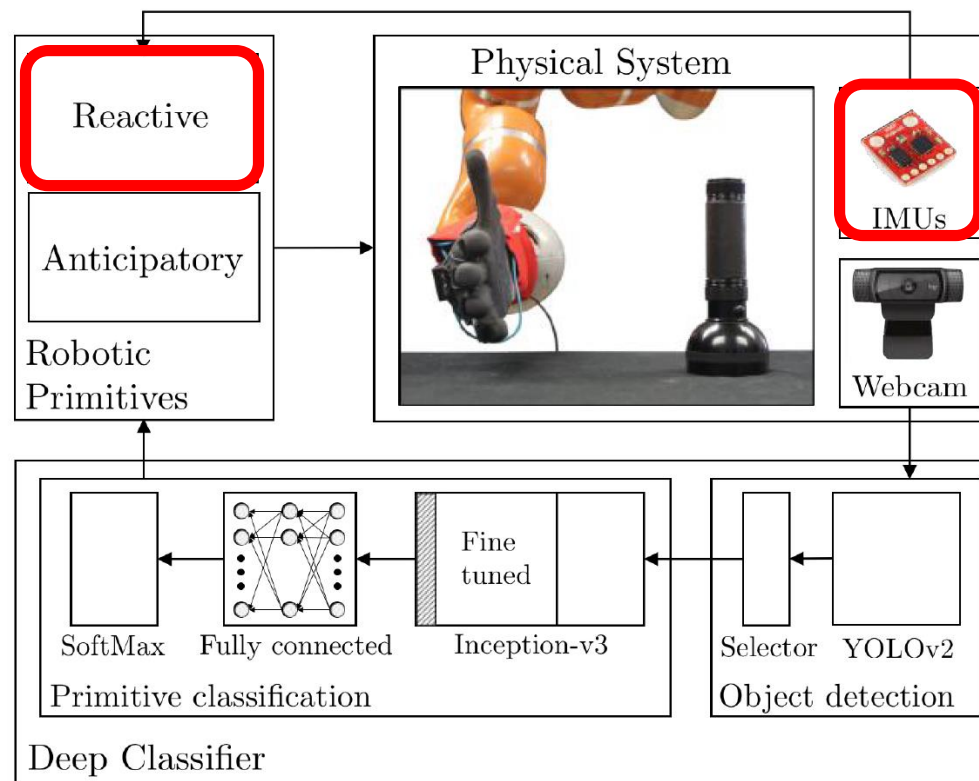
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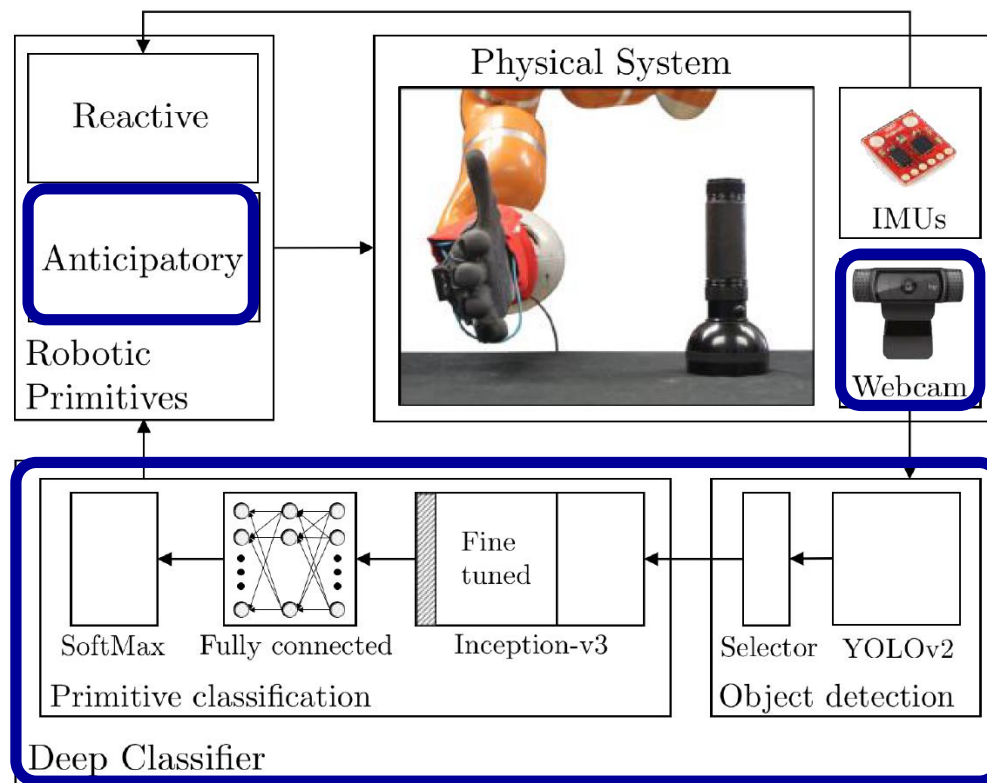
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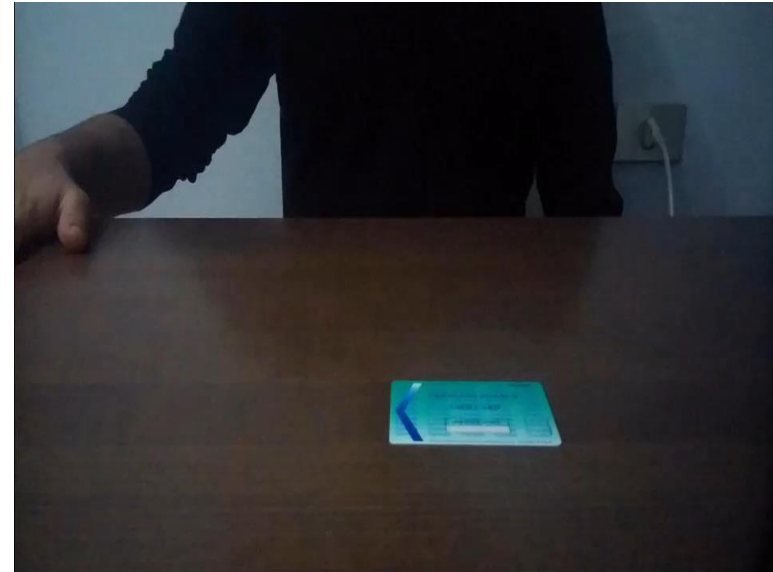
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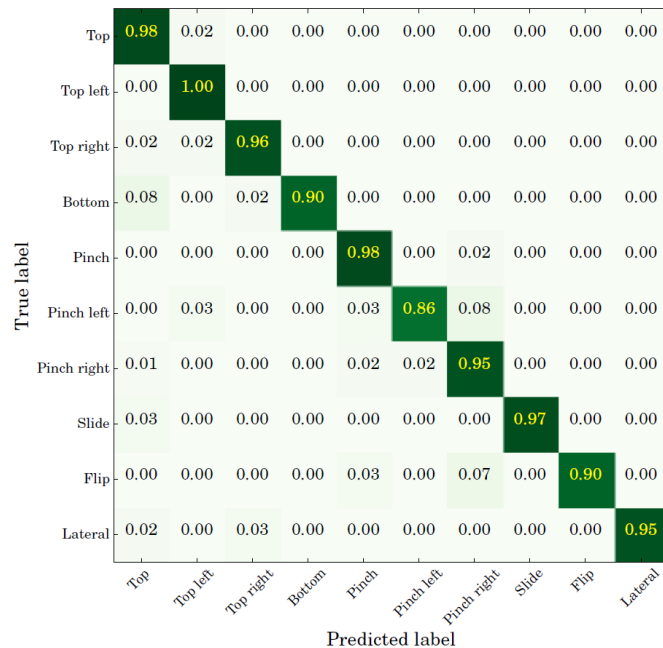
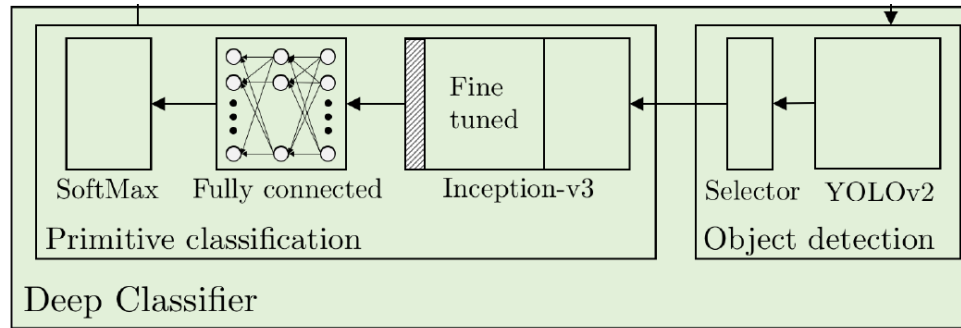


Anticipatory Actions: Building a Dataset

- **Dataset:** 6336 single-object table-top first person videos (RGB images), from 11 right-handed subjects grasping 36 objects
 - Each task was repeated 4 times from 4 points of view (the four central points of the table edges)
- **Approach Primitive Extraction and Labeling**



Anticipatory Action: Deep Classifier



Object detection



Primitive classification

Paper → Slide
 Phone → Top Right
 Bracelet → Pinch
 Vase → Lateral
 Pen → Pinch Left
 Tablet → Slide

Anticipatory Action: Implementation

- Human hand tends to follow **straight lines** connecting the starting position and the target

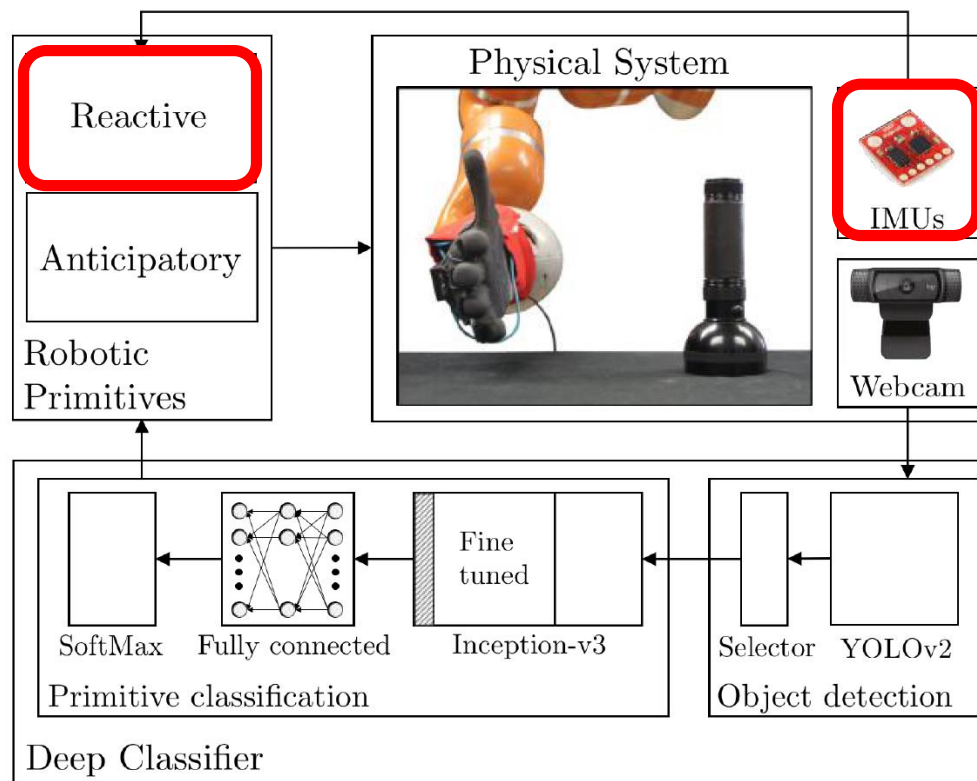
$$x(t) = x_0 + d t , \quad Q(t) = Q_0$$

TABLE I
INITIAL ORIENTATION Q_0 AND NORMALIZED DIRECTION OF APPROACH \hat{d}
FOR EACH PRIMITIVE.

Strategy	Q_0^T	\hat{d}^T
Top	[0.0 0.711 0.0 0.703]	[0 0 - 1]
Top left	[0.269 0.6570 - 0.2721 0.6496]	[0 0 - 1]
Top right	[0.269 - 0.657 - 0.272 - 0.649]	[0 0 - 1]
Bottom	[0.145 - 0.696 0.701 0.030]	[0 1 0]
Pinch	[0.084 0.816 0.17 0.458]	[0 0 - 1]
Pinch left	[0.116 0.733 0.483 0.463]	[0 0 - 1]
Pinch right	[0.186 0.890 - 0.110 0.400]	[0 0 - 1]
Slide	[0.0 0.711 0.0 0.703]	[0 0 - 1]
Lateral	[0 - 1 0 0]	[0 1 0]

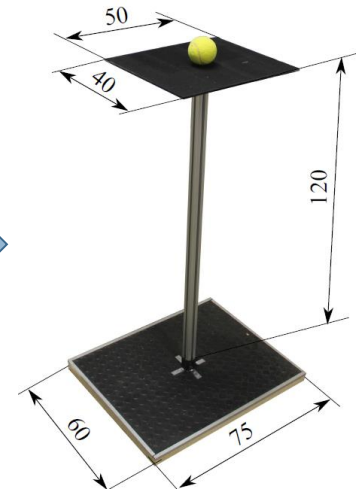
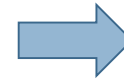
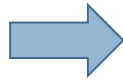
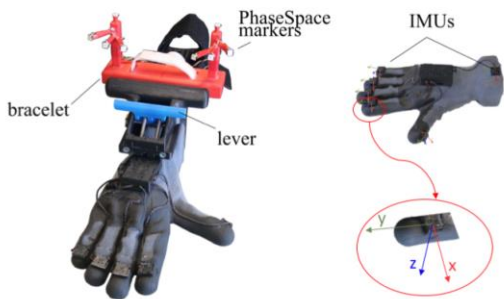
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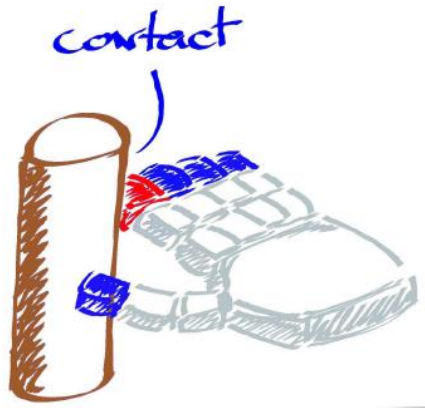
Reactive Grasping: Preliminary Work

[Bianchi et al. ICRA 2018]



Grasp actions on a single object from user
(**wrist pose, approaching direction, closure
timing and speed**) are recorded and
correlated to sensor data

Method



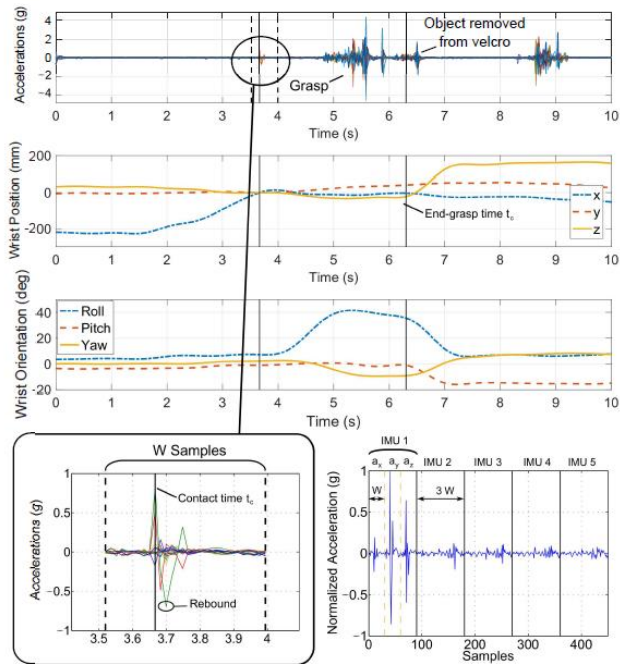
Method



Method



Method



IMU



Correlation with Human Wrist Pose

Experiments: Handover

86% of successful grasps

Handover Task

Handover Task

Handover Task

Handover Task

Robotic hand mounted on the Kuka Robot arm
replicates and generalizes **reflexes (13 primitives for distal phalanx contact)** on
different fingers, objects and **approach directions**

Experiments: Towards Autonomous Grasping

Grasping from a Table:
Top Approach

Grasping from a Table:
Top Approach

Grasping from a Table:
Top Approach

Grasping from a Table:
Top Approach

Reactive Action: Implementation

$$a : [0, T]$$

Acceleration Profile

Reactive Action: Implementation

$$a : [0, T]$$

Acceleration Profile

$$j = \arg \max_i \int_0^T a^T(\tau) \alpha_i(\tau) d\tau$$

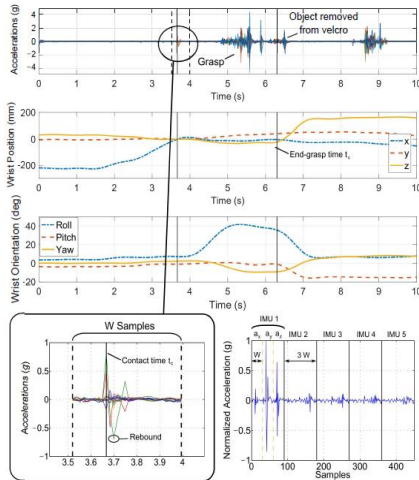


Re-arrangement

Reactive Action: Implementation

$$a : [0, T] \rightarrow \mathbb{R}^5$$

Acceleration Profile



IMU



$$j = \arg \max_i \int_0^T a^T(\tau) \alpha_i(\tau) d\tau$$

Re-arrangement

Correlation with Wrist Pose

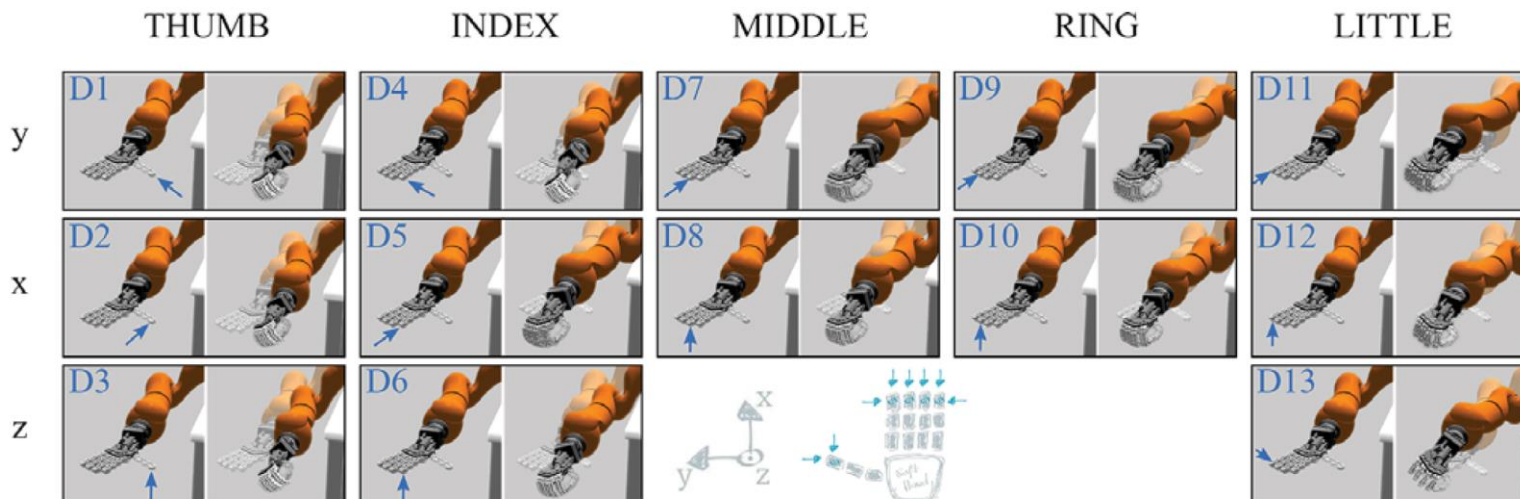
Reactive Action: Implementation

$a : [0, T]$

Acceleration profile

$$j = \arg \max_i \int_0^T a^T(\tau) \alpha_i(\tau) d\tau$$

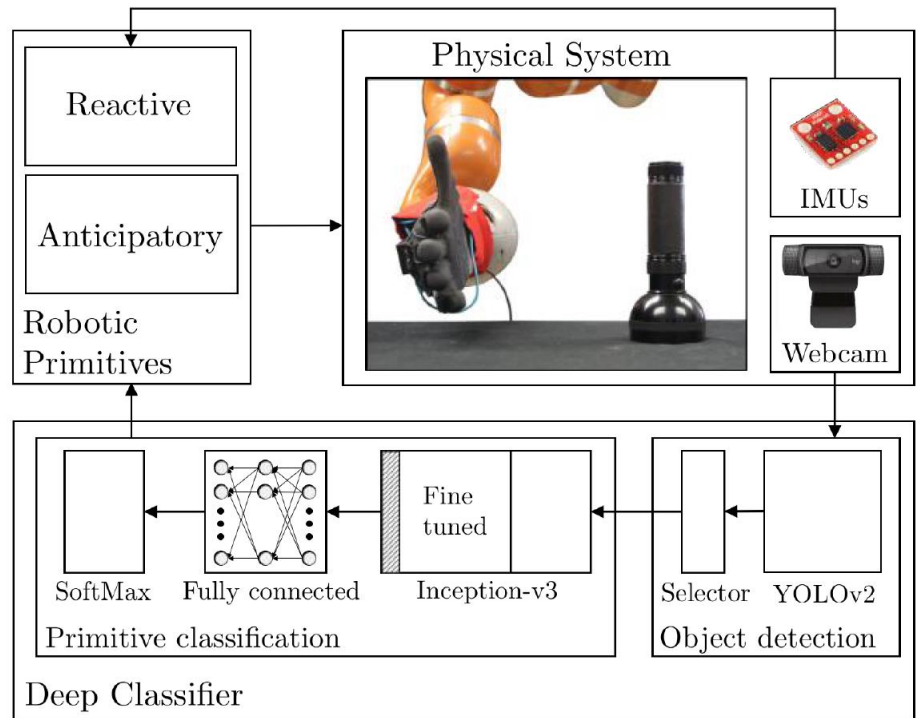
Re-Arrangement



[Bianchi et al. 2018]

Anticipatory and Reactive Actions on the Robotic Side

- **Approach Primitive Implemented**
- **IMU sensing** triggers the **human-inspired reactive action**
- **Hand compliance enables to generalize to different objects exploiting the environment**

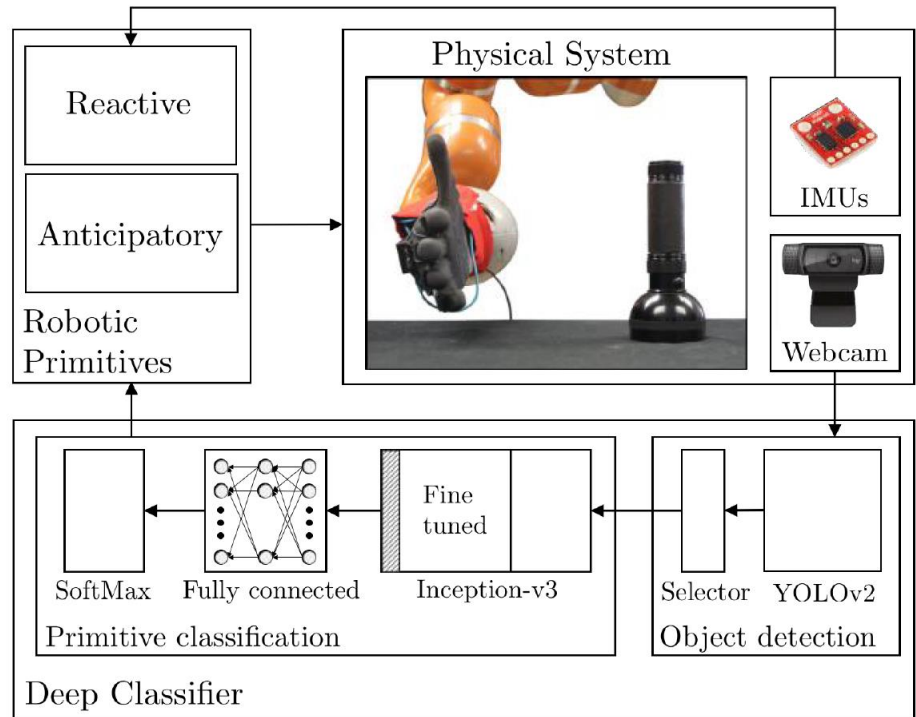


[C. Della Santina, V. Arapi, G. Averta, F. Damiani, G. Fiore, A. Settini, M. G. Catalano, D. Bacciu, A. Bicchi and M. Bianchi. Learning from humans how to grasp: a data-driven architecture for autonomous grasping with an anthropomorphic soft hand. ICRA + RAL 2019]

Anticipatory and Reactive Actions on the Robotic Side

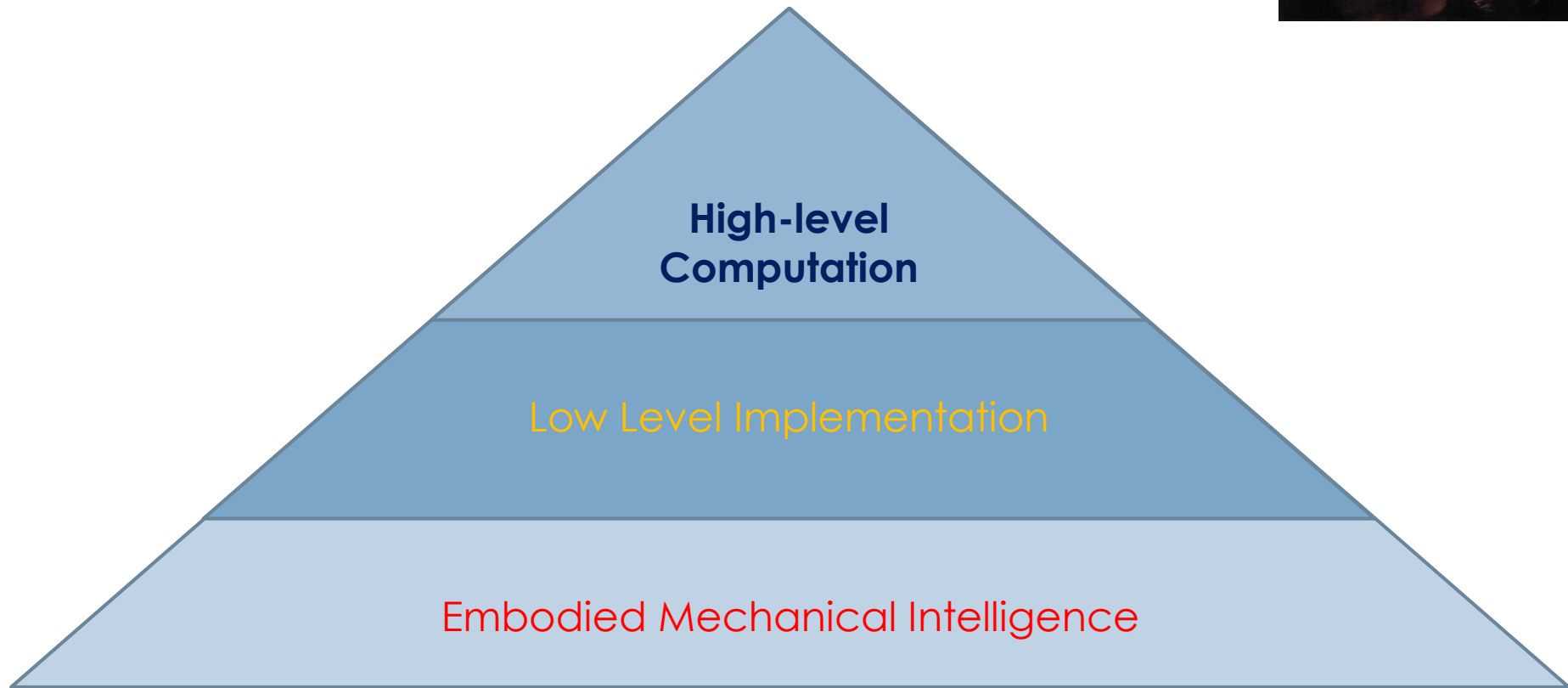
EMBODIED INTELLIGENCE + COMPUTATION

- **Approach Primitive Implemented**
- **IMU sensing** triggers the **human-inspired reactive action**
- **Hand compliance enables to generalize to different objects exploiting the environment**

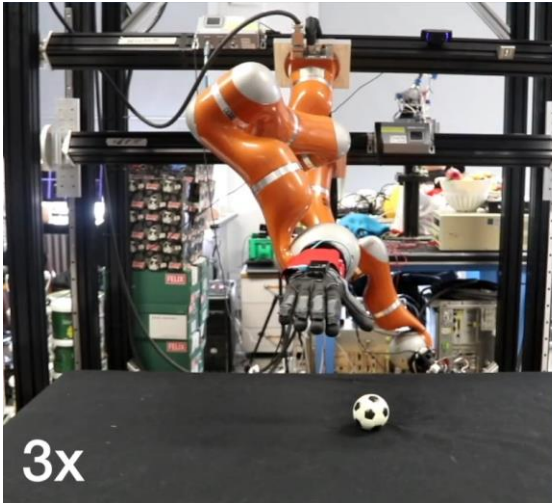


[C. Della Santina, V. Arapi, G. Averta, F. Damiani, G. Fiore, A. Settini, M. G. Catalano, D. Bacciu, A. Bicchi and M. Bianchi. Learning from humans how to grasp: a data-driven architecture for autonomous grasping with an anthropomorphic soft hand. ICRA + RAL 2019]

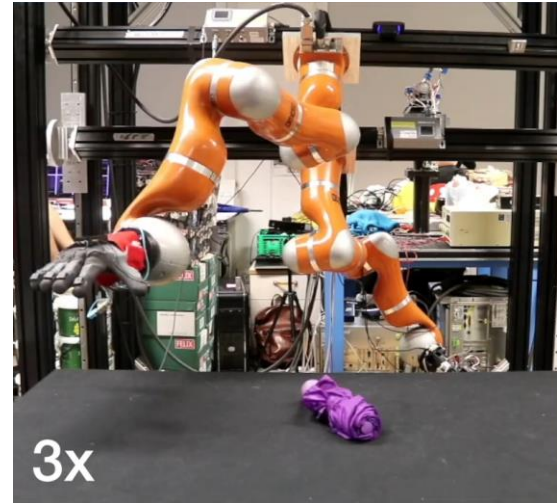
Distributed Intelligence for Grasping and Manipulation



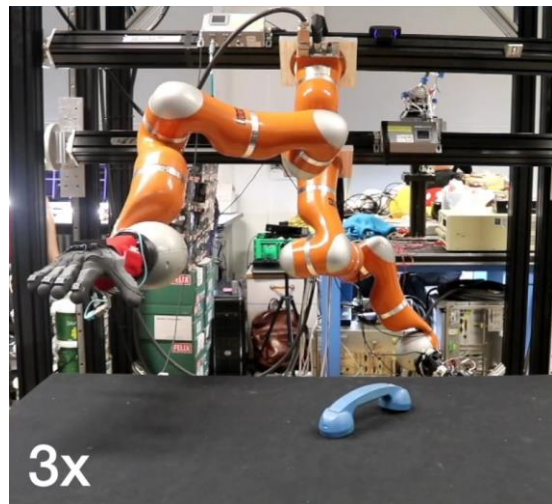
Anticipatory and Reactive Actions on the Robotic Side: **Top Primitives**



Top primitive:
the object is approached from the top with palm down parallel to the table. Object center is approximatively at the level of middle phalanx. When contact is established all fingers are simultaneously closed, achieving a firm power-like grasp.

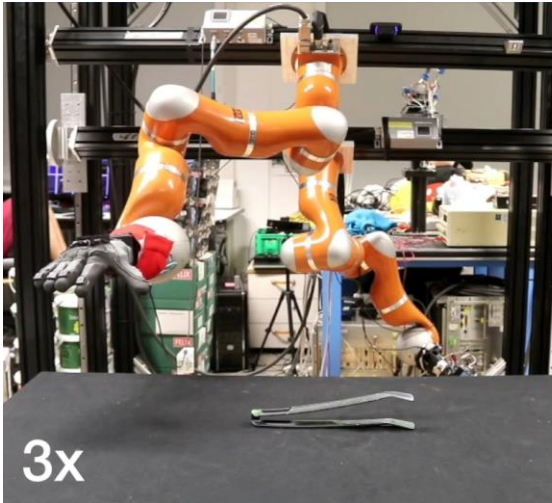


Top left primitive:
Same for the top grasp, but with the palm rotates clockwise.

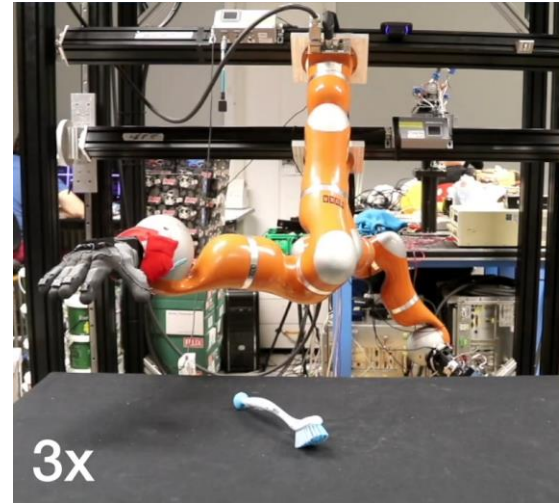


Top right primitive:
Same for the top grasp, but with the palm rotates anti-clockwise.

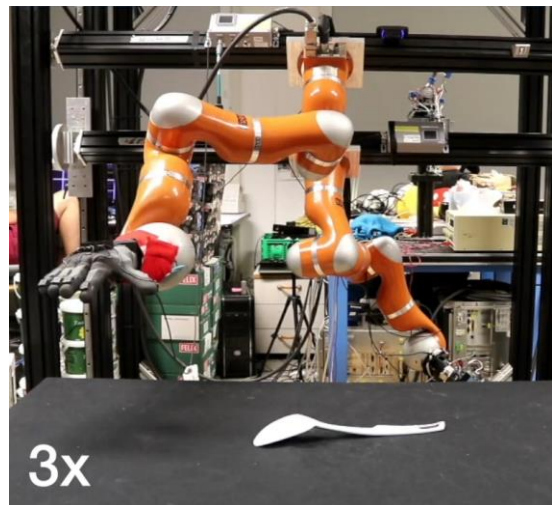
Anticipatory and Reactive Actions on the Robotic Side: **Pinch Primitives**



Pinch primitive:
Same for the top grasp, but the primitive concludes with a pinch grasp.



Pinch right primitive:
Same for the top right grasp, but the primitive concludes with a pinch grasp.

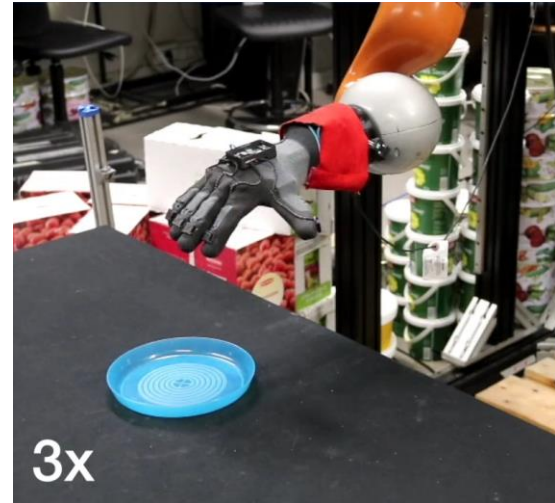


Pinch left primitive:
Same for the top left grasp, but the primitive concludes with a pinch grasp.

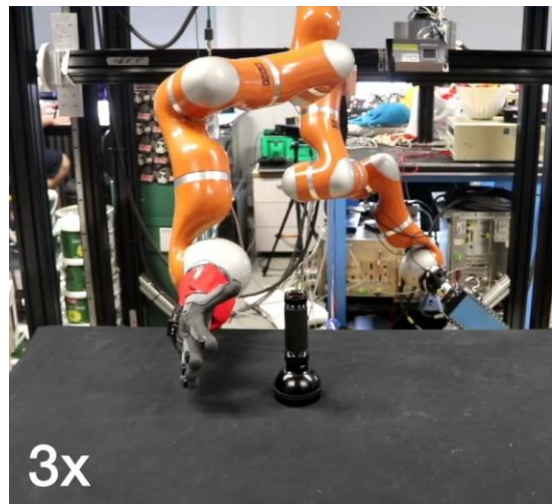
Anticipatory and Reactive Actions on the Robotic Side: **Bottom, Slide, Lateral**



Bottom primitive:
the object is approached from its right side. The palm is roughly perpendicular to the table, but slightly tilted so that the fingers tips are more close to the object than the wrist. When the contact is reached, the hand closes with the thumb opposing the four long fingers.



Slide primitive:
the hand is placed on the object from above as to push it toward the surface. Maintaining this hand posture, the object is moved towards the edge of the table until it partially protrudes. A grasp is then achieved by moving the thumb below the object, and opposing it to the long fingers.



Lateral primitive:
the same as for the top grasp, but the palm is perpendicular to the object during the approaching phase

Anticipatory and Reactive Actions on the Robotic Side

We extensively tested the proposed architecture with 20 objects, achieving a success rate of 81.1% over 111 grasps.

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Take Home Message

- **Human inspiration**
- **Distributed Intelligence:**
 - the **Brain** *plus* the **Body** it inhabits
 - *More than the sum of the parts*
 - ***Mechanics + Computation***
- **Minimization of Resource Usage**
- **Effectiveness**

Human-inspired strategies for grasping with SoftHands

Matteo Bianchi

with: *C. Della Santina, G. Averta*

*credits to: A. Bicchi (UNIFI-IIT), E. Battaglia, S. Ciotti, C. Piazza, S. Casini (UNIFI),
M.G. Catalano, G. Grioli (IIT), A. Tondo (qbrobotics), M. Santello (ASU)*

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