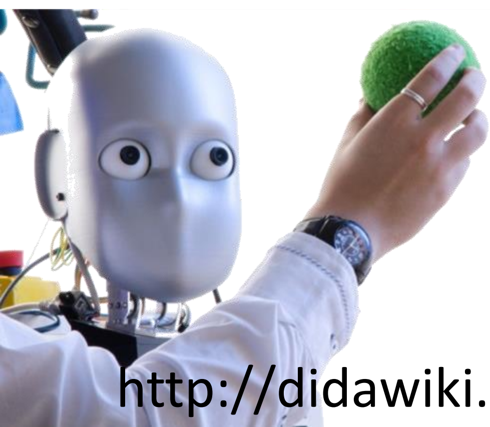
University of Pisa
Master of Science in Computer Science
Course of Robotics (ROB)
A.Y. 2019/20

Bioinspired robotics

Cecilia Laschi
The BioRobotics Institute
Scuola Superiore Sant’Anna
cecilia.laschi@santannapisa.it



cecilia.laschi@santannapisa.it

http://didawiki.cli.di.unipi.it/doku.php/magistraleinformatica/rob/start

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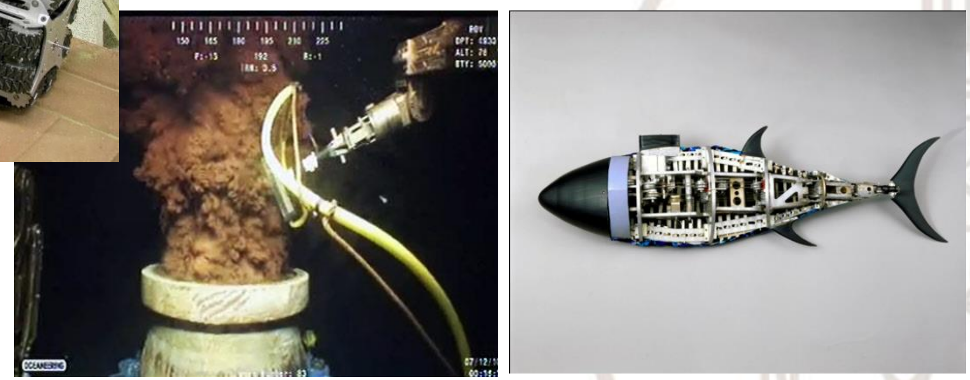
Robots outside factories…

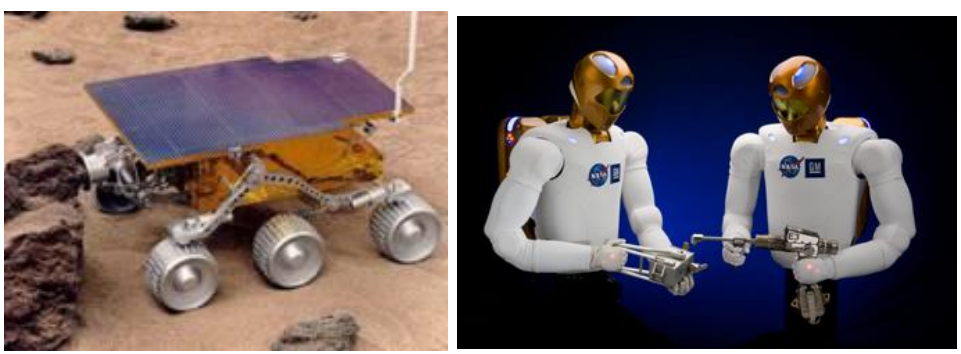
…need to negotiate real-world environments and promptly react to changes and unexpected situations

Biological systems stand as an excellent source of inspiration

Search & rescue



Underwater applications



Space applications

- Unstructured environments
- Workspace shared among people and robots
- Perception
- Reactive behaviour

Bioinspiration and biomimetics

- Using principles in biology to stimulate research in non-biological science and technology
- Otto Schmitt, an American academic and inventor, coined the term biomimetics to describe the transfer of ideas from biology to technology.
- The term biomimetics only entered the Websters Dictionary in 1974 and is defined as "the study of the formation, structure, or function of biologically produced substances and materials (as enzymes or silk) and biological mechanisms and processes (as protein synthesis or photosynthesis) especially for the purpose of synthesizing similar products by artificial mechanisms which mimic natural ones".

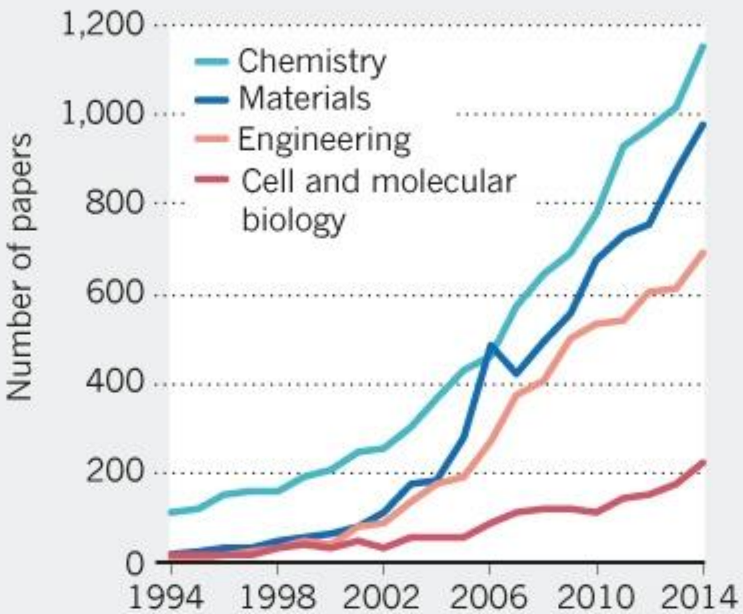
Bioinspiration and biomimetics

Interdisciplinarity:
Bring biologists into biomimetics

nature International weekly journal of science

TRENDS IN BIOMIMETICS

A search of the more than 25,000 papers in biomimicry shows the rising interest in the field over the past decade, but studies are mainly restricted to the physical sciences.



Data obtained by searching the Web of Science Core Collection with the term "biomim* or bioinspir*".

"Engineers, chemists and others taking inspiration from biological systems for human applications must team up with biologists"

"[…] **Fewer than 8%** of the nearly 300 studies on biomimetics published in the past 3 months and indexed in the Thomson Reuters Web of Science **had an author working in a biology department** — a crude proxy for 'a biologist'."

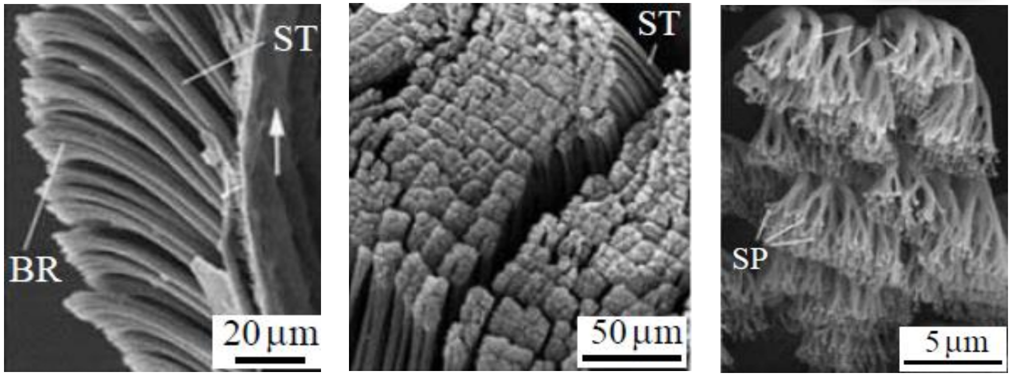
"[…] With around **1.5 million described species**, and probably some 9 million eukaryotic species in existence, researchers pursuing biomimetic approaches have barely **scratched the surface of biological inspiration**."

More biology education for engineers, in academy and in industry

Emilie Snell-Rood, "Interdisciplinarity: Bring biologists into biomimetics", *Nature* 529, 277–278 (21 January 2016) doi:10.1038/529277a

Examples of bioinspiration and biomimetics

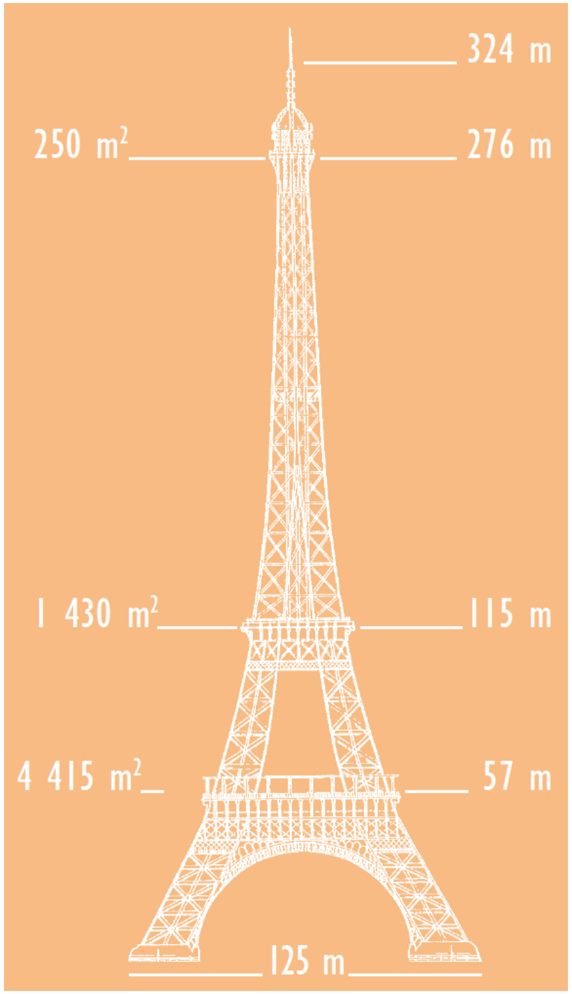
A gecko is the largest animal that can produce (dry) adhesion to support its weight. The gecko foot comprises of a complex hierarchical structure of lamellae, setae, branches, and spatula.



Velcro resulted in 1948 from a Swiss engineer, George de Mestral, seeing how the hooks of a plant burrs (*Arctium lappa*) stuck to his dog's fur.

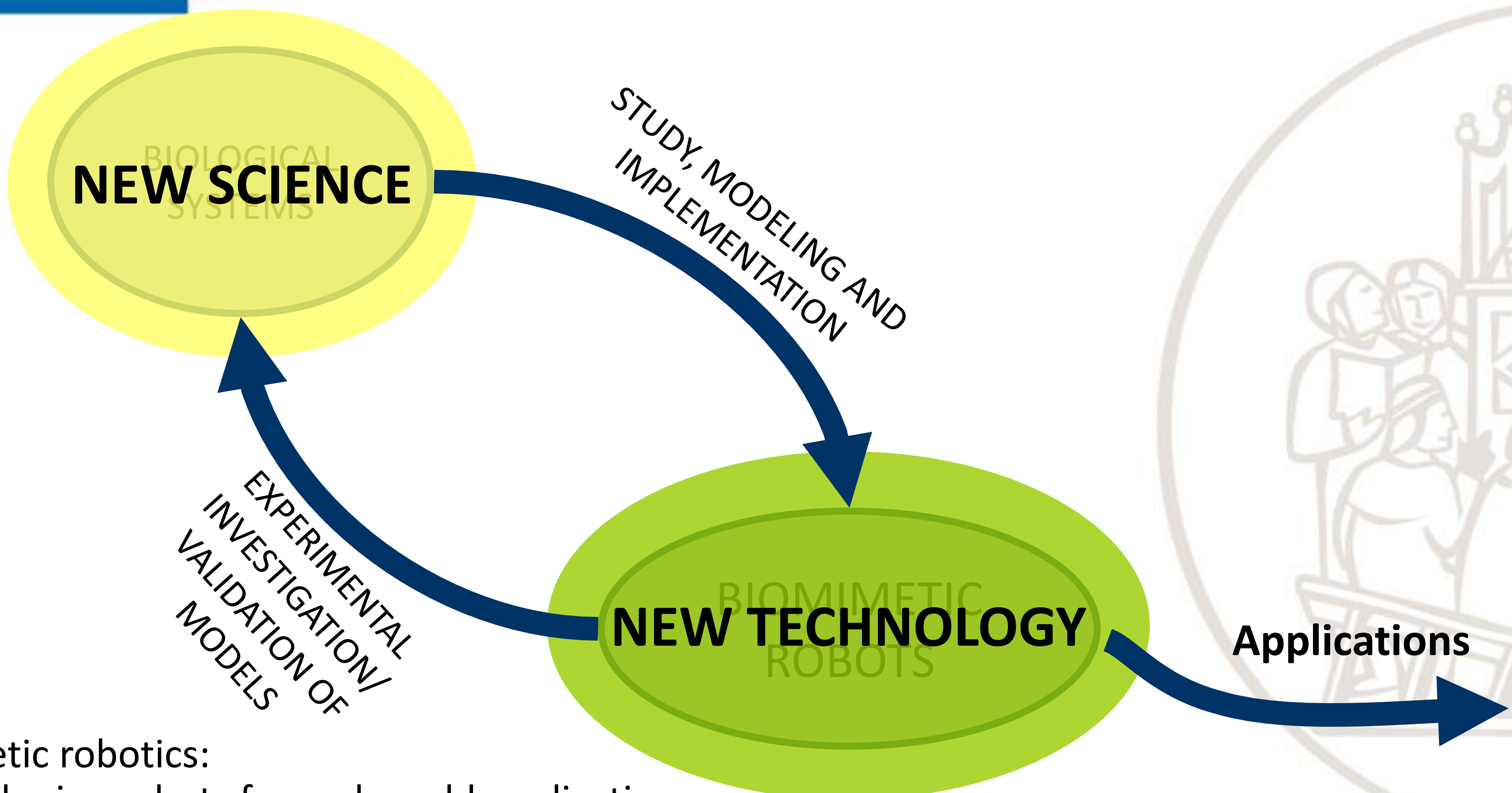
M. R. Cutkosky, Climbing with adhesion: From bioinspiration to biounderstanding. *Interface Focus* 5, 20150015 (2015).

Examples of bioinspiration and biomimetics



The **Eiffel Tower**: the perfect structure of trabecular struts in the head of the human femur inspired a French engineer at the end of the 19th Century. He was intended to design the higher structure all the world. The name of this engineer is Gustave Eiffel. In 1889 the Tower is completed.

The two-fold relation between robotics and biology



Biomimetic robotics:

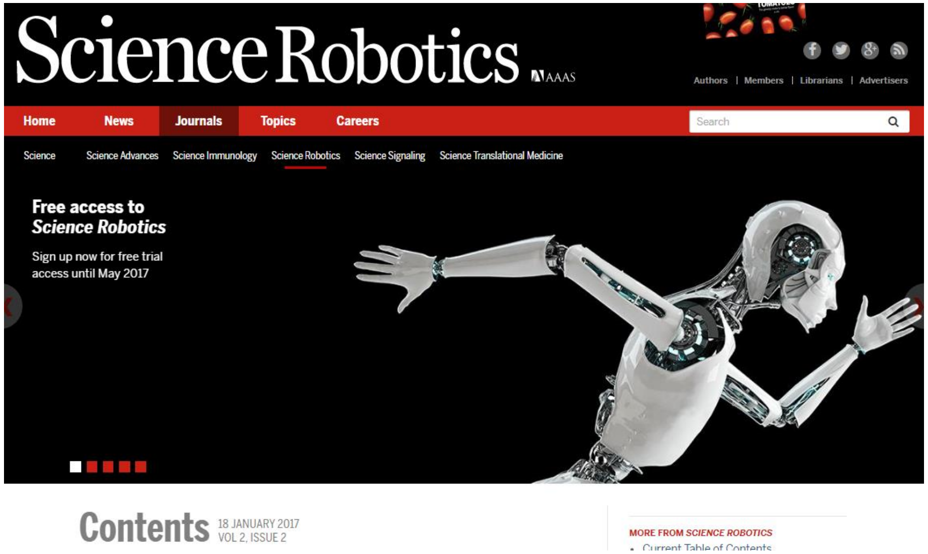
- developing robots for real-world applications
- studying biological systems by robotic platforms

Unified approach to the study of living organisms and robots

Biorobotics Science and Engineering

Biorobotics Science:
using robotics to
discover new principles...

Biorobotics Engineering:
using robotics to
invent new solutions....



Science for Robotics and Robotics for Science

Paolo Dario, Editorial Board

Scuola Superiore Sant'Anna, Pisa, Italy

One of the ambitions of *Science Robotics* is to root robotics research deeply into science. Biorobotics represents such an ambition: It keeps the living world (and thus life sciences) at its core and investigates different applications of bioinspired machines and robots, as well as validates scientific hypotheses. The power of the latter is somewhat underestimated, but in fact it may represent what really makes robotics worthy of constituting a scientific and not only a technological or engineering pursuit. Robotics science can be pursued in two different ways: the first, according to the model of synthetic science, in which engineers create new knowledge (and thus science) by addressing and solving a series of problems; the second, by using robots to unveil natural principles. The latter approach has been pursued explicitly by some seminal papers in robotics that have appeared in the past 15 years.

Bioinspiration and biomimetics

Goals of natural selection

- Survival
- Reproduction

Result of incremental adaptations

Not optimal design

"**Simply copying** a biological system is either **not feasible** (even a single neuron is too complicated to be synthesized artificially in every detail) or is **of little interest** (animals have to satisfy multiple constraints that do not apply to robots, such as keeping their metabolism running and getting rid of parasites), or **the technological solution is superior** to the one found in nature (for example, the biological equivalent of the wheel has yet to be discovered).

Rather, the goal is to work out **principles** of biological systems and transfer those to robot design."

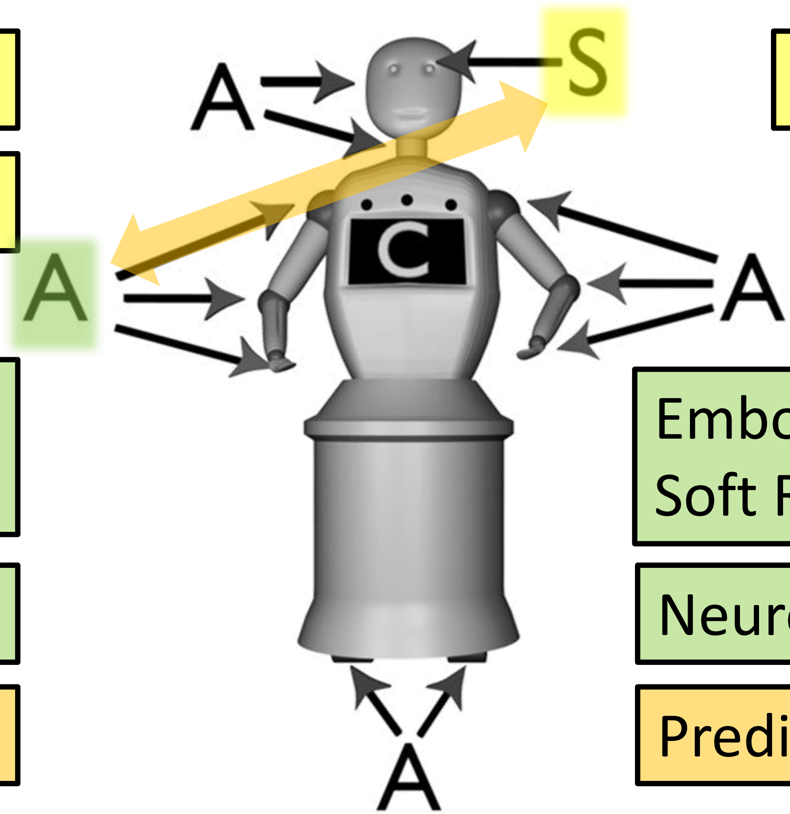
Rolf Pfeifer

R. Pfeifer, M. Lungarella, F. Iida (2007). "Self-Organization, Embodiment, and Biologically Inspired Robotics", *Science* 318, 1088

Summary of bioinspired approaches to robotics (in this course…)

Robot vision

Robot sensors



Bioinspired vision

Robot mechanics and kinematics

Robot control

Robot behaviour

Embodied Intelligence, Soft Robotics

Neurocontrollers

Predictive behaviour

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Summary of bioinspired approaches to robotics (in this course…)

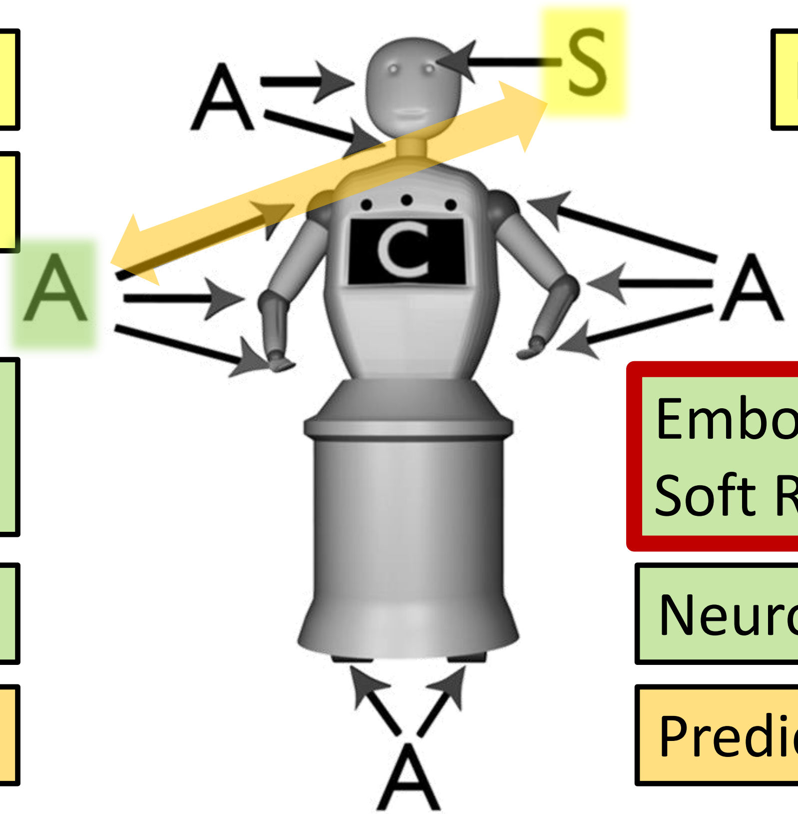
Robot vision

Robot sensors

Robot mechanics and kinematics

Robot control

Robot behaviour



Bioinspired vision

Embodied Intelligence, Soft Robotics

Neurocontrollers

Predictive behaviour

Embodied Intelligence: the modern view of Artificial Intelligence

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Classical approach
The focus is on the brain and central processing

Modern approach
The focus is on interaction with the environment. Cognition is emergent from system-environment interaction

Rolf Pfeifer and Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Properties of complete agents

1. *They are subject to the laws of physics* (energy dissipation, friction, gravity).
2. *They generate sensory stimulation* through motion and generally through interaction with the real world.
3. *They affect the environment* through behavior.
4. *They are complex dynamical systems* which, when they interact with the environment, have *attractor states*.
5. *They perform morphological computation.*

These properties are simply unavoidable consequences of **embodiment**.

These are also the properties that can be exploited for generating behavior, and how this can be done is specified in the design principles.

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Properties of complete agents

1. *A complete agent is subject to the laws of physics.*

Walking requires energy, friction, and gravity in order to work. Because the agent is embodied, it is a physical system (biological or not) and thus subject to the laws of physics from which it cannot possibly escape; it must comply with them. If an agent jumps up in the air, gravity will inevitably pull it back to the ground.

Properties of complete agents

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2. *A complete agent generates sensory stimulation.*

When we walk, we generate sensory stimulation, whether we like it or not: when we move, objects seem to flow past us (this is known as optic flow);

by moving we induce wind that we then sense with our skin and our hair;

walking also produces pressure patterns on our feet;

and we can feel the regular flexing and relaxing of our muscles as our legs move.

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Properties of complete agents

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3. *A complete agent affects its environment.*
When we walk across a lawn, the grass is crushed underfoot;
when we breathe, we blow air into the environment;
when we walk and burn energy, we heat the environment;
when we drink from a cup, we reduce the amount of liquid in the glass;
when we drop a cup it breaks;
when we talk we put pressure waves out into the air;
when we sit down in a chair it squeaks and the cushion is squashed.

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Properties of complete agents

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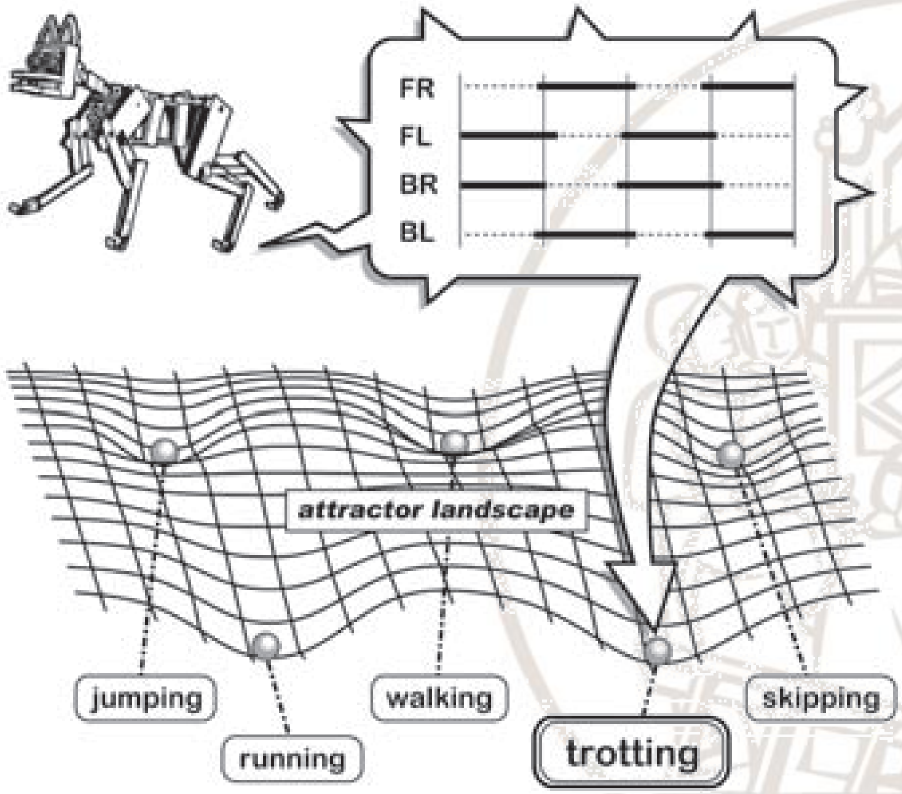
4. *Agents tend to settle into attractor states.*
Agents are dynamical systems, and as such they have a tendency to settle into so-called attractor states. Horses, for example, can walk, trot, canter, and gallop, and we—or at least experts—can clearly identify when the horse is in one of these walking modes, or gaits, the more technical word for these behaviors.
These gaits can be viewed as **attractor states**. The horse is always in one of these states, except for short periods of time when it transitions between two of them, for example from canter to gallop.
We should point out here that the attractor states into which an agent settles are always the result of the interaction of three systems: the agent's body, its brain (or control system), and its environment.



Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Properties of complete agents

5. *Complete agents perform morphological computation.*

By “morphological computation” we mean that certain processes are performed by the body that otherwise would have to be performed by the brain.

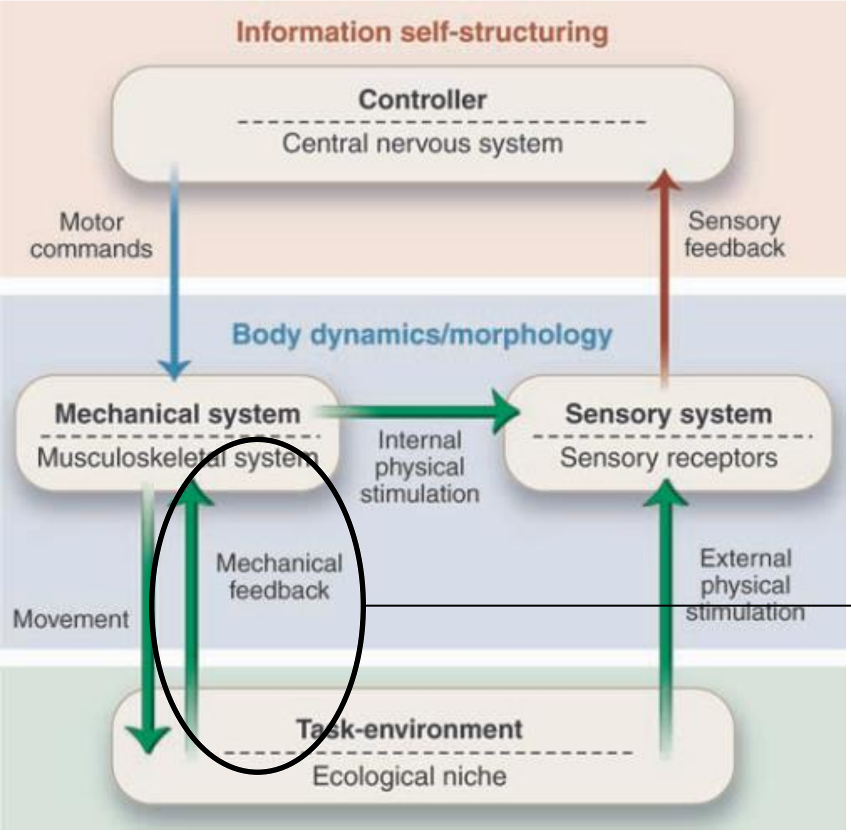
An example is the fact that the human leg’s muscles and tendons are elastic so that the knee, when the leg impacts the ground while running, performs small adaptive movements without neural control.

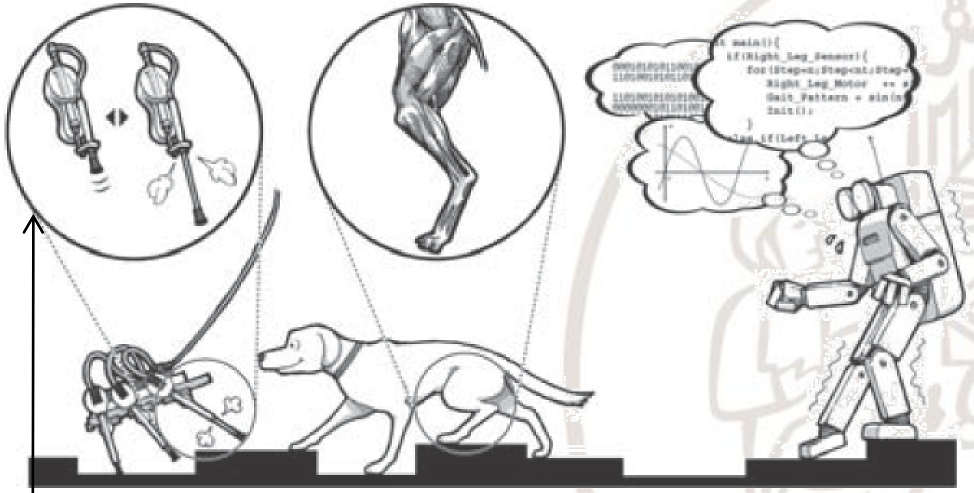
The control is supplied by the muscle-tendon system itself, which is part of the morphology of the agent.

It is interesting to note that systems that are not complete, in the sense of the word used here, hardly ever possess all of these properties. For example, a vision system consisting of a fixed camera and a desktop computer does not generate sensory stimulation because it cannot produce behavior, and it influences the environment only by emitting heat and light from the computer screen. Moreover, it does not perform morphological computation and does not have physical attractor states that could be useful to the system.

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Morphological computation

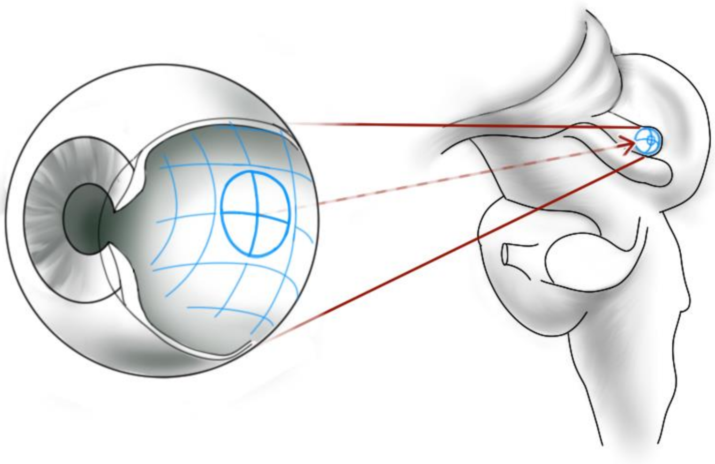


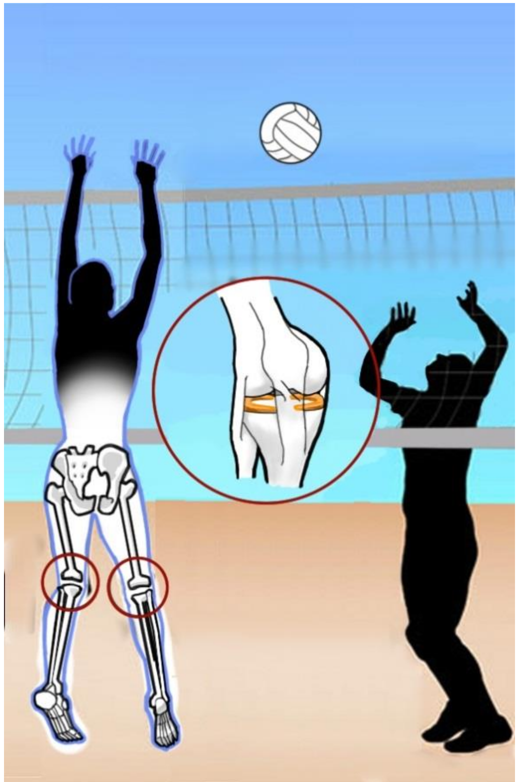


Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Morphological Computation

As any transformation of information can be named as *computing*, *Morphological Computation* endows all those behaviours where computing is mediated by the mechanical properties of the physical body





The arrangement
of the motor, perceptive and processing units

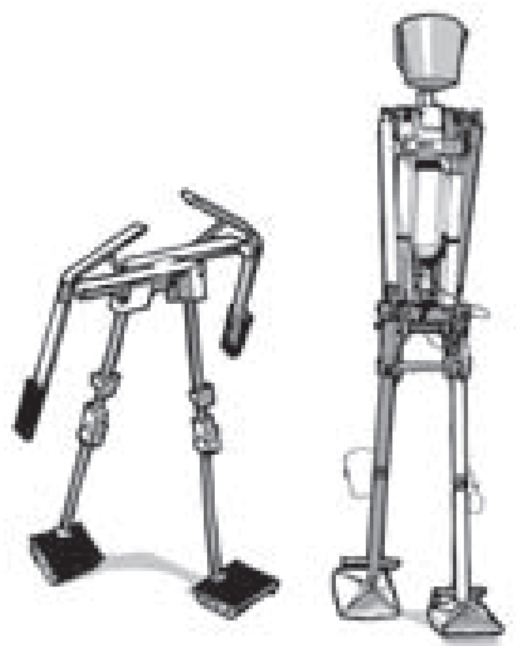
The shape
as body structure, specifies the behavioral response of the agent

The mechanical properties
allow emergent behaviors and highly adaptive interaction with the environment

Zambrano D, Cianchetti M, Laschi C (2014) "The Morphological Computation Principles as a New Paradigm for Robotic Design" in *Opinions and Outlooks on Morphological Computation*, H. Hauser, R. M. Füchslin, R. Pfeifer (Ed.s), pp. 214-225.

Morphological Computation …more precisely

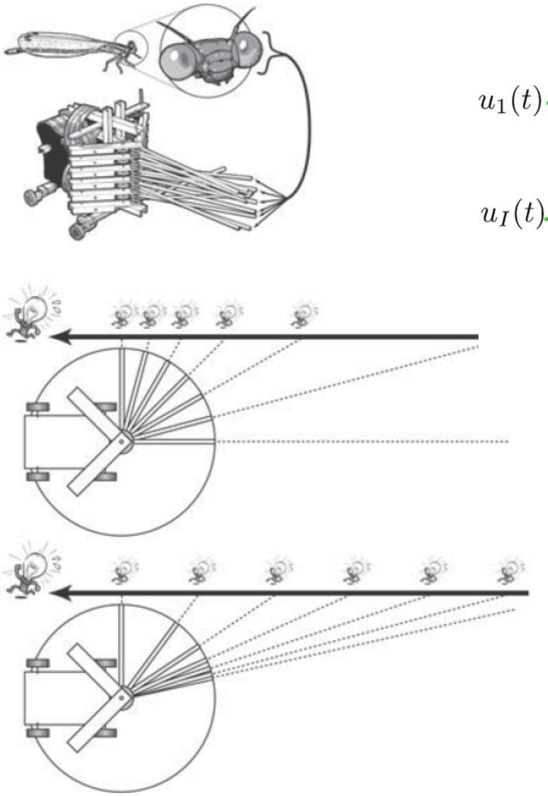
A) Morphology facilitating control



Passive walker

http://www.space-eight.com/walker.html

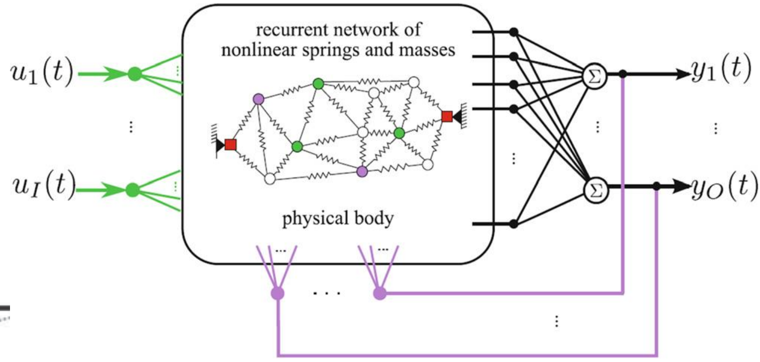
B) Morphology facilitating perception



Compound eyes

Objects nearby move faster across the visual field than objects farther away

C) Morphological Computation



Reservoir computing
Physical body acts as a reservoir

V.C. Muller, M. Hoffmann, "What is morphological computation? On how body contributes to congnition and control", *Artificial Life* 23:1-24 (2017)

Agent Design Principle 1

The **three-costituents** principle:

- define the ecological niche — ENVIRONMENT
- define the desired behaviour and tasks — TASK
- design the agent — BODY

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Agent Design Principle 2

The **complete-agent** principle:

- think about the complete agent behaving in the real world

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

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Agent Design Principle 3

Cheap design:

- If agents are built to exploit the properties of the ecological niche and the characteristics of the interaction with the environment, their design and construction will be much easier, or 'cheaper'

Passive walker video

http://www.space-eight.com/walker.html

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Agent Design Principle 4

Redundancy:

- Intelligent agents must be designed in such a way that
  - (a) their different sub-systems function on the basis of different physical processes, and
  - (b) there is partial overlap of functionality between the different sub-systems

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Agent Design Principle 5

Sensory-Motor Coordination:

- through sensory-motor coordination, structured sensory stimulation is induced.

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

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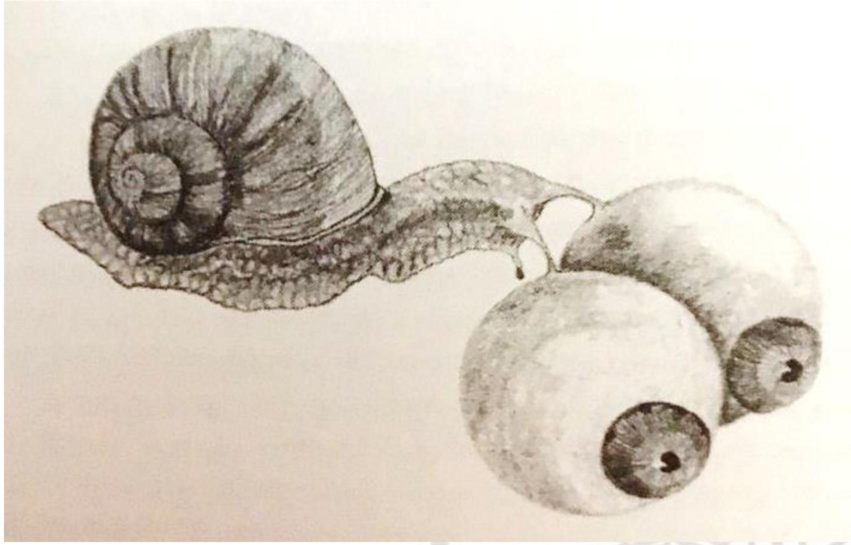
Agent Design Principle 6

Ecological balance:

1. given a certain task environment, there has to be a match between the complexities of the agent's sensory, motor, and neural systems
2. there is a certain balance or task distribution between morphology, materials, control, and environment.



From *Climbing Mount Improbable* by Dawkins. A snail with human-like, and human-sized, eyes. This snail would have a hard time carrying along these giant eyes, but more importantly, they would be only moderately useful, if at all: why bother detecting fast-moving predators if you cannot run away from them, or detecting running prey if you are vegetarian? The complexity, weight, and size of the human eyes would only constitute unnecessary baggage, an example of an entirely unbalanced system.

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Agent Design Principle 7

Parallel, loosely coupled processes:
intelligence is emergent from a large number of parallel processes that are often coordinated through embodiment, in particular via the embodied interaction with the environment

Reactive architectures

Rolf Pfeifer & Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

Agent Design Principle 8

Value:

agents are equipped with a value system which constitutes a basic set of assumptions about what is good for the agent

Embodied Intelligence and soft robotics

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Any cognitive activity arises from the ***interaction*** between the body, the brain and the environment.

Adaptive behaviour is not just control and computation, but it emerges from the complex and dynamic interaction between the morphology of the body, sensory-motor control, and environment.

<u>Many tasks become much easier if morphological computation is taken into account.</u>

=> A new soft bodyware is needed

Modern approach

The focus is on interaction with the environment. Cognition is emergent from system-environment interaction

Rolf Pfeifer and Josh C. Bongard, *How the body shapes the way we think: a new view of intelligence*, The MIT Press, Cambridge, MA, 2007

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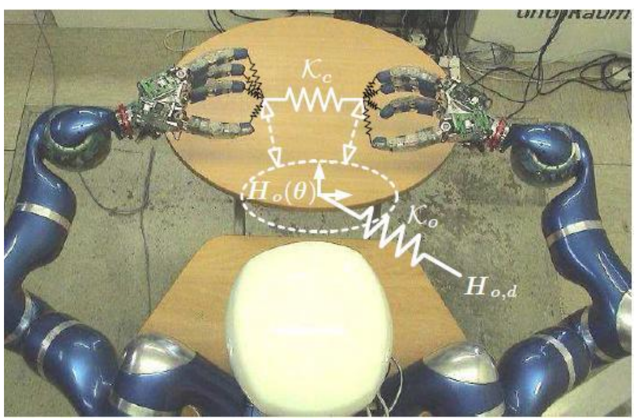
Defining Soft Robotics: a first broad classification

Variable impedance actuators and stiffness control

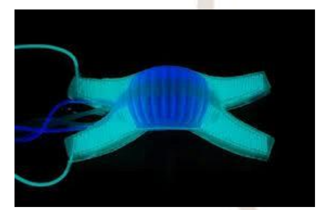
- mechanically (or passively) compliant joints with variable stiffness
- compliance or impedance control

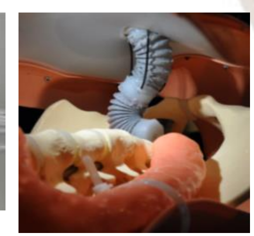


IEEE Robotics and Automation Magazine, Special Issue on Soft Robotics, 2008

Use of soft materials in robotics

- Robots made of soft materials or structures that undergo high deformations in interaction
- Soft actuators and soft components


Laschi C. and Cianchetti M. (2014) “Soft Robotics: new perspectives for robot bodyware and control” *Frontiers in Bioengineering & Biotechnology*, 2(3)

A ‘soft’ animal world

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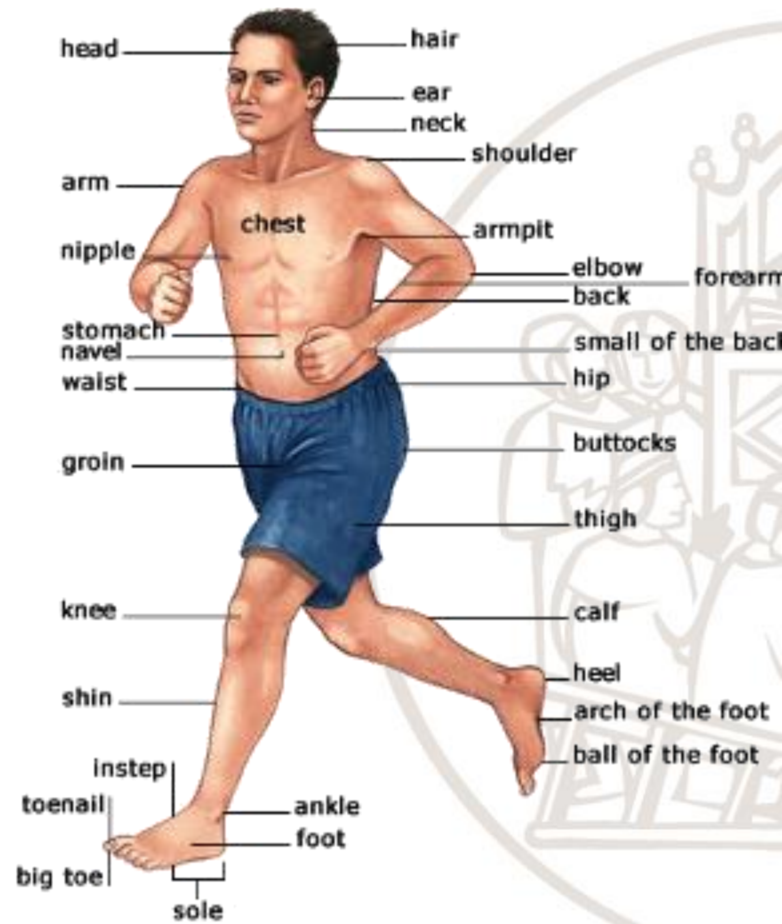
the human skeleton typically contributes only 11% of the body mass of an adult male

- The vast majority of animals are soft-bodied
- Animals with stiff exoskeletons such as insects have long-lived life stages wherein they are almost entirely soft (maggots, grubs, and caterpillars).
- Animals with stiff endoskeletons are mainly composed of soft tissues and liquids.



skeletal muscle contributes an average 42% of body mass

Kim S., Laschi C., and Trimmer B. (2013) Soft robotics: a bioinspired evolution in robotics, *Trends in Biotechnology*, April 2013.

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A ‘soft’ animal world

- Soft animals tend to be **small** because it is difficult for them to support their own body weight without a skeleton.
- All of the extremely large soft invertebrates are found either
  - **in water** (squid and jellyfish) or
  - **underground** (giant earthworms),

  where their body is supported by the surrounding medium.

Kim S., Laschi C., and Trimmer B. (2013) Soft robotics: a bioinspired evolution in robotics, *Trends in Biotechnology*, April 2013.

Defining Soft Robotics

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- "Soft-bodied robots", in analogy with soft-bodied animals

Kim S., Laschi C., and Trimmer B. (2013) Soft robotics: a bioinspired evolution in robotics, *Trends in Biotechnology*, April 2013.

- "Robots built with soft materials"

Laschi C. and Cianchetti M. (2014) "Soft Robotics: new perspectives for robot bodyware and control" *Frontiers in Bioengineering & Biotechnology*, 2(3)

Defining Soft Robotics

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- "systems that are capable of autonomous behavior, and that are primarily composed of materials with moduli in the range of that of soft biological materials"

D. Rus, M. T. Tolley, Design, fabrication and control of soft robots. *Nature* 521, 467-475 (2015).

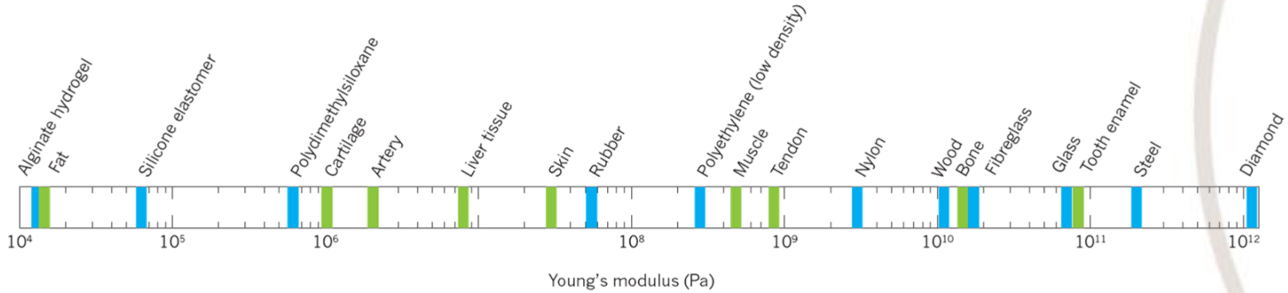

Figure 2 | Approximate tensile modulus (Young's modulus) of selected engineering and biological materials. Soft robots are composed primarily of materials with moduli comparable with those of soft biological materials (muscles, skin, cartilage, and so on), or of less than around 1 gigapascal. These materials exhibit considerable compliance under normal loading conditions.

- "soft-matter robotics", based on the well-known concept of "soft matter" used for materials

L. Wang, F. Iida, Deformation in Soft-Matter Robotics: A Categorization and Quantitative Characterization. *IEEE Robotics & Automation Magazine* 22(3), 125-139 (2015).

Defining Soft Robotics

RoboSoft

First RoboSoft Working Paper – September 2014

On the basis of the above statements, the RoboSoft community proposed and agreed on the following definition of Soft Robotics:

> *"Soft robot/devices that can actively interact with the environment and can undergo 'large' deformations relying on inherent or structural compliance"*

Definition of Soft Robotics by RoboSoft Community

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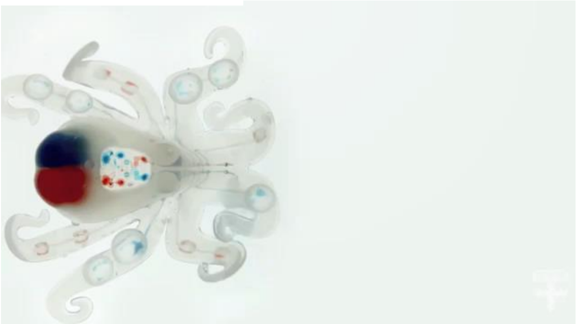
RoboSoft is a Coordination Action on Soft Robotics funded by the European Commission.
The RoboSoft Community accounts for 34 member institutions for a total of 100+ scientists

"Soft robot/devices that can actively interact with the environment and can undergo 'large' deformations relying on inherent or structural compliance"

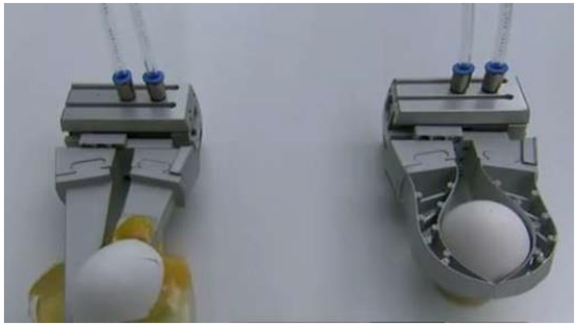
Soft Robotics may exploit materials which present:

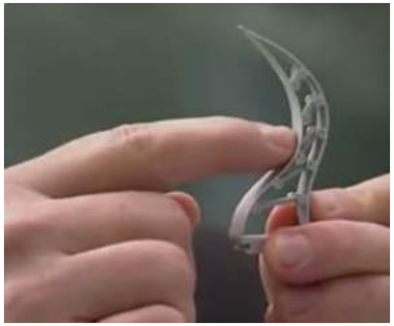
- INHERENT MATERIAL compliance: bulk material properties (elastomers, low elastic modulus polymers, gels…)



M. Wehner, R.L. Truby, D.J. Fitzgerald, B. Mosadegh, G.M. Whitesides, J.A. Lewis, R.J. Wood, An integrated design and fabrication strategy for entirely soft, autonomous robots, *Nature* 536, 451–455

- STRUCTURAL compliance: geometric features or arrangement can allow magnified strains compared with local material deformation





Low Elastic Modulus → **Soft Robotics**

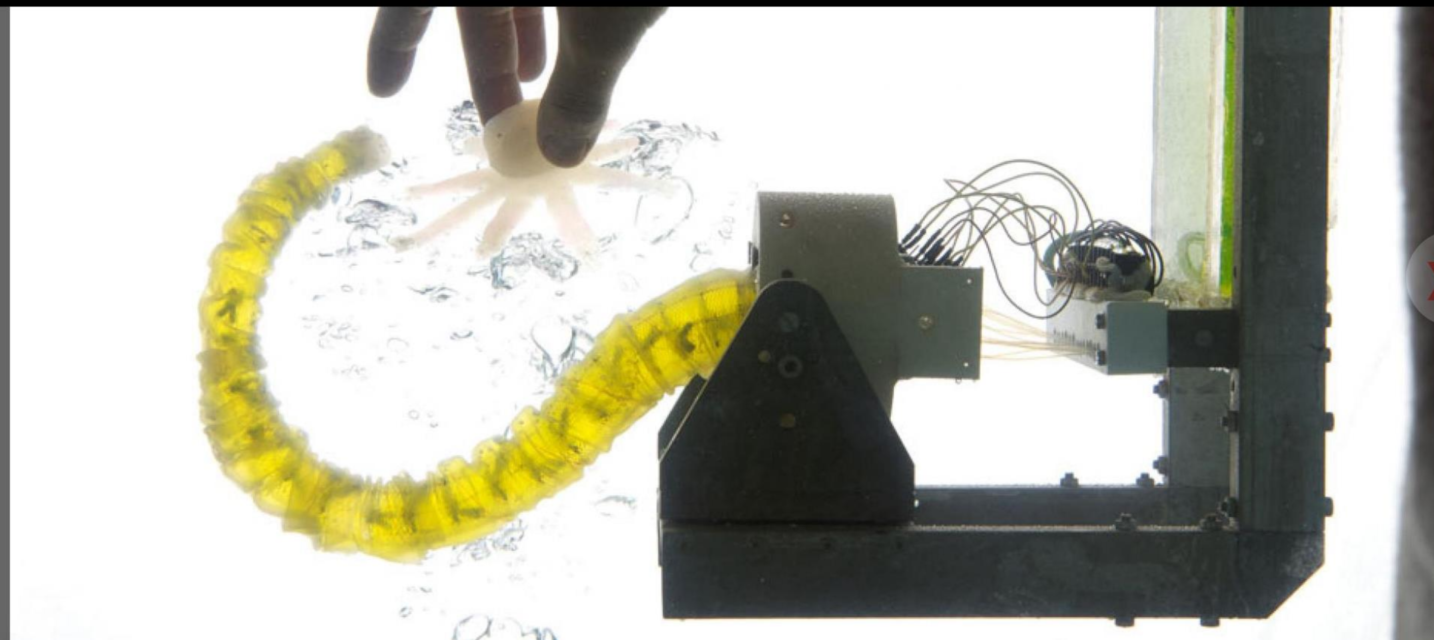
Geometry

High Elastic Modulus → **Hard Robotics**

Softness is a strength

Soft robotics expand the boundaries of robot abilities

Massimo Brega/Kepach Production



REVIEW | SOFT ROBOTICS

Soft robotics: Technologies and systems pushing the boundaries of robot abilities

Cecilia Laschi[1,*], Barbara Mazzolai[2] and Matteo Cianchetti[1]

+ Author Affiliations

*Corresponding author. Email: cecilia.laschi@sssup.it

Science Robotics 06 Dec 2016:
Vol. 1, Issue 1,
DOI: 10.1126/scirobotics.aah3690

PRE Peer Reviewed ← see details

Science Robotics

Vol 1, Issue 1
06 December 2016

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Summary of bioinspired approaches to robotics (in this course…)

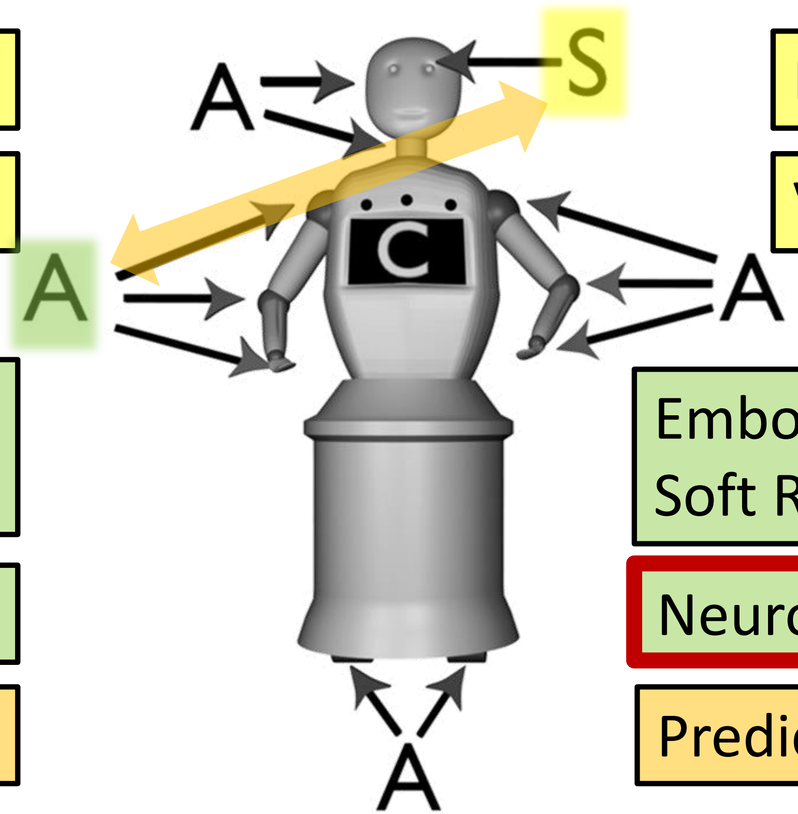
Robot vision

Robot sensors

Robot mechanics and kinematics

Robot control

Robot behaviour



Bioinspired vision

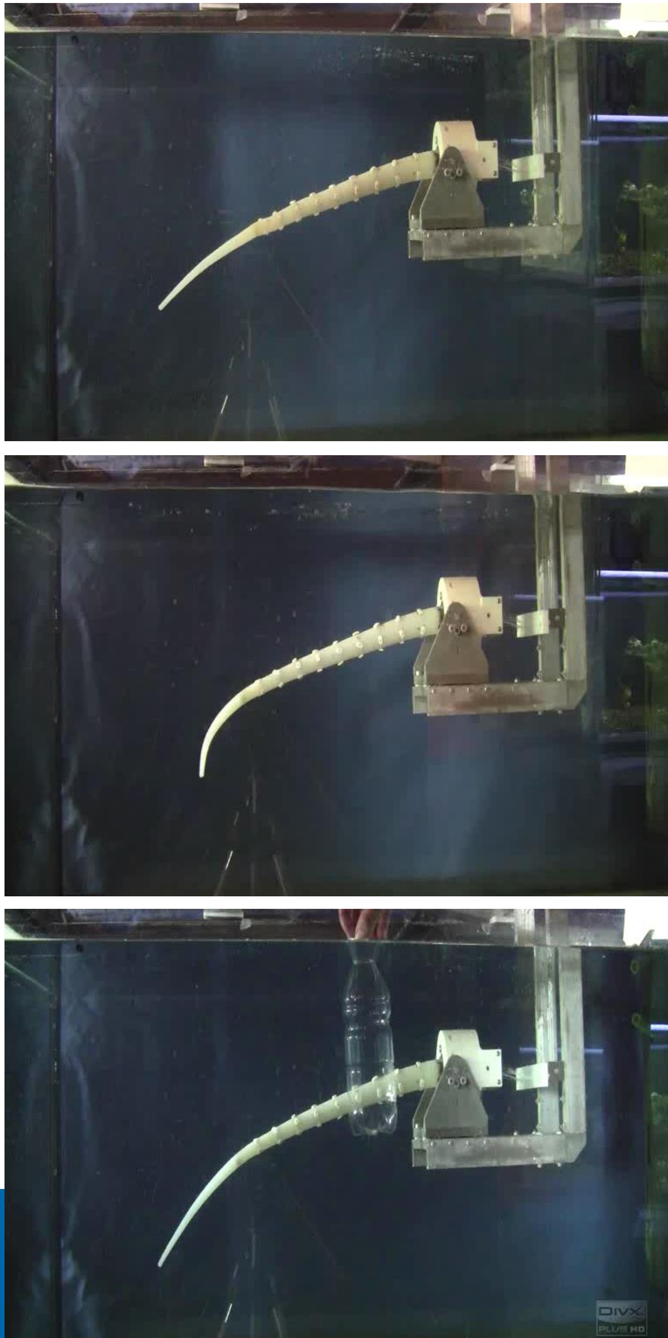
Vestibular system

Embodied Intelligence, Soft Robotics

Neurocontrollers

Predictive behaviour

Octopus-inspired robot arm



- Silicone
- 9 sections of transverse and longitudinal cables (coupled)
- Cables pulled by electric motors
- Simple activation pattern: sequential activation of sections, with equal activation of 4 longi-transverse cables per section

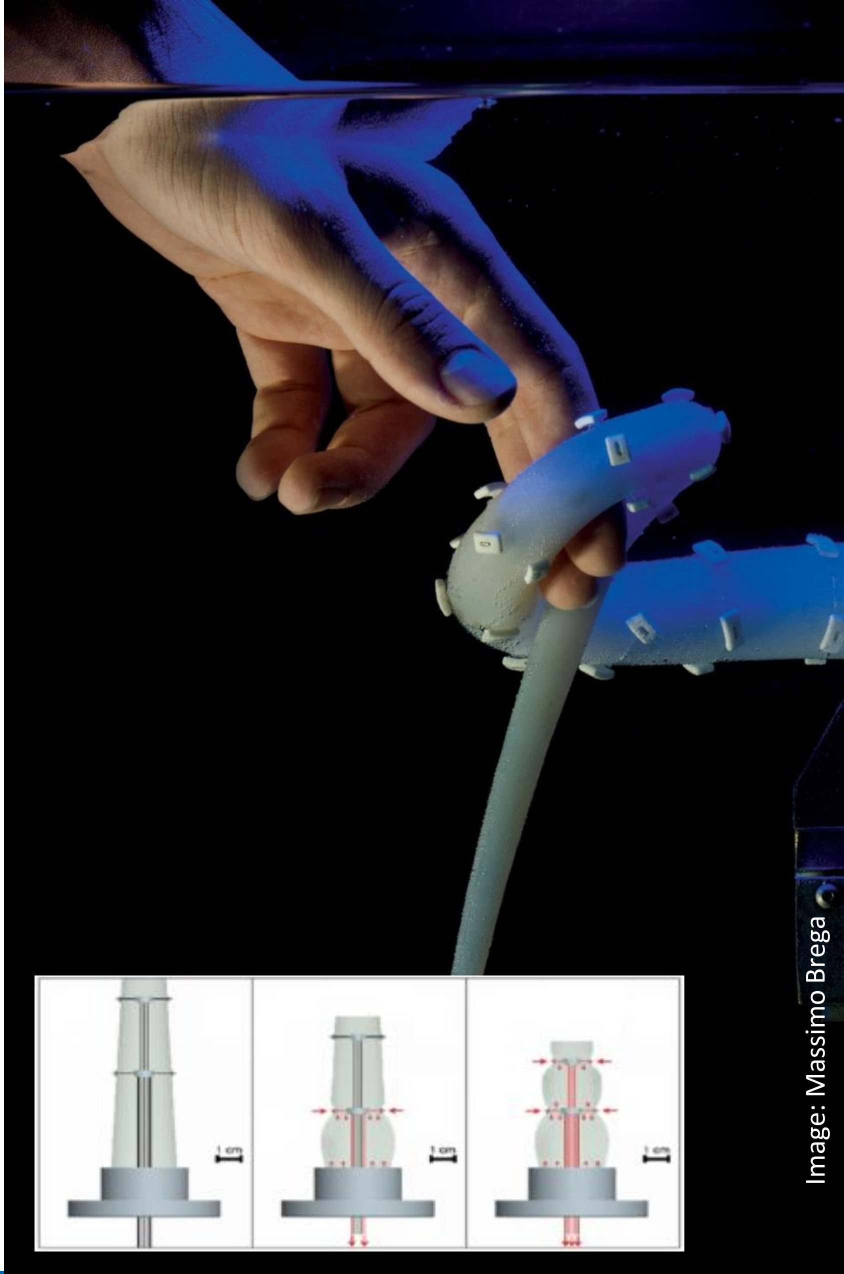
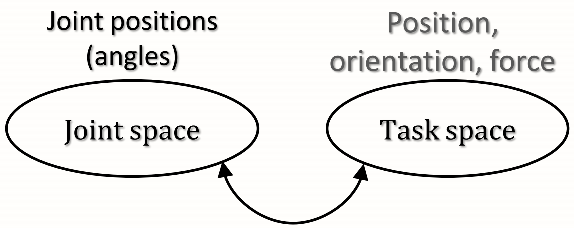


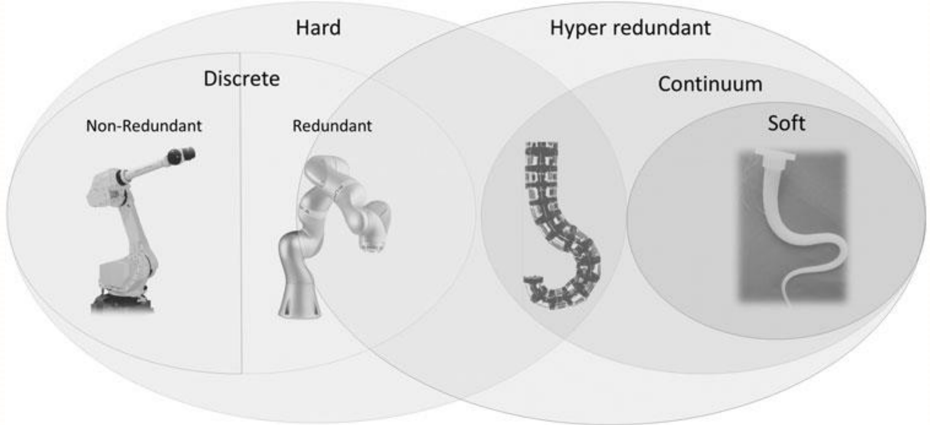
Image: Massimo Brega

Cianchetti, M., Arienti, A., Follador, M., Mazzolai, B., Dario, P., Laschi, C. “Design concept and validation of a robotic arm inspired by the octopus”, *Materials Science and Engineering C*, Vol.31, 2011, pp.1230-1239.

Soft robot control

FROM:





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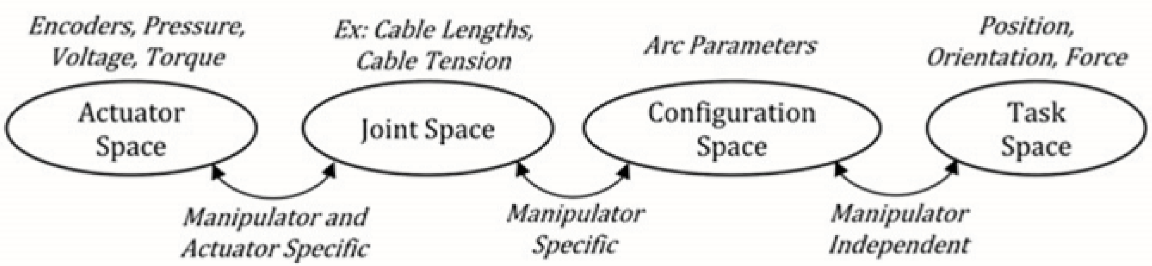


Model–based Approaches

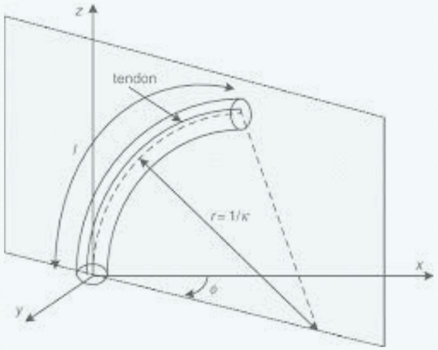
Model–Free (learning-based) approaches

T. George Thuruthel, Y. Ansari, E. Falotico, C. Laschi (2018) "Control Strategies for soft robotic manipulators: a survey", *Soft Robotics* 5(2)

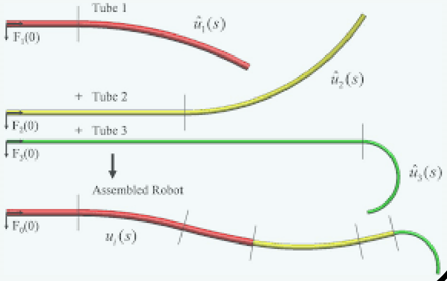
Model-based approaches for soft robot control

Continuous-functions

Constant Curvature Model

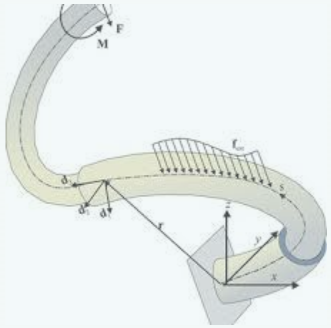


Piecewise Constant Curvature

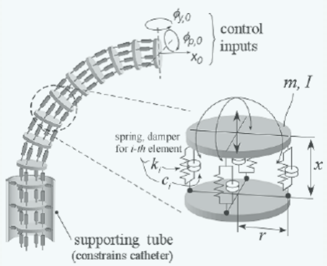


Discretized-functions

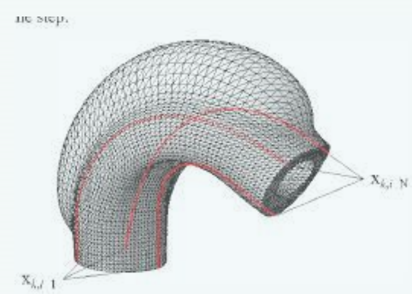
Cosserat-Rod Model



Lumped-Parameter Model



Finite Element Method



Increasing Computational Complexity and ‘Accuracy’

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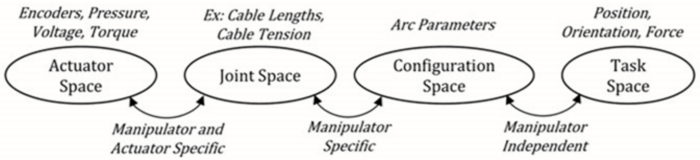
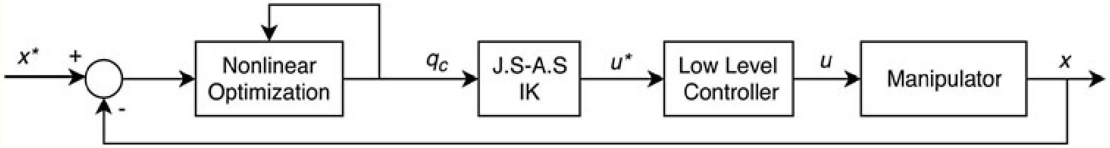
Model-based approaches for soft robot control

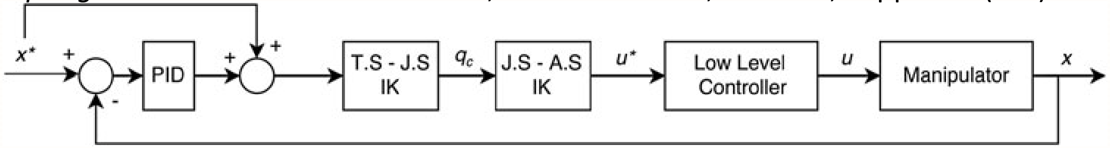


Based on CC modeling



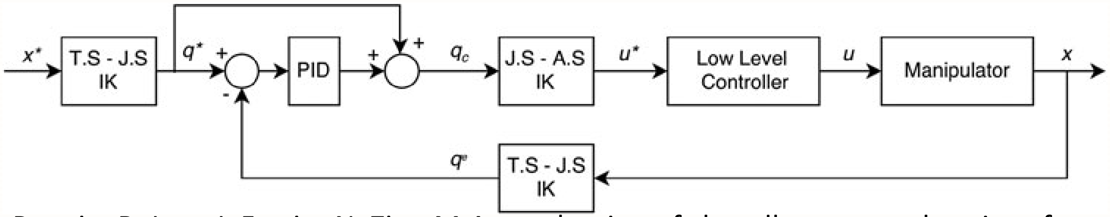
Closed-loop task space controller

Camarillo DB, Carlson CR, Salisbury JK. Task-space control of continuum manipulators with coupled tendon drive. In: *Experimental Robotics. Springer Tracts in Advanced Robotics*, vol 54. Khatib O, Kumar V, Pappas GJ (Eds). Berlin, Heidelberg; Springer: 2009, pp. 271–280.



Closed-loop controller in task space

Bajo A, Goldman R, Simaan N. Configuration and joint feedback for enhanced performance of multi-segment continuum robots. *2011 IEEE International Conference on Robotics and Automation (ICRA)*, Shanghai, China, 2011.



Closed-loop controller in joint space

PenningR, Jung J, Ferrier N, Zinn M.An evaluation of closedloop control options for continuum manipulators. *2012 IEEE International Conference on Robotics and Automation (ICRA)*, Saint Paul, MN, 2012.

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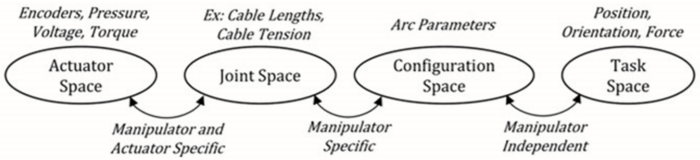
Model-based approaches for soft robot control



Discussion:

- Most widely used in quasi static conditions
- Mostly relying on CC approximation
- More complex models are computationally expensive

- Need for alternative methods, better addressing the complexity of soft robot control, at affordable computational cost

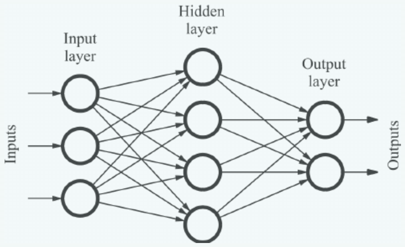
=> model-free approaches

T. George Thuruthel, Y. Ansari, E. Falotico, C. Laschi (2018) "Control Strategies for soft robotic manipulators: a survey", *Soft Robotics* 5(2)

Model-free approaches for soft robot control

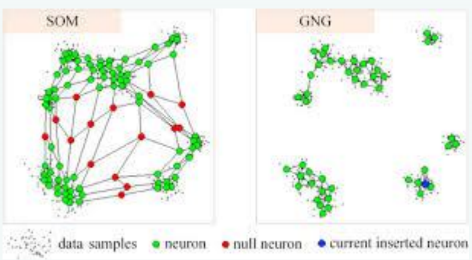
Supervised-learning

Feed-forward Neural Networks

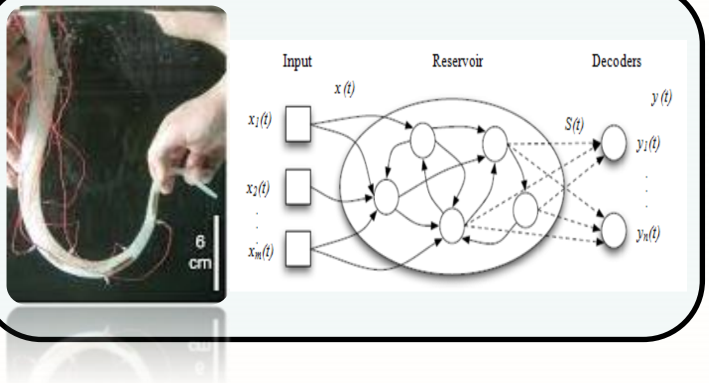


Unsupervised Learning

SOM and Growing Neural Gas

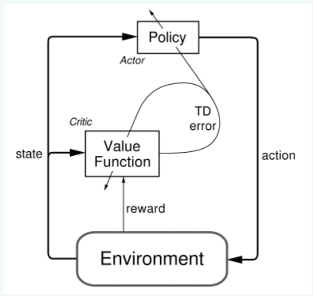


Reservoir computing

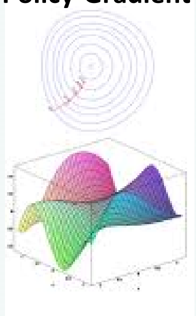


Reinforcement Learning

Actor-Critic



Policy-Gradient



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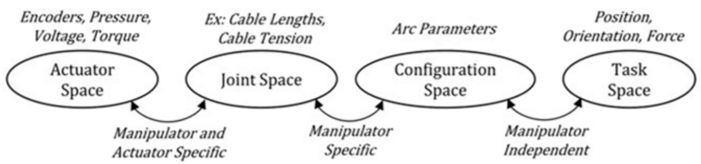
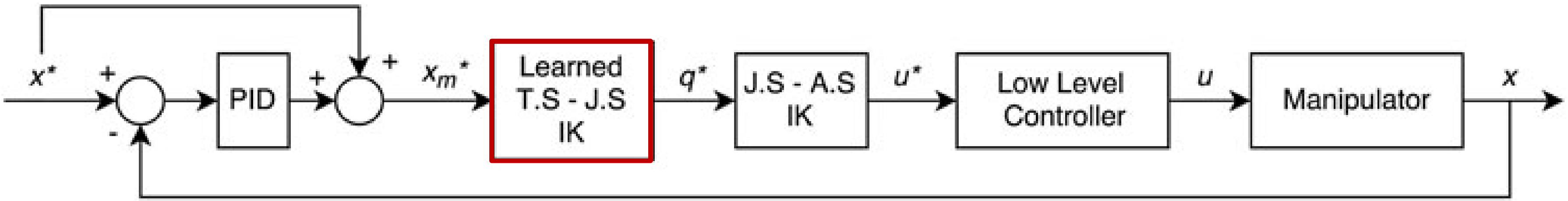
Model-free approaches for soft robot control



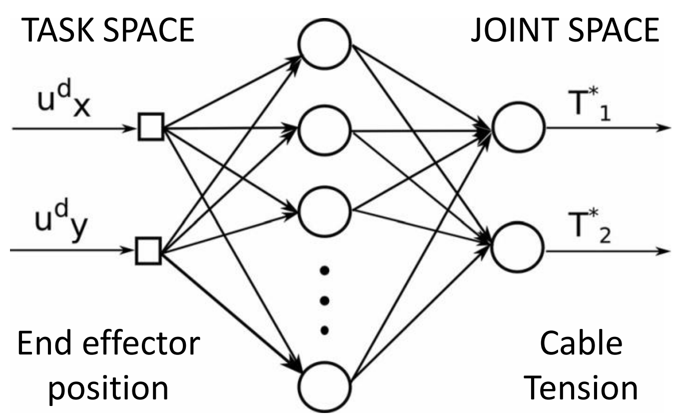
Model-free closed-loop task space controller



Rolf M, Steil JJ. Efficient exploratory learning of inverse kinematics on a bionic elephant trunk. *IEEE Trans Neural Netw Learn Syst* 2014;25:1147–1160.

Learning-based Control, by learning the inverse model.

Learning by collecting points and exploiting the approximation capability of a FNN, as for rigid robots



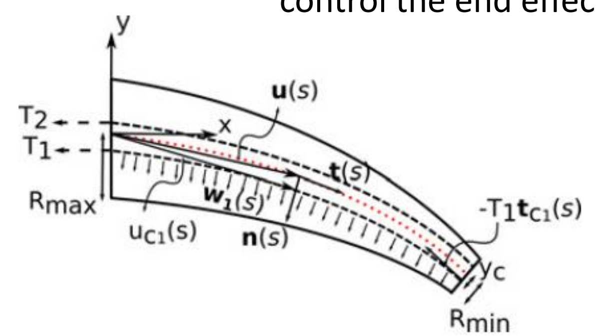
Giorelli M, Renda F, Calisti M, Arienti A, Ferri G, Laschi C. Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Trans Robot* 2015;31:823–834.
Giorelli M, Renda F, Calisti M, Arienti A, Ferri G, Laschi C. Learning the inverse kinetics of an octopus-like manipulator in three-dimensional space. *Bioinspir Biomim* 2015; 10:035006.

T. George Thuruthel, Y. Ansari, E. Falotico, C. Laschi (2018) “Control Strategies for soft robotic manipulators: a survey”, *Soft Robotics* 5(2)

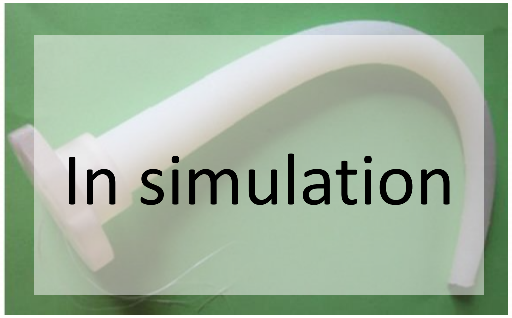
Comparison of a model-based and a model-free approaches

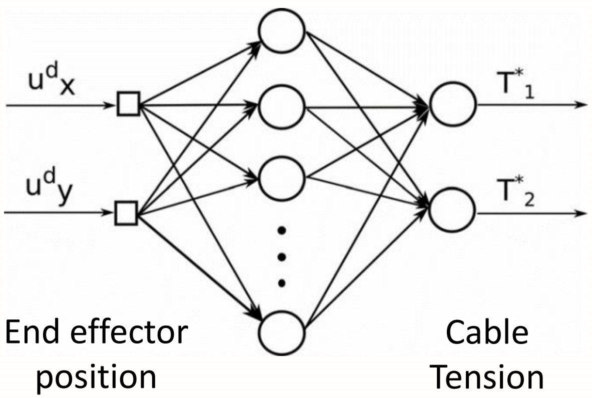
1. Jacobian-based Inverse Static Controller
2. Learning-based Control, by learning the inverse model.

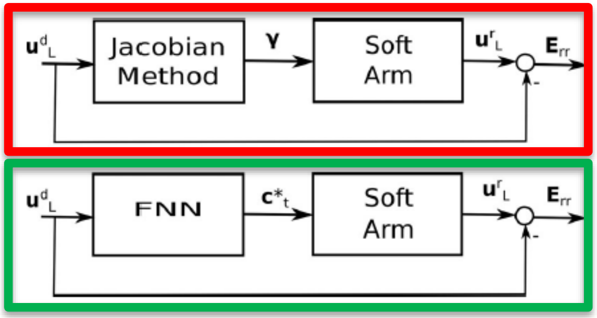
control the end effector position through the cable tension



Cosserat-based model







Method (Cost)	Statistics Index	ERR/L [%]
JM (351ms)	Mean	0.27
	Std	0.03
	Max	0.32
NN (0.125ms)	Mean	0.73
	Std	0.55
	Max	3.1

Giorelli, M., Renda, F., Calisti, M., Arienti, A., Ferri, G., & Laschi, C. (2015). Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Transactions on Robotics*, *31*(4), 823-834.

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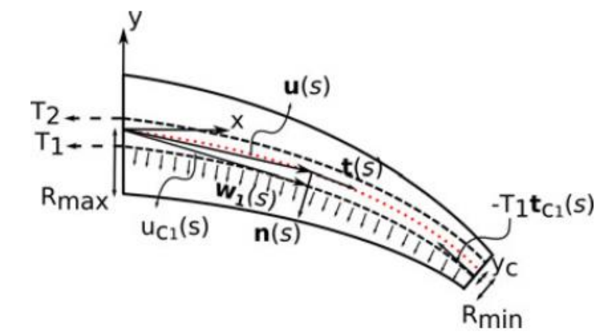
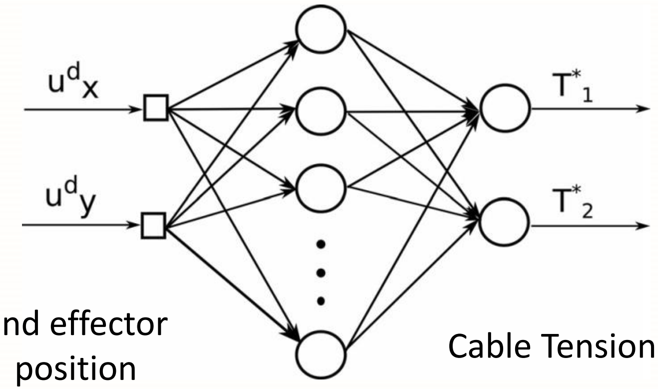
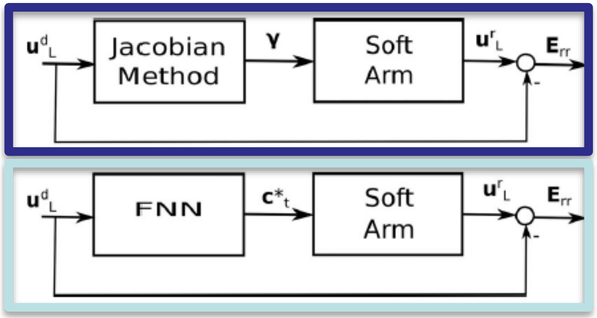


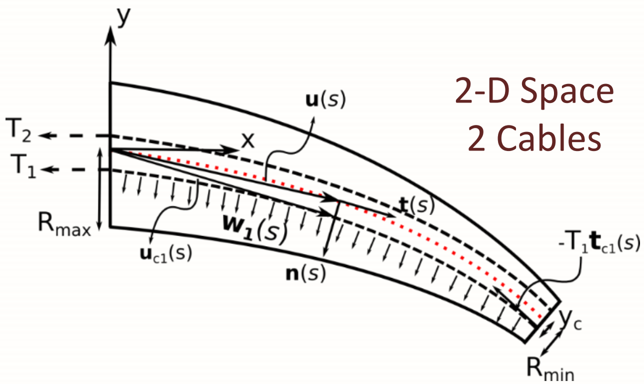




Method		Absolute (mm)	Percentage (%)
Jacobian method	*mean*	15.12	5.4
	std	8.10	2.89
	max	31.76	11.34
	$p_{\%}$		43.18
FNN	*mean*	7.35	2.62
	std	4.75	1.7
	max	22.22	7.94
	$p_{\%}$		91

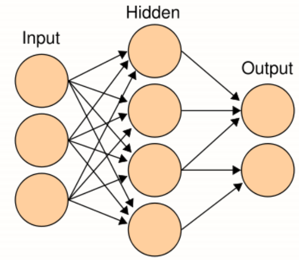
Giorelli, M., Renda, F., Calisti, M., Arienti, A., Ferri, G., & Laschi, C. (2015). Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Transactions on Robotics*, *31*(4), 823-834.

Comparison of a model-based and a model-free approaches



2-D Space
2 Cables

Tip Position



Cable Forces

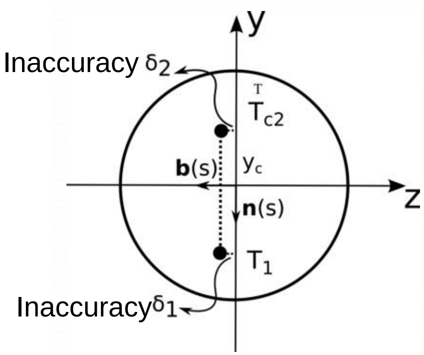
Increasing inaccuracy values

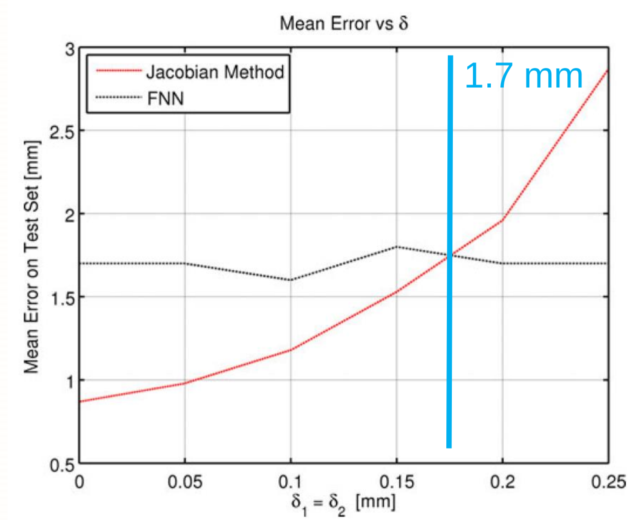
Case	δ_1	δ_2	Jacobian *mean*	FNN *mean*
1	−0.25	0.25	1.02	1.5
2	0.25	0	1.26	1.8
3	0	0	0.87	1.7
4	0.05	0.05	0.98	1.7
5	0.1	0.1	1.18	1.6
6	0.15	0.15	1.53	1.8
7	0.2	0.2	1.96	1.7
8	0.25	0.25	2.87	1.7

Inaccuracies

All values are expressed in millimeters.

Simulated Defective Model





Giorelli, M., Renda, F., Calisti, M., Arienti, A., Ferri, G., & Laschi, C. (2015). Neural network and Jacobian method for solving the inverse statics of a cable-driven soft arm with nonconstant curvature. *IEEE Transactions on Robotics*, *31*(4), 823-834.

Inverse Kinematic Controller

Kinematics: based on steady state assumptions

$\dot{x} = J(q)\dot{q} \;\Rightarrow\; \Delta x \approx J(q)\Delta q$

Learning a **Differential Inverse Kinematics** formulation : $\dot{\boldsymbol{x}} = J(\boldsymbol{q^o})\,\dot{\boldsymbol{q}}$

This allows for redundancy resolution, robustness to modelling errors

The learned mapping is : $(\boldsymbol{x}_{i+1}, \boldsymbol{q}_i, \boldsymbol{x}_i) \rightarrow (\boldsymbol{q}_{i+1})$

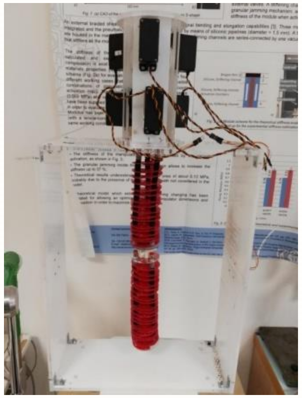
LEARNING

- 2000 sample points divided in the ratio 70:30 for training and testing respectively
- 2 hours for data collection, training, set-up

TESTS

25 random points selected from workspace

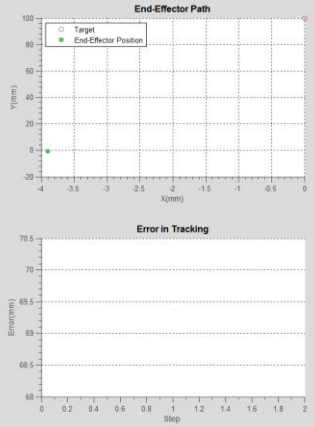
	Mean Error	Standard Deviation
Position (mm)	5.58	3.08
X- axis rotation (degrees)	2.76	5.42
Y- axis rotation (degrees)	1.84	1.83
Z- axis rotation (degrees)	3.85	7.02



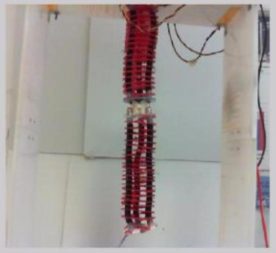
I-Support Prototype

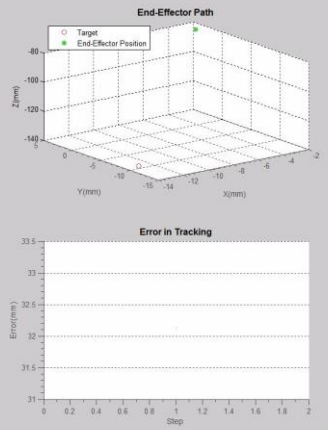
Six DoF Hybrid System (Pneumatic and Tendon)

Line Following



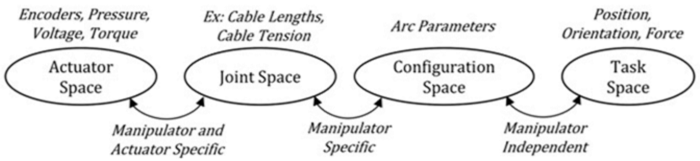
Disturbance Rejection





George Thuruthel T, Falotico E., et al. "Learning closed loop kinematic controllers for continuum manipulators in unstructured environments." *Soft robotics* 4.3 (2017): 285-296.

Model-free approaches for soft robot control



Discussion:

- No need for defining the parameters of the configuration space or joint space
- Independent from manipulator shape
- Arbitrarily complex kinematic models, depending on sample data and sensory noise
- Better performance with highly nonlinear, non-uniform, gravity-influenced systems
- Suitable for unstructured environments where modelling is almost impossible

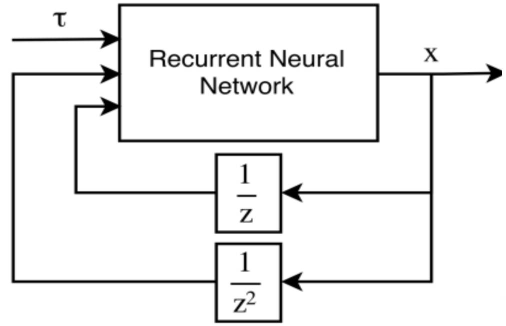
Better encoding of morphological computation?

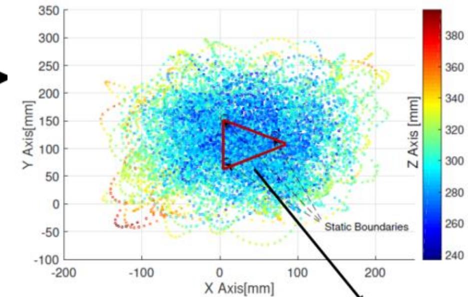
Dynamic Controllers – open loop

Controlling the soft manipulator both in space and time

$(\boldsymbol{\tau}, \boldsymbol{x}, \dot{\boldsymbol{x}}) \rightarrow \ddot{\boldsymbol{x}}$

$(\boldsymbol{\tau}, \boldsymbol{x}^{i}, \boldsymbol{x}^{i-1}) \rightarrow \boldsymbol{x}^{i+1}$





Static workspace

Sampling

Slow circle task

Fast circle task

Thuruthel, T. G., Manti, M., Falotico, E., Laschi, C. 2018. "Stable Open Loop Control of Soft Robotic Manipulators." *IEEE Robotics and Automation Letters* 3(2):1292-1298.

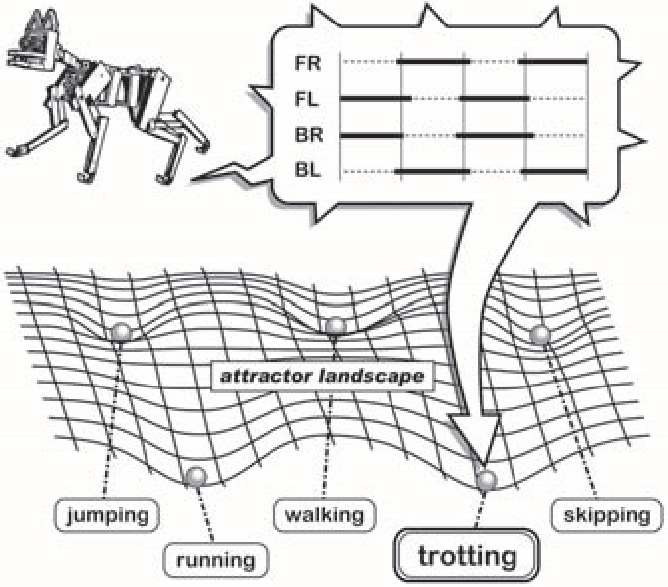
Self-Stabilizing Trajectories


THE BIOROBOTICS INSTITUTE
Scuola Superiore Sant'Anna

Stable Open Loop Control of Soft Robotic Manipulators

Thomas George Thuruthel, Egidio Falotico, Mariangela Manti and Cecilia Laschi, Senior Member, IEEE

The unique dynamics of a soft manipulator exhibits larger number of dynamic attractors that can be used for stable open loop control



Thuruthel T. G., Falotico E., Manti M., Laschi C. (2018). Stable Open Loop Control of Soft Robotic Manipulators. *IEEE Robotics and Automation Letters*, *3*(2), 1292-1298.

Summary of bioinspired approaches to robotics (in this course...)

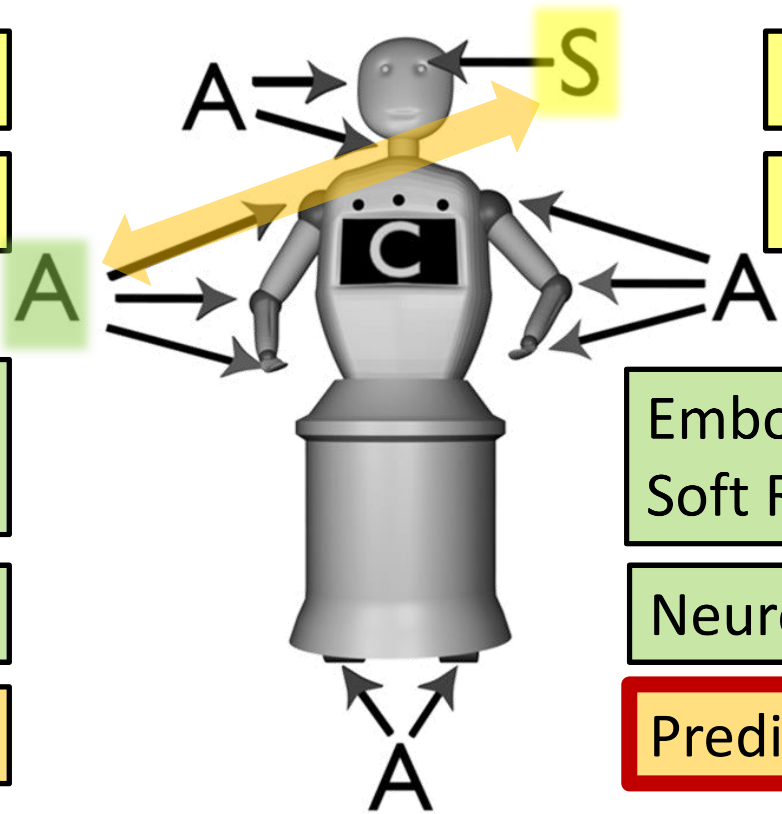
Robot vision

Robot sensors

Robot mechanics and kinematics

Robot control

Robot behaviour



Bioinspired vision

Vestibular system

Embodied Intelligence, Soft Robotics

Neurocontrollers

Predictive behaviour

Behaviour: Perception-Action loops
Robotics perception and action architectures

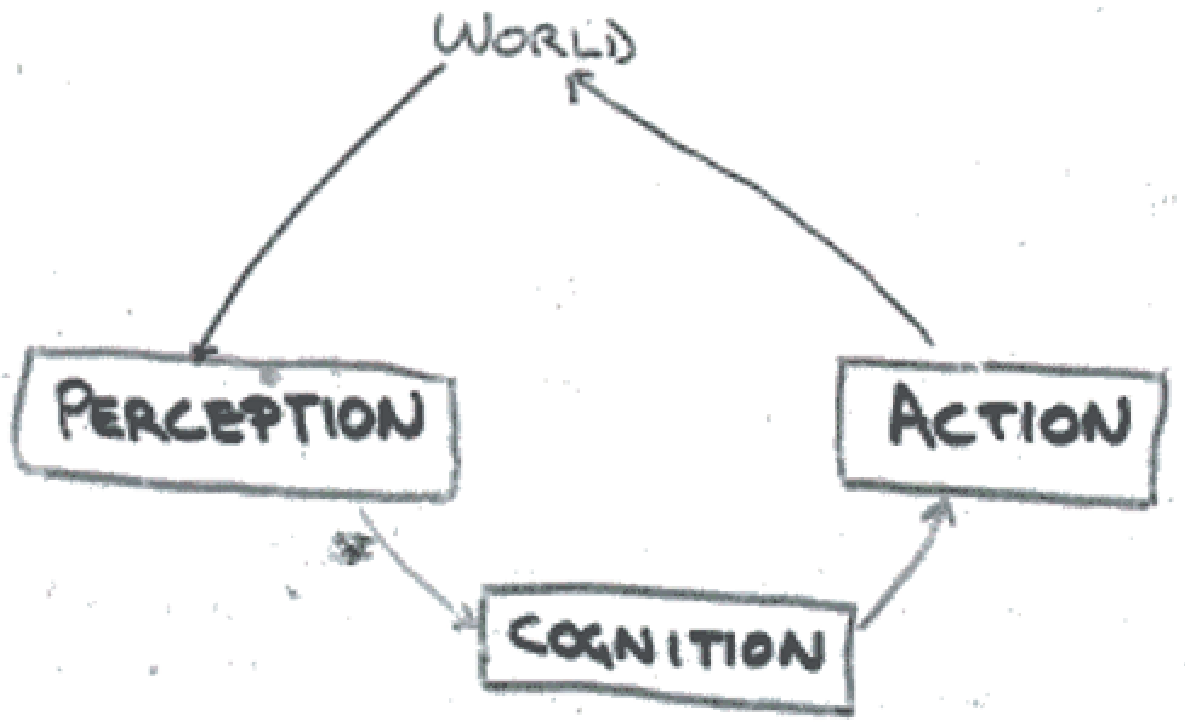
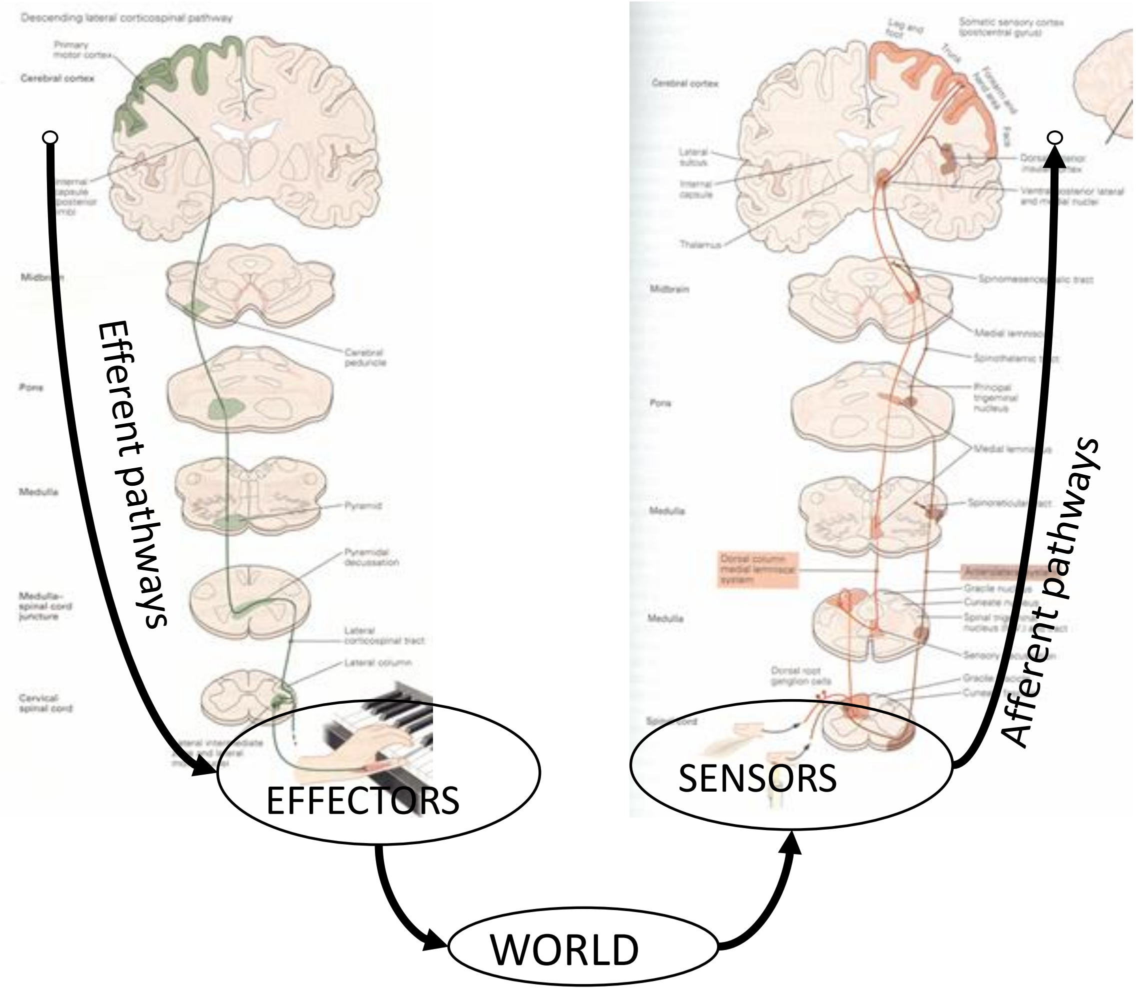


Figure 1: The traditional model where cognition mediates between perceptions and plans of actions.

R. Brooks, *Cambrian Intelligence*, MIT Press, 2000

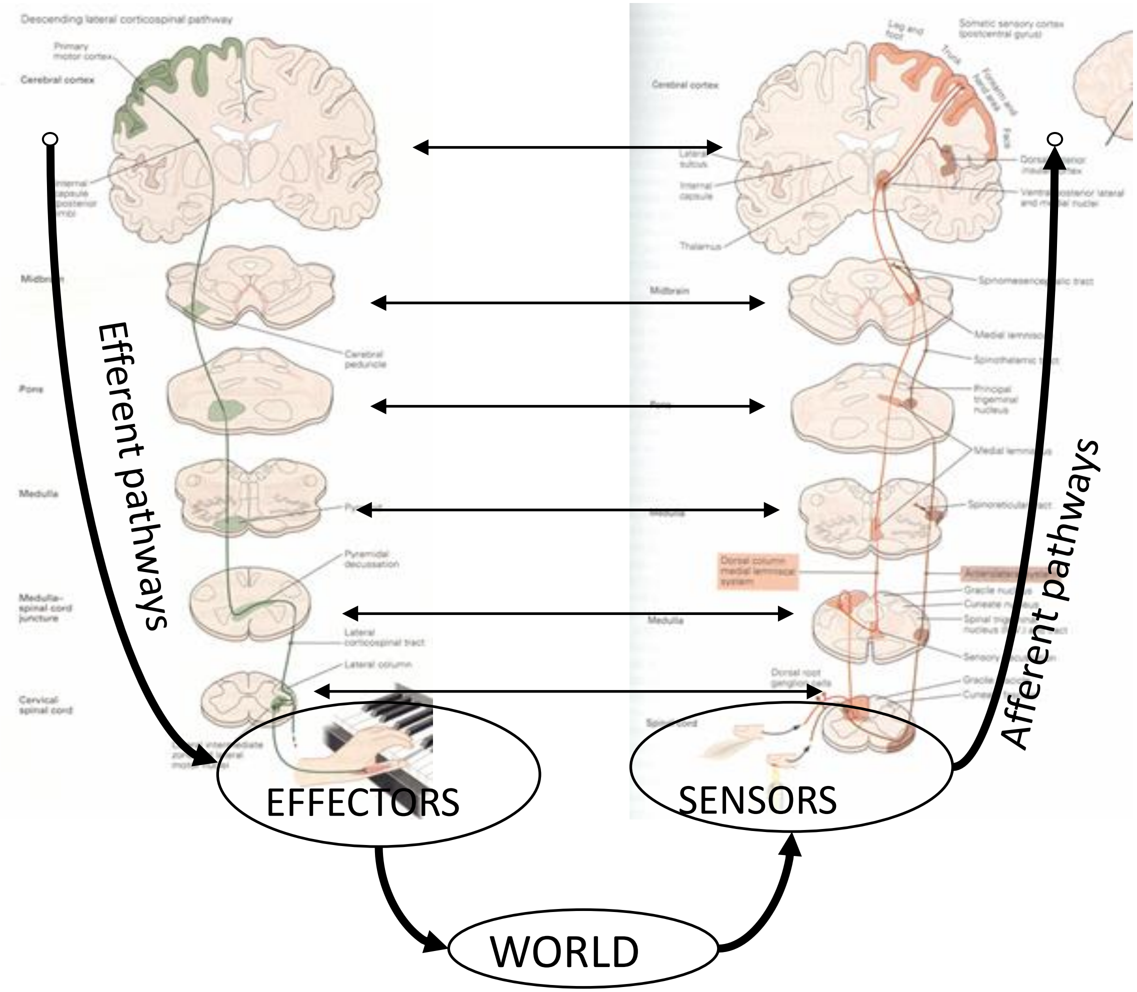
Behaviour: Perception-Action loops
Natural perception and action pathways



from Kandel et al., *Principles of Neuroscience*, McGraw-Hill

Natural perception and action pathways

Perception and action not so different…

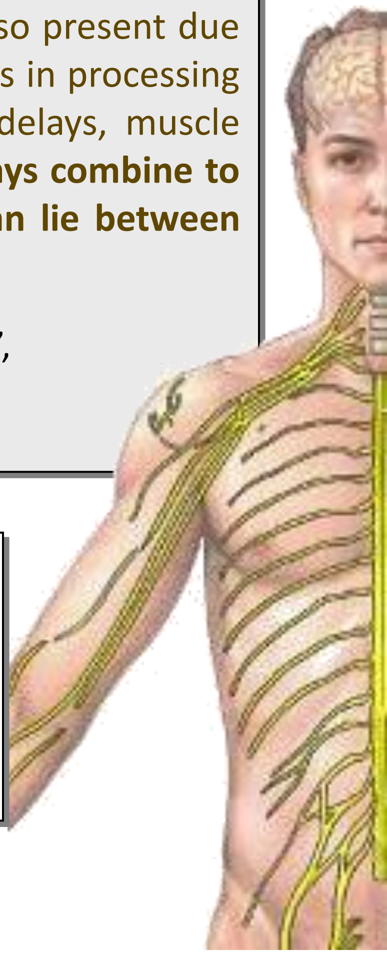


from Kandel et al., *Principles of Neuroscience*, McGraw-Hill

Delays in the human nervous system

"In motor control **delays** arise in **sensory transduction**, **central processing**, and in the **motor output**. Sensor transduction latencies are most noticeable in the visual system where the retina introduces a delay of 30-60 ms, but sensory conduction delays can also be appreciable. Central delays are also present due to such ill-defined events such as neural computation, decision making and the bottlenecks in processing command. Delays in the motor output result from motorneuronal axonal conduction delays, muscle exictation-contraction delays, and phase lags due to the intertia of the system. **These delays combine to give an unavoidable feedback delay within the negative feedback control loop, and can lie between about 30 ms for a spinal reflex up to 200-300 ms for a visually guided response."**

R.C. Miall, D.J. Weir, D.M. Wolpert, J.F. Stein, "Is the cerebellum a Smith predictor?", *Journal of Motor Behavior*, vol. 25, no. 3, pp. 203-216, 1993



"Fast and coordinated arm movements **cannot be executed under pure feedback control** because biological feedback loops are both too slow and have small gains"

M. Kawato, Internal models for motor control and trajectory planning. *Current Opinion in Neurobiology*, 9, 718-727(1999). Elsevier Science Ltd.

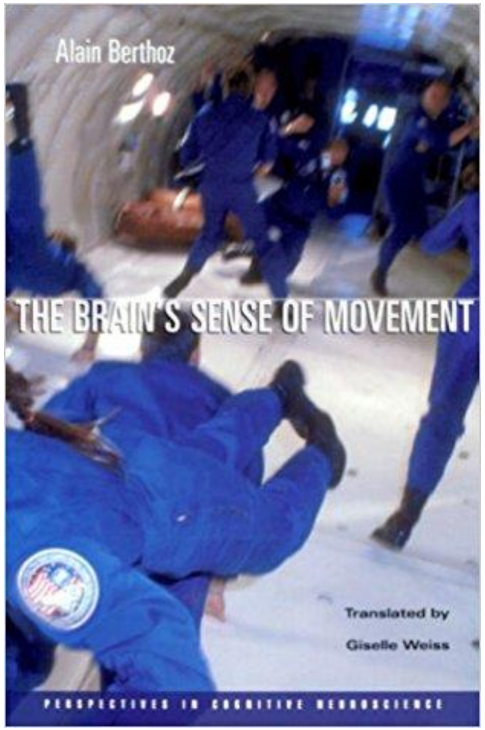
A. Berthoz, *Le sens du mouvement*. Odile Jacob, Paris, 1997

R.S. Johansson, "Sensory input and control of grip", in M. Glickstein (Ed.), *Sensory Guidance of Movements*. John Wiley, Chichester, UK, pp. 45-59,1998

Prediction and anticipation strategies in the human brain

In humans, perception is not just the interpretation of sensory signals, but a prediction of consequences of actions

“Perception can be defined as a ***simulated action***: perceptual activity is not confined to the interpretation of sensory information but it **anticipates** the consequences of action, so it is an internal simulation of action.
Each time it is engaged in an **action**, the brain constructs hypotheses about the state of a variegated group of **sensory** parameters throughout the movement.”



Berthoz A. (2002), *The brain’s sense of movement*. Harvard University Press

From hierarchical to reactive architectures in robotics

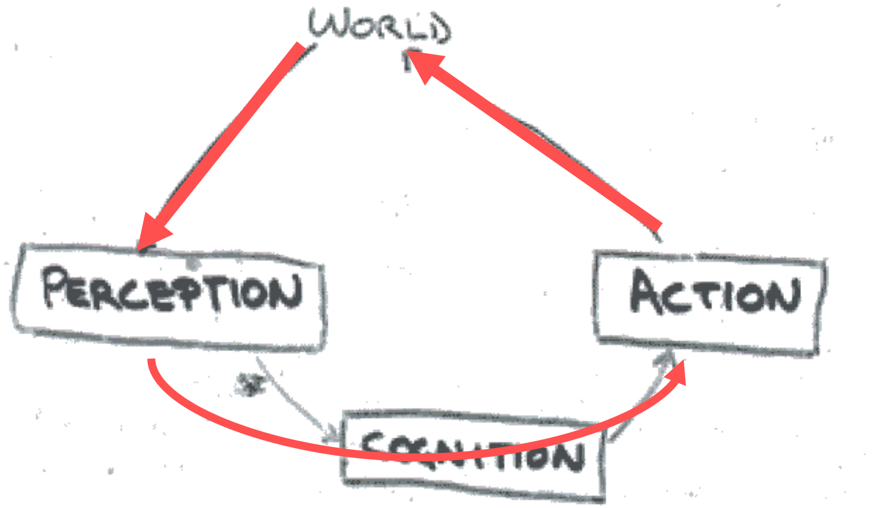


Figure 1: The traditional model where cognition mediates between perceptions and plans of actions.

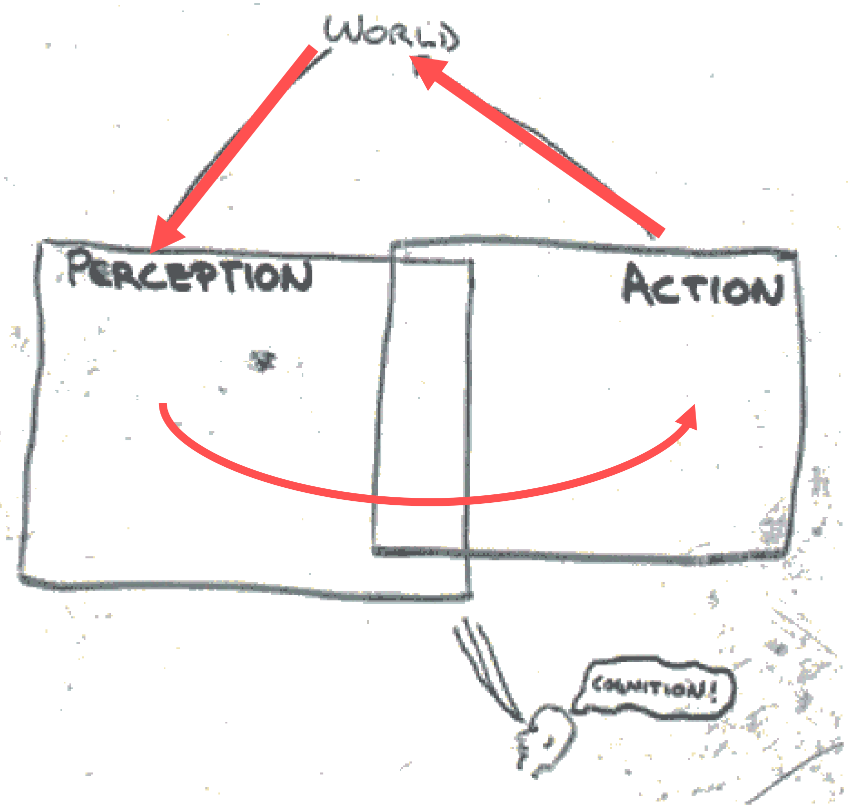
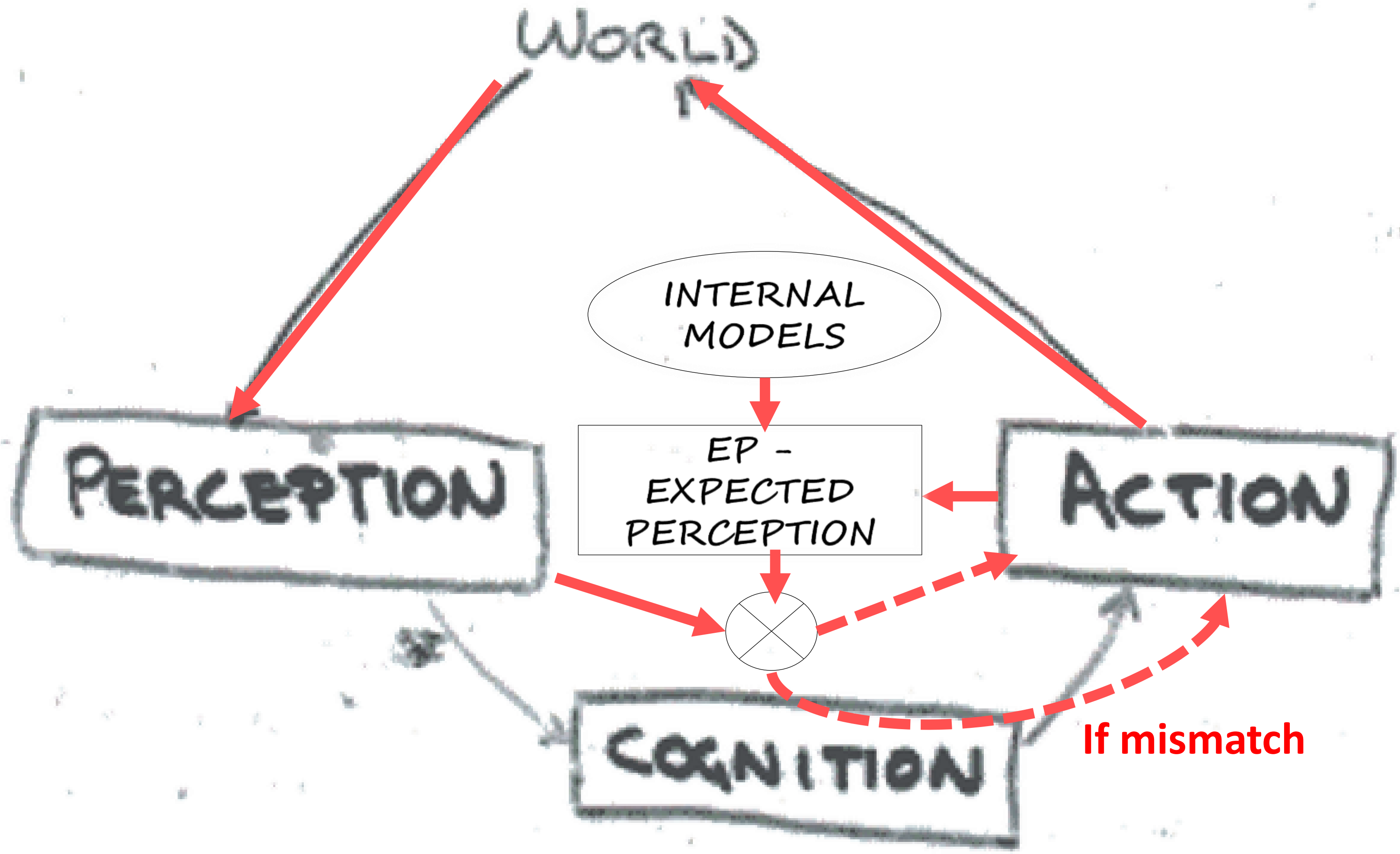


Figure 2: The new model, where the perceptual and action subsystems are all there really is. Cognition is only in the eye of an observer.

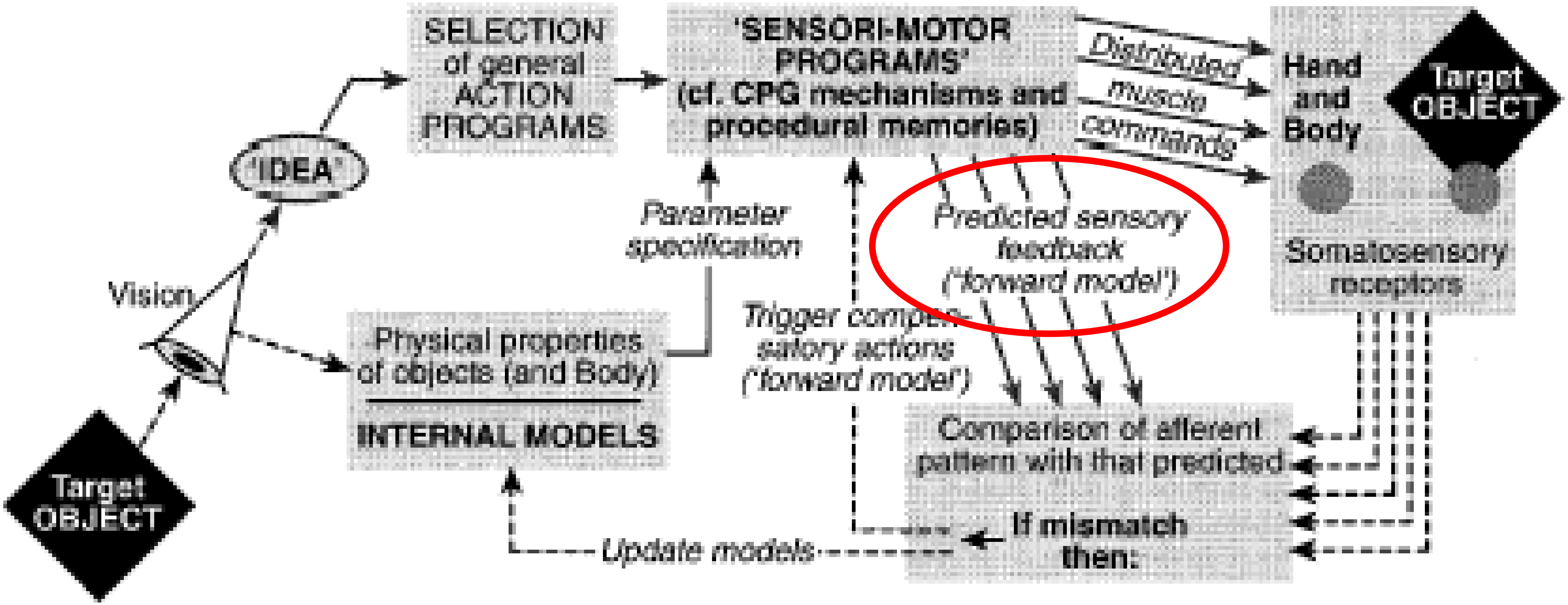
R. Brooks, *Cambrian Intelligence”* MIT Press, 2000

Predictive architectures



Sensory prediction in grasping tasks

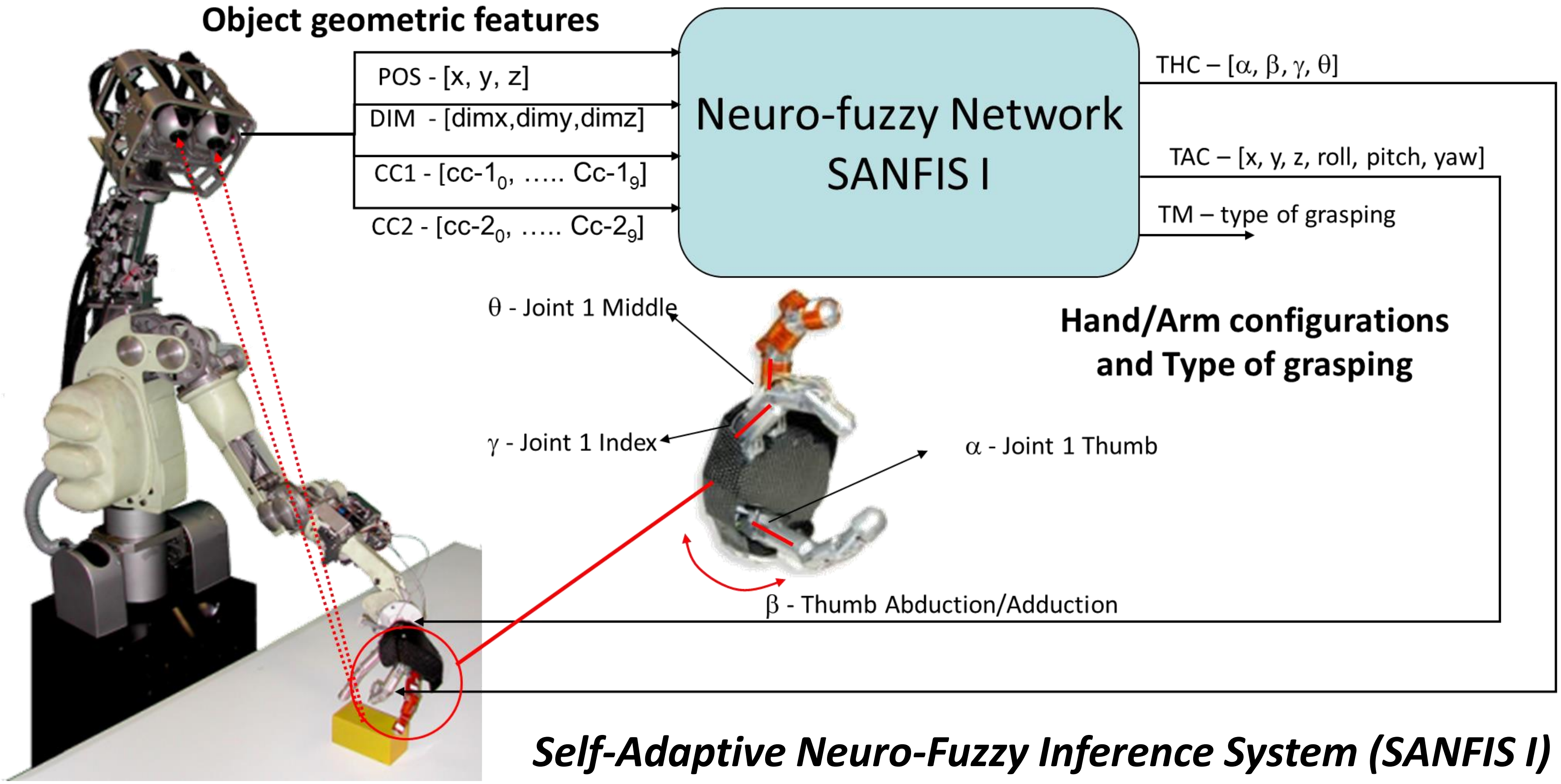
"Because of the long time delays with feedback control, the swift coordination of fingertip forces during self-paced everyday manipulation of ordinary 'passive' objects must be explained by other mechanisms.
Indeed, the brain relies on feedforward control mechanisms and takes advantage of the stable and predictable physical properties of these objects by parametrically adapting force motor commands to the relevant physical properties of the target object."



Corrections are generated when expected sensory inputs do not match the actual ones

R.S. Johansson, "Sensory input and control of grip". In *Sensory Guidance of Movements*, John Wiley, Chichester, UK, pp. 45-59, 1998

Preshaping Module

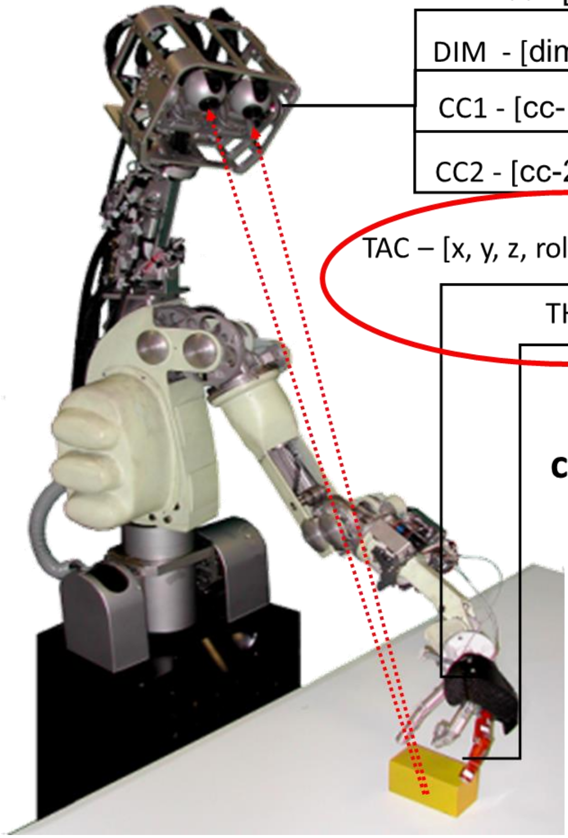


Self-Adaptive Neuro-Fuzzy Inference System (SANFIS I)

- *Combine advantages NN and Fuzzy Logic*
- *Learning, adaptation, and connectionist structure*
- *Ability to exact explicit IF-THEN rules from training data*

EP Generator (preshaping) Module

Object geometric features



POS - [x, y, z]

DIM - [dimx,dimy,dimz]

CC1 - [$cc\text{-}1_0$, ….. $Cc\text{-}1_9$]

CC2 - [$cc\text{-}2_0$, ….. $Cc\text{-}2_9$]

TAC – [x, y, z, roll, pitch, yaw]

THC – [α, β, γ, θ]

Hand/Arm configurations

Neuro-fuzzy Network
SANFIS II

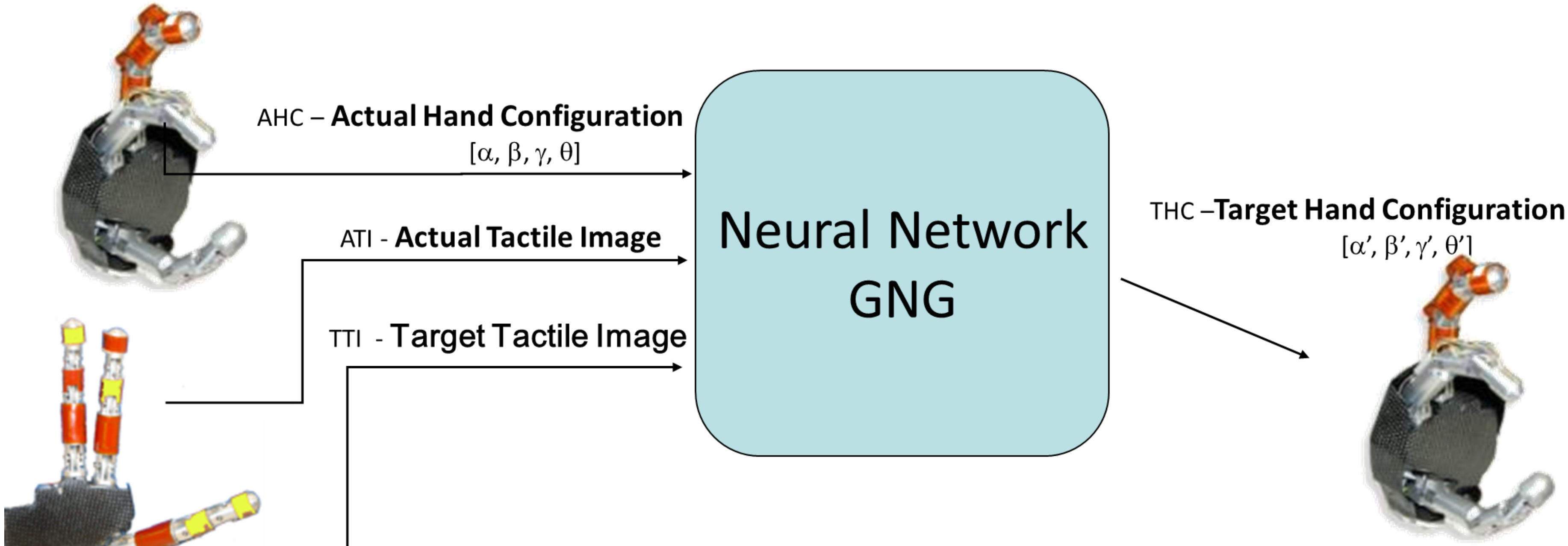
TTI - **Target Tactile Image**

[tt_1, tt_2, …, tt_m]
where:
m=9
tt_i = i-th value for the tactile sensor $\in$ {0,1}

SANFIS II

- *Combine advantages NN and Fuzzy Logic*
- *Learning, adaptation, and connectionist structure*
- *Ability to exact explicit IF-THEN rules from training data*
- *Output space not very complex*

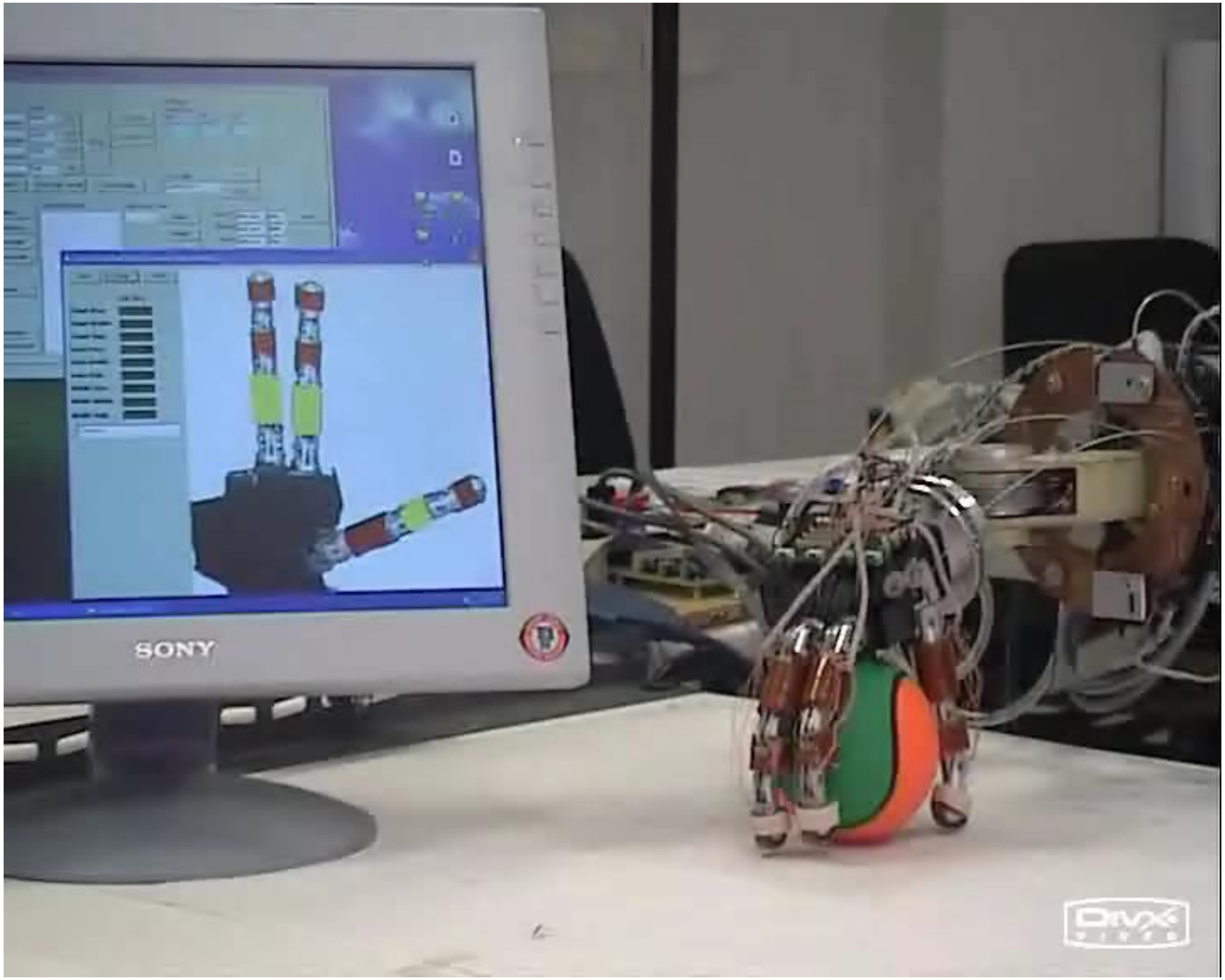
EP-based Grasping Module



Growing Neural Gas + Grossberg's Outstars

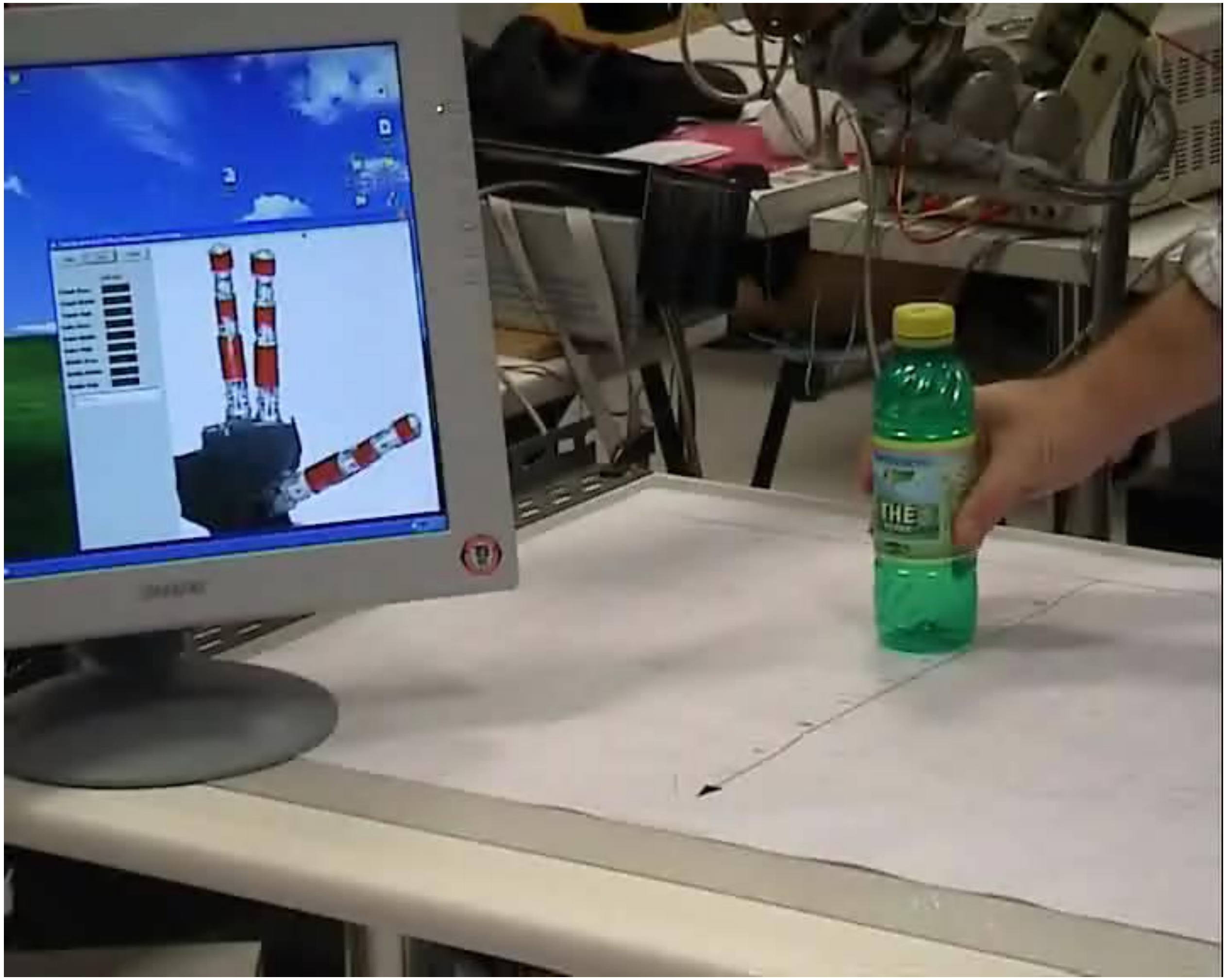
- *Unsupervised learning paradigm*
- *Competitive learning methods (winner-takes-all)*
- *Generation of a topology-preserving mapping from the input space onto a topological structure of equal or lower dimension*
- *Network topology is unconstrained*
- *Uses growth mechanism (the network size does not need be predefined)*

Learning of grasping module



Learning phase:
About 40000 random movements

Grasping the bottle



C. Laschi, G. Asuni, E. Guglielmelli, G. Teti, R. Johansson, M.C. Carrozza, P. Dario, "A Bio-inspired Neural Sensory-Motor Coordination Scheme for Robot Reaching and Preshaping", *Autonomous Robots*, Vol.5, 2008, pp.85-101.

Expected Perception in the visual space

EP architecture applied to 3D reconstruction of the environment

09ar0078cl [RF] © www.visualphotos.com

Task: <u>free walking in an unknown room with obstacles</u>

Classical approach:

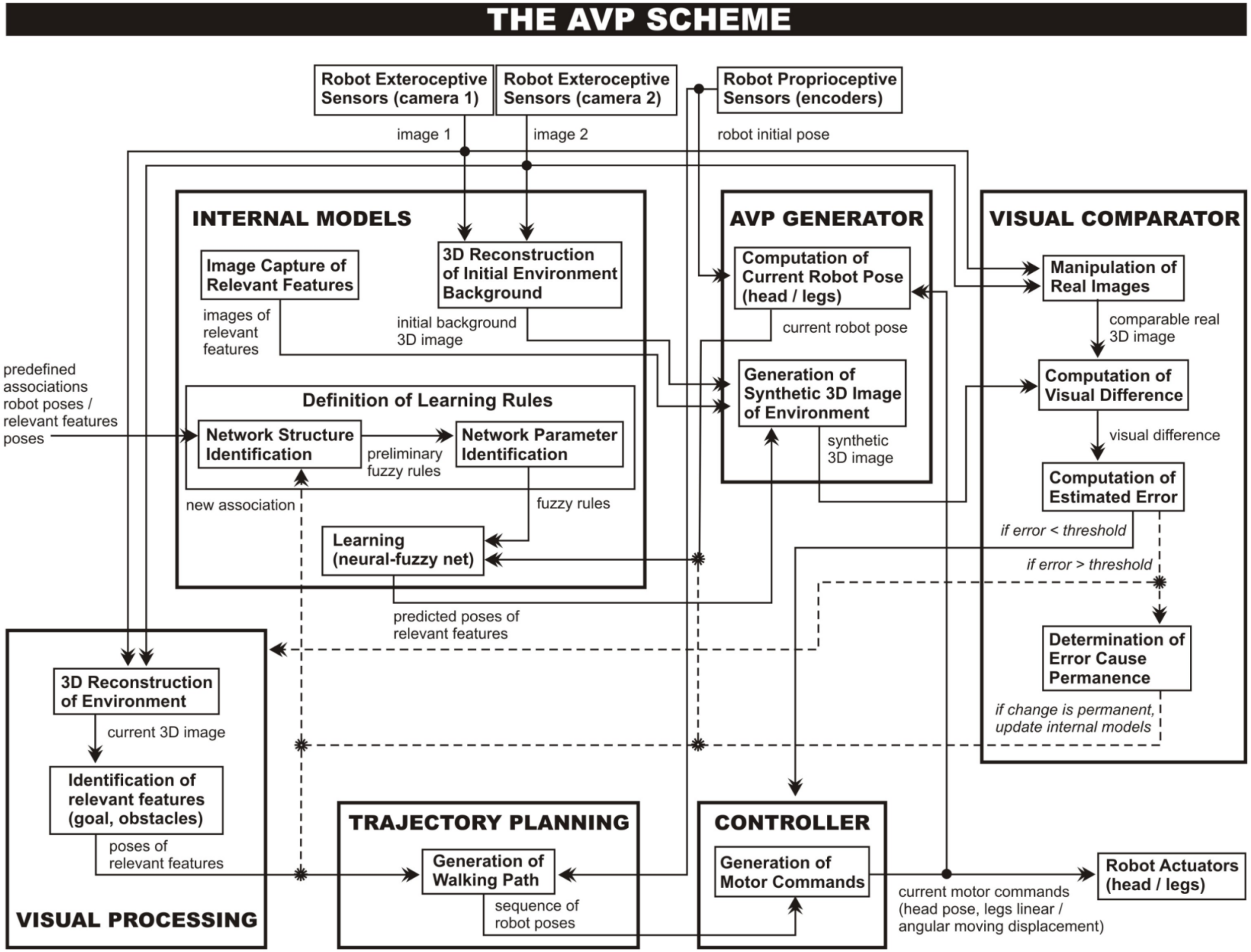
- 3D reconstruction of the environment
- path planning for collision-free walking

-> large computational burden

In a Visual EP architecture, after a first 3D reconstruction of the environment, images can be predicted, based on internal models and on the ongoing movement.

Predicted images are compared with actual ones and in case of unexpected obstacles a mismatch occurs and the motor action is re-planned

Visual EP scheme



Barrera, A. & Laschi, C. "Anticipatory visual perception as a bio-inspired mechanism underlying robot locomotion ", *IEEE Int. Conf. on Engineering in Medicine and Biology Society (EMBC)*, Minneapolis, MN, USA, September 2010, pp.3206-3209

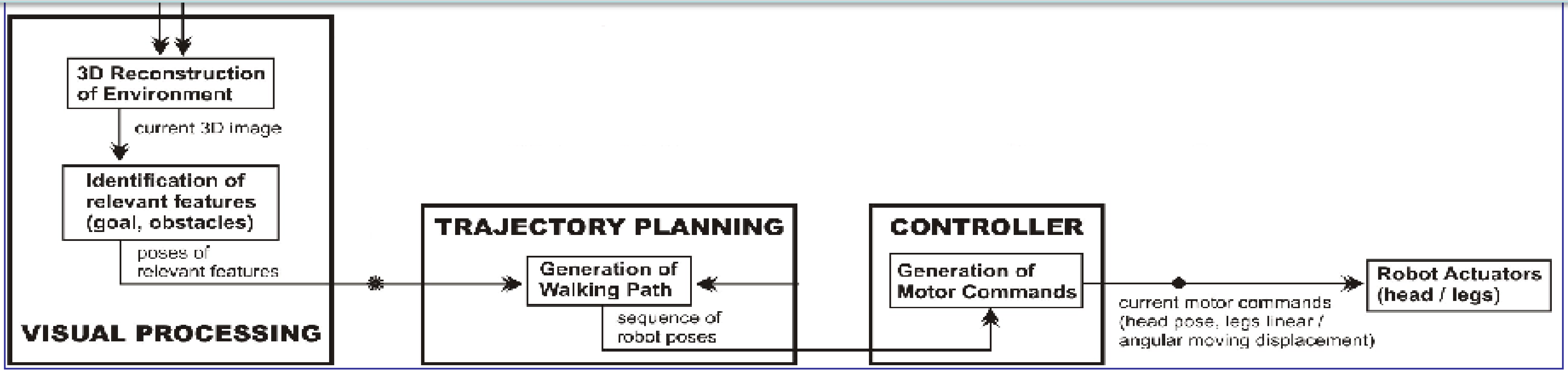
AVP architecture (I)

- **Visual Processing** module takes as input current images from both robot cameras to reconstruct the environment producing the **relevant feature position.**

- The poses of relevant features are sent to a **Trajectory Planning** module to generate the walking path

- The **Controller** module then takes the first robot pose from the sequence of poses planned by the Trajectory Planning module and produces the corresponding motor commands

-This cycle continues until the robot reaches the target.

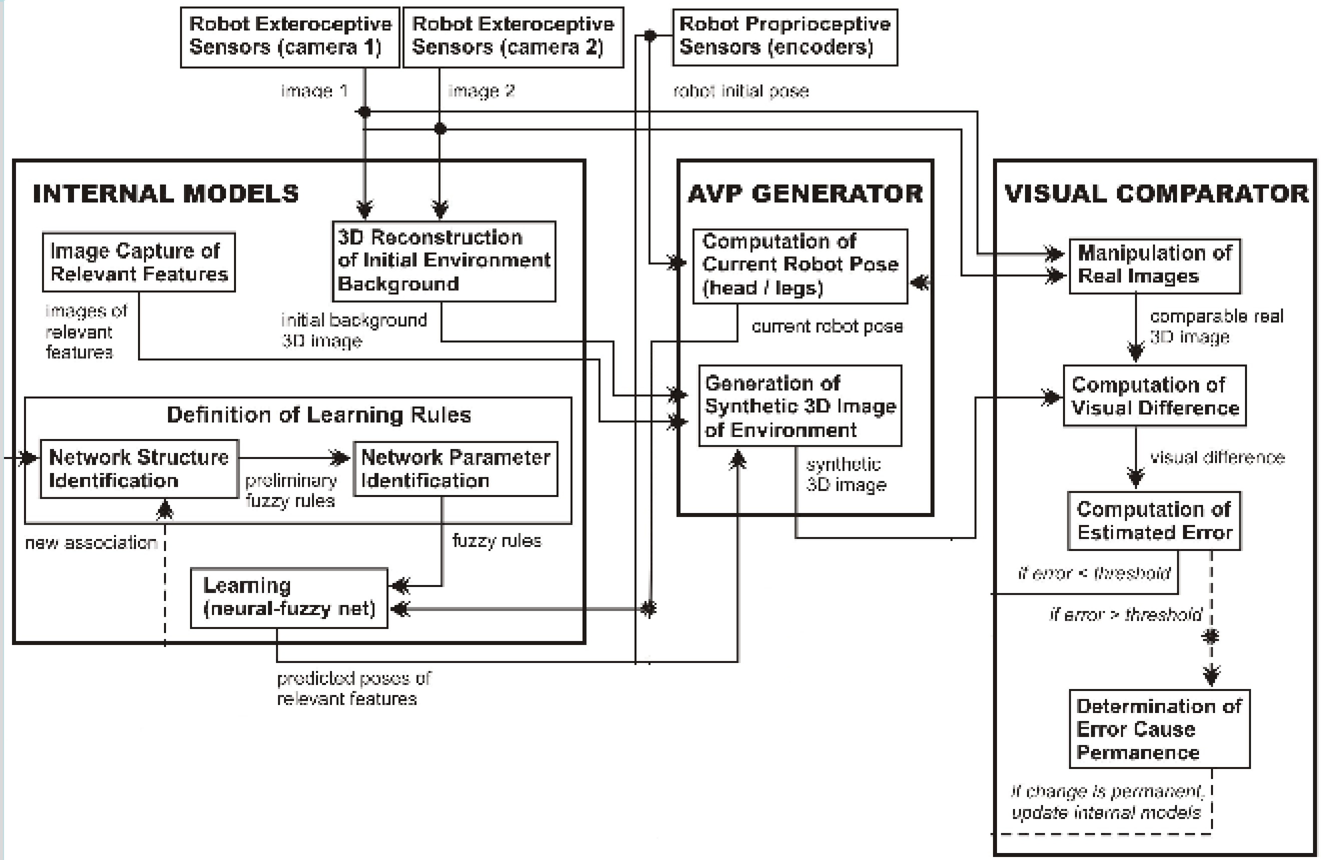


Barrera, A. & Laschi, C. "Anticipatory visual perception as a bio-inspired mechanism underlying robot locomotion ", *IEEE Int. Conf. on Engineering in Medicine and Biology Society (EMBC)*, Minneapolis, MN, USA, September 2010, pp.3206-3209

AVP architecture (II)

- **Internal Models** of the environment and of the task to be performed are necessary to *predict future visual perceptions*.

- Images of different features relevant to the locomotion task are captured and memorized



Barrera, A. & Laschi, C. "Anticipatory visual perception as a bio-inspired mechanism underlying robot locomotion ", *IEEE Int. Conf. on Engineering in Medicine and Biology Society (EMBC)*, Minneapolis, MN, USA, September 2010, pp.3206-3209

Visual EP System (implementation)

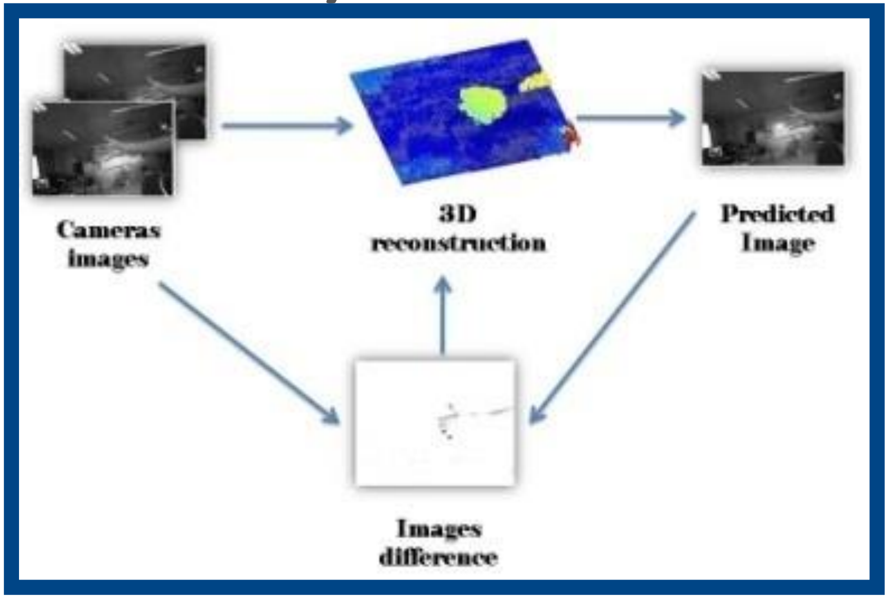
The system performs a real time 3D reconstruction of the environment (30fps) used to generate an **expected synthetic camera image**. The cloud of 3D points is updated using an image sensory-motor prediction.

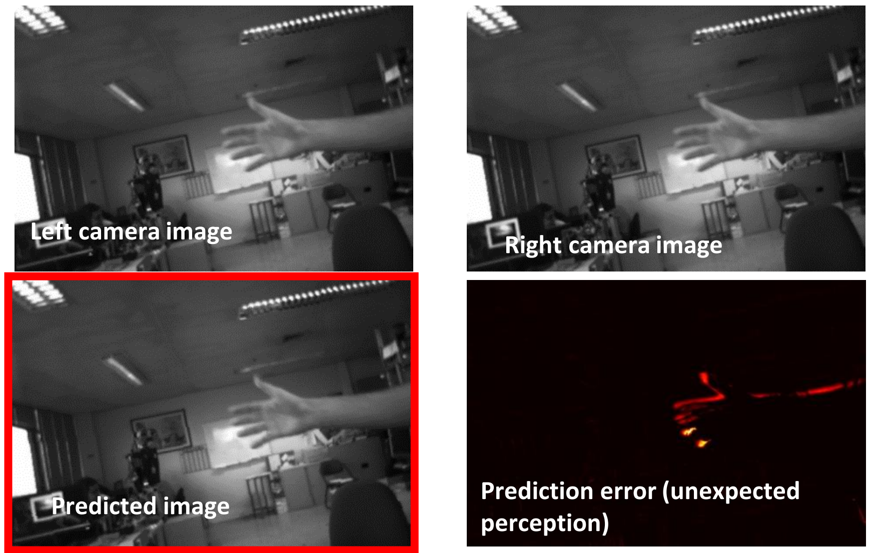
At each step:

- the next predicted image (EP) is calculated.
- the predicted and actual cameras images are compared.
- the 3D reconstruction of the visible environment is updated based on the prediction error

The system has 2 advantages:

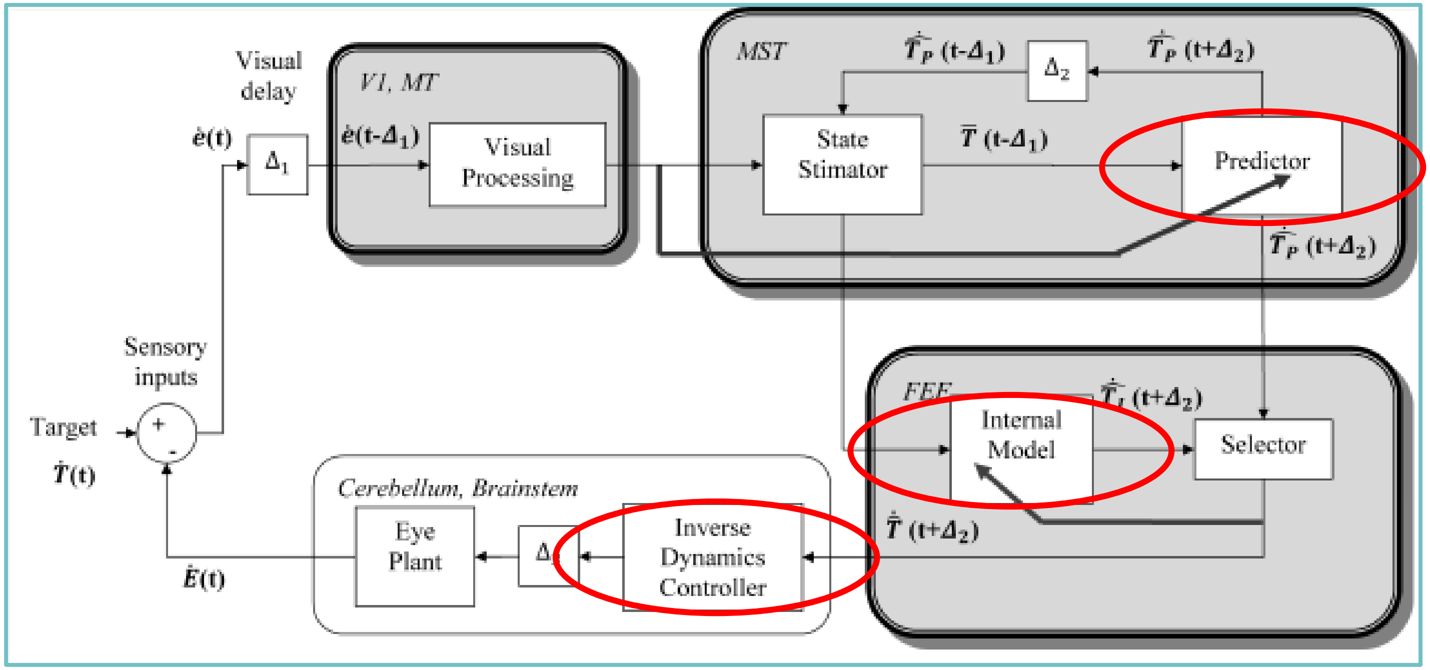
- A faster real-time 3D reconstruction
- Recognition of the unexpected objects in the scene





Moutinho, N.; Cauli, N.; Falotico, E.; Ferreira, R.; Gaspar, J.; Bernardino, A.; Santos-Victor, J.; Dario, P.; Laschi, C.; 2011. "An expected perception architecture using visual 3D reconstruction for a humanoid robot," *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems - IROS*, San Francisco, CA, USA, 25-30 Sept. 2011 , pp.4826-4831.

A predictive model for smooth pursuit

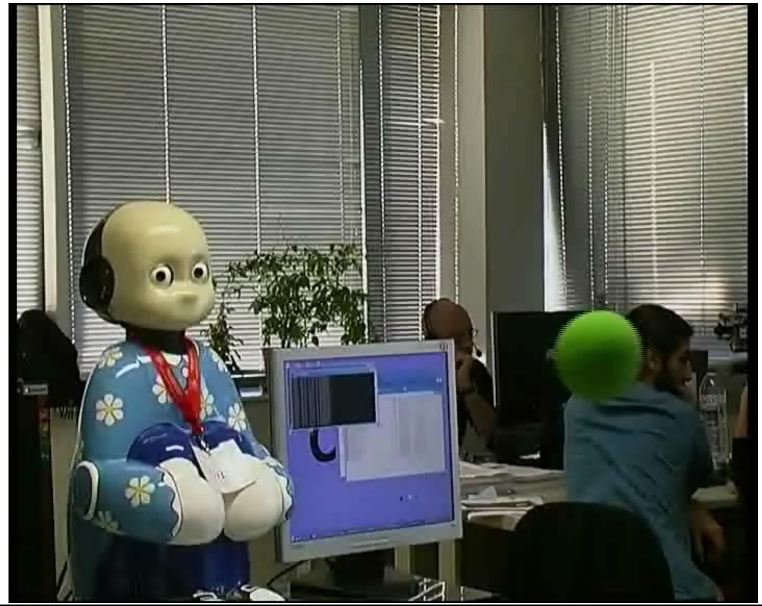


This circuit is based on Shibata and Schaal's model (*Shibata 2005*) of smooth pursuit and consists of **three subsystems**:

1. a **recurrent neural network** (RNN) mapped onto medial superior temporal area (MST), which receives the retinal slip with delays and ***predicts*** the current target motion,
2. an **inverse dynamics controller** (IDC) of the oculomotor system, mapped onto the cerebellum and the brainstem,
3. and **a memory block** that recognizes the target dynamics and provides the correct weights values before the RNN.

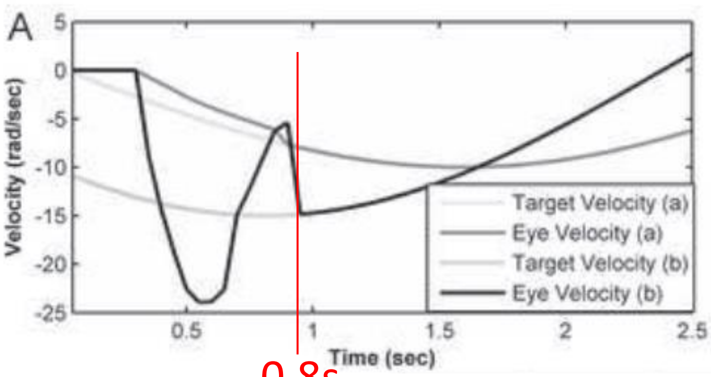
Zambrano D, Falotico E, Manfredi L, and Laschi C. (2010). "A model of the smooth pursuit eye movement with prediction and learning". *Applied Bionics and Biomechanics*

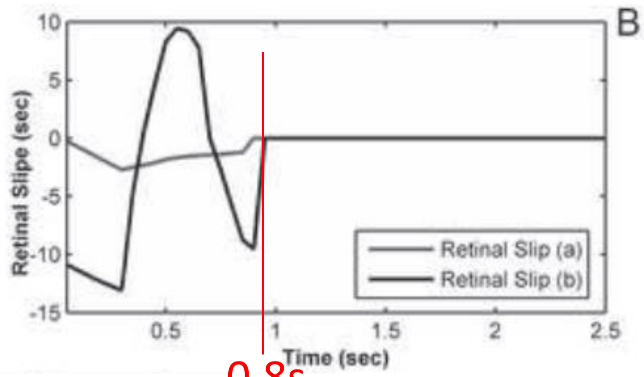
Predictive smooth pursuit on a robot head



iCub platform head, 6 dof:
3 for the eyes
3 for the neck

The *retinal slip* (target velocity onto the retina) reaches zero after that the algorithm converges.
When the target is unexpectedly stopped, the system goes on tracking the target for a short time.





Sinusoidal dynamics:

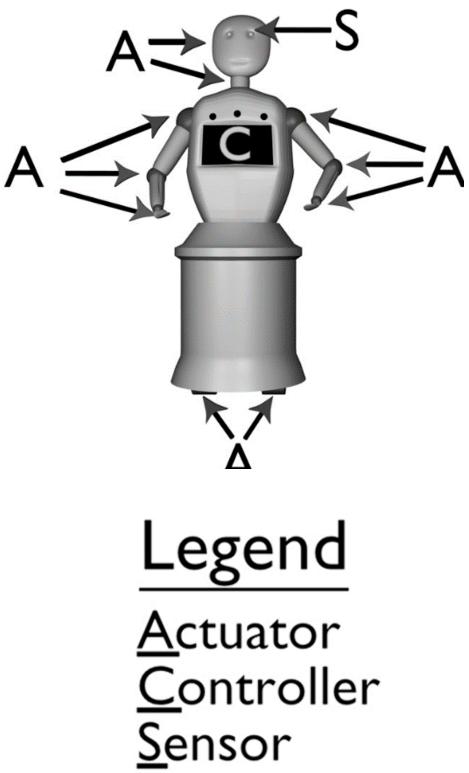
a) angular frequency: 1 rad/s, amplitude: 10 rad, phase: π/2
b) angular frequency: 1 rad/s, amplitude: 15 rad, phase of ¾ π

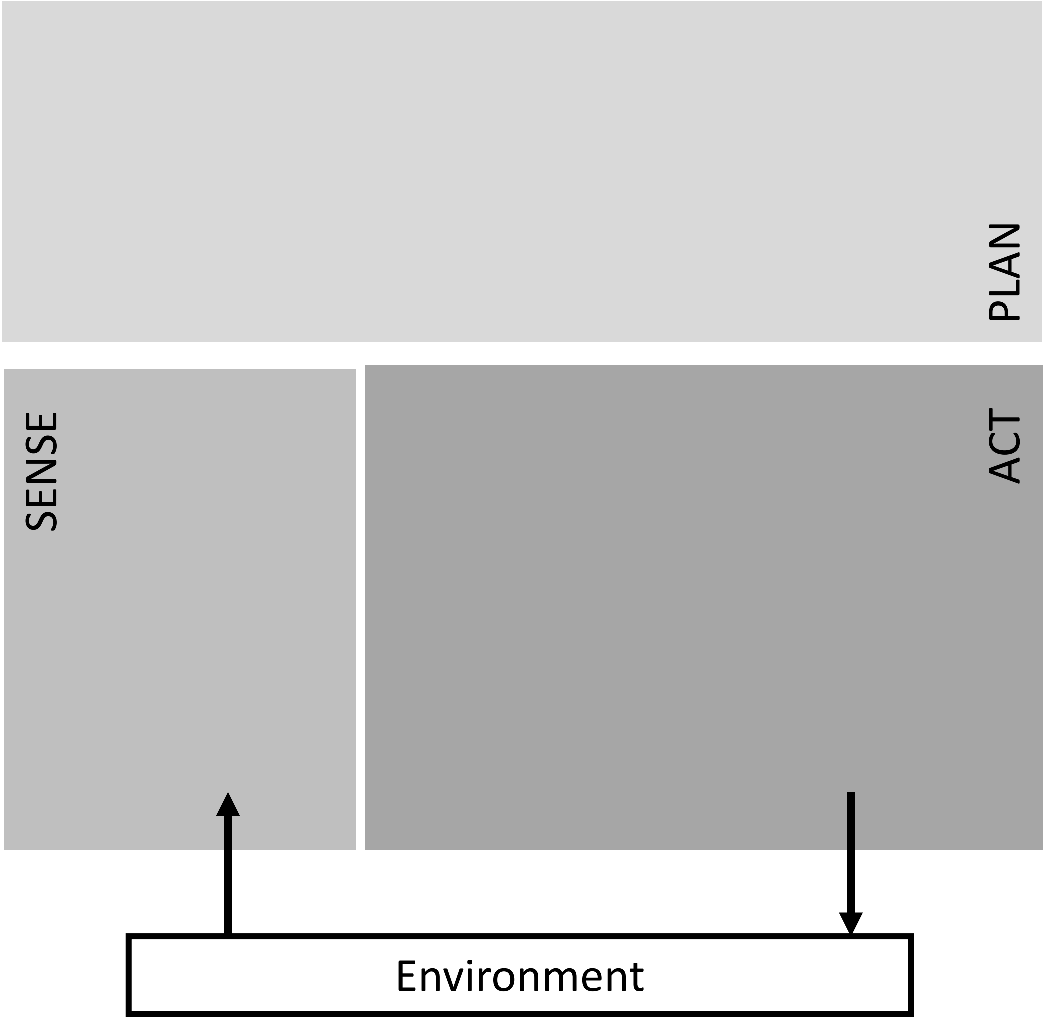
Punching a moving target - robot experiments

The prediction is iterated ahead 0.5 seconds
As the predicted target is inside the arm workspace, the robot executes a movement to punch the ball in the ***predicted position***

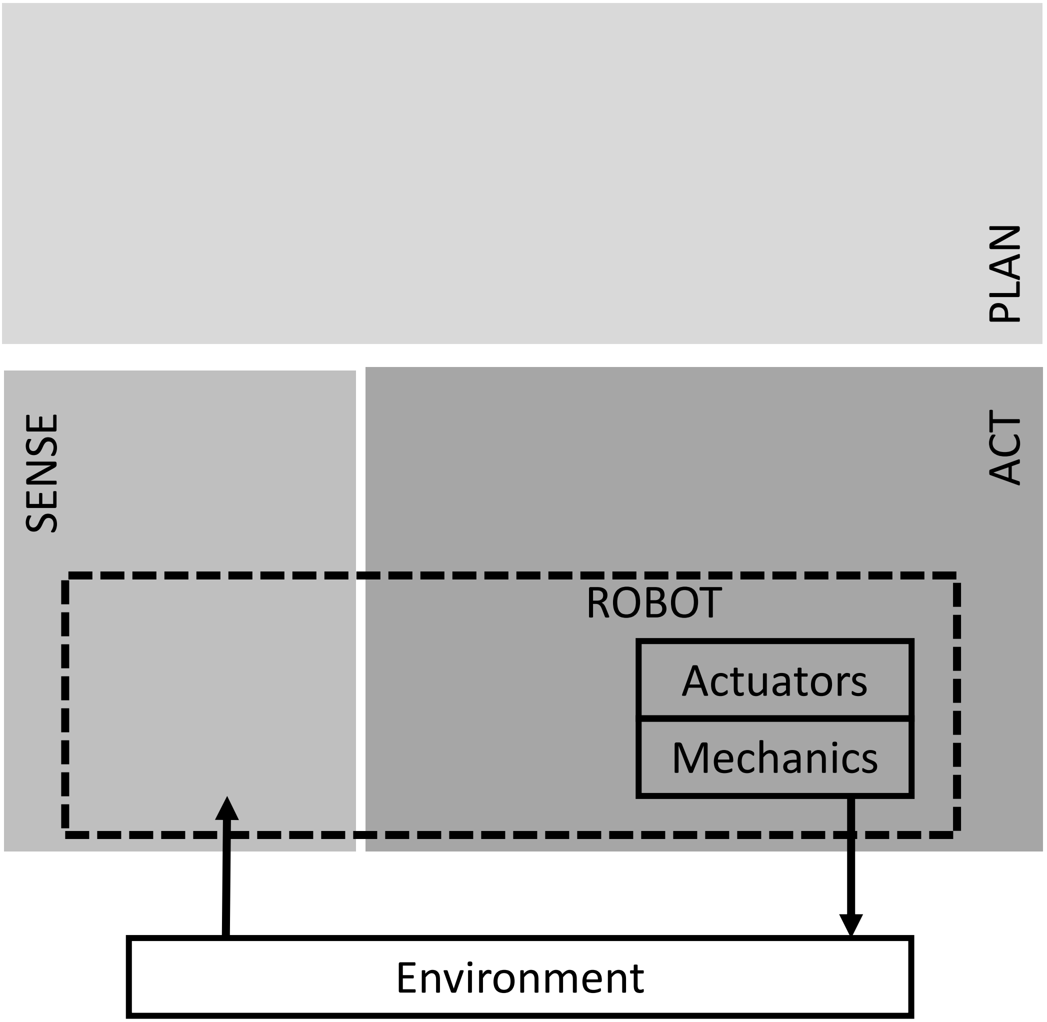
N. Cauli, E. Falotico, A. Bernardino, J. Santos-Victor, C. Laschi, “Correcting for Changes: Expected Perception-Based Control for Reaching a Moving Target”, *IEEE Robotics and Automation Magazine*, 23 (1), pp.63-70, 2016.

Architectures for robot sensory-motor behaviour

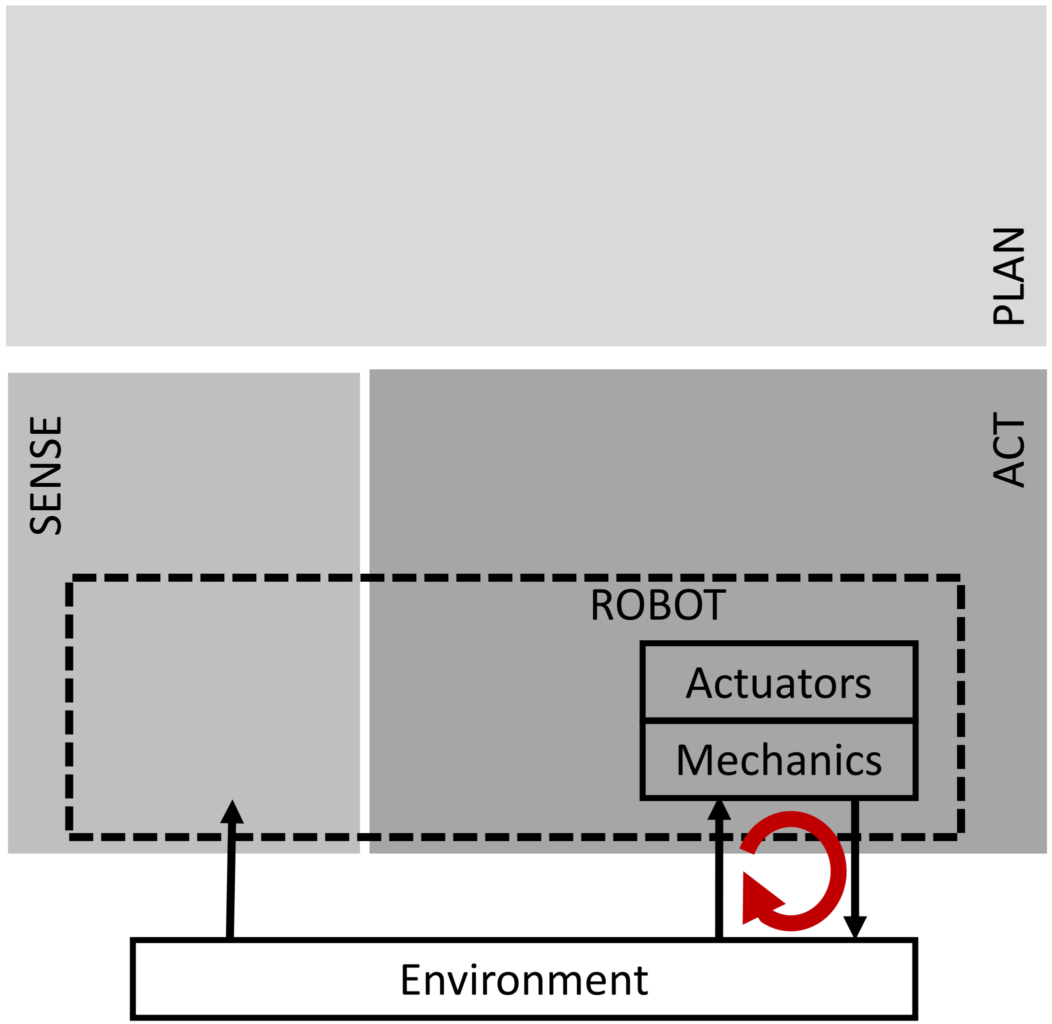




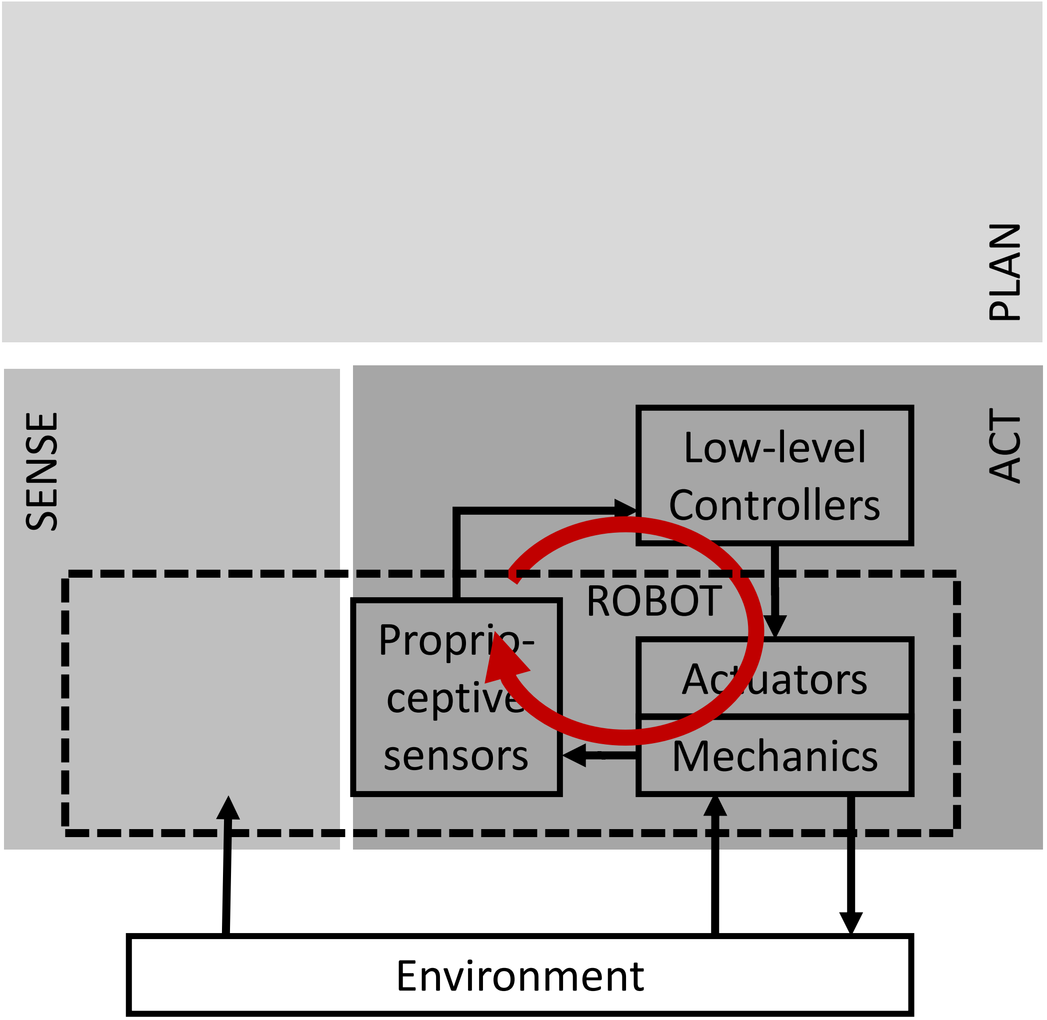
Architectures for robot sensory-motor behaviour



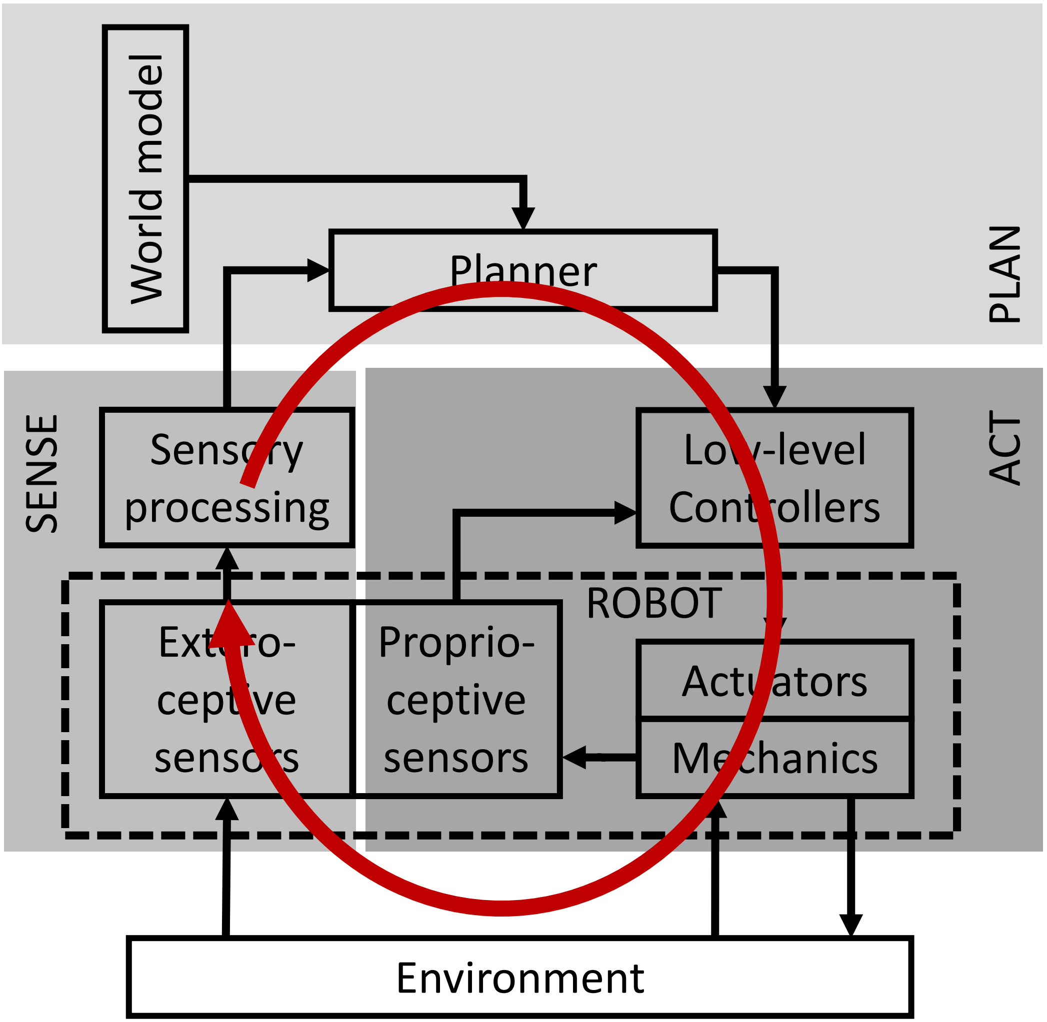
Embodied Intelligence & Morphological Computation



Robot low-level control

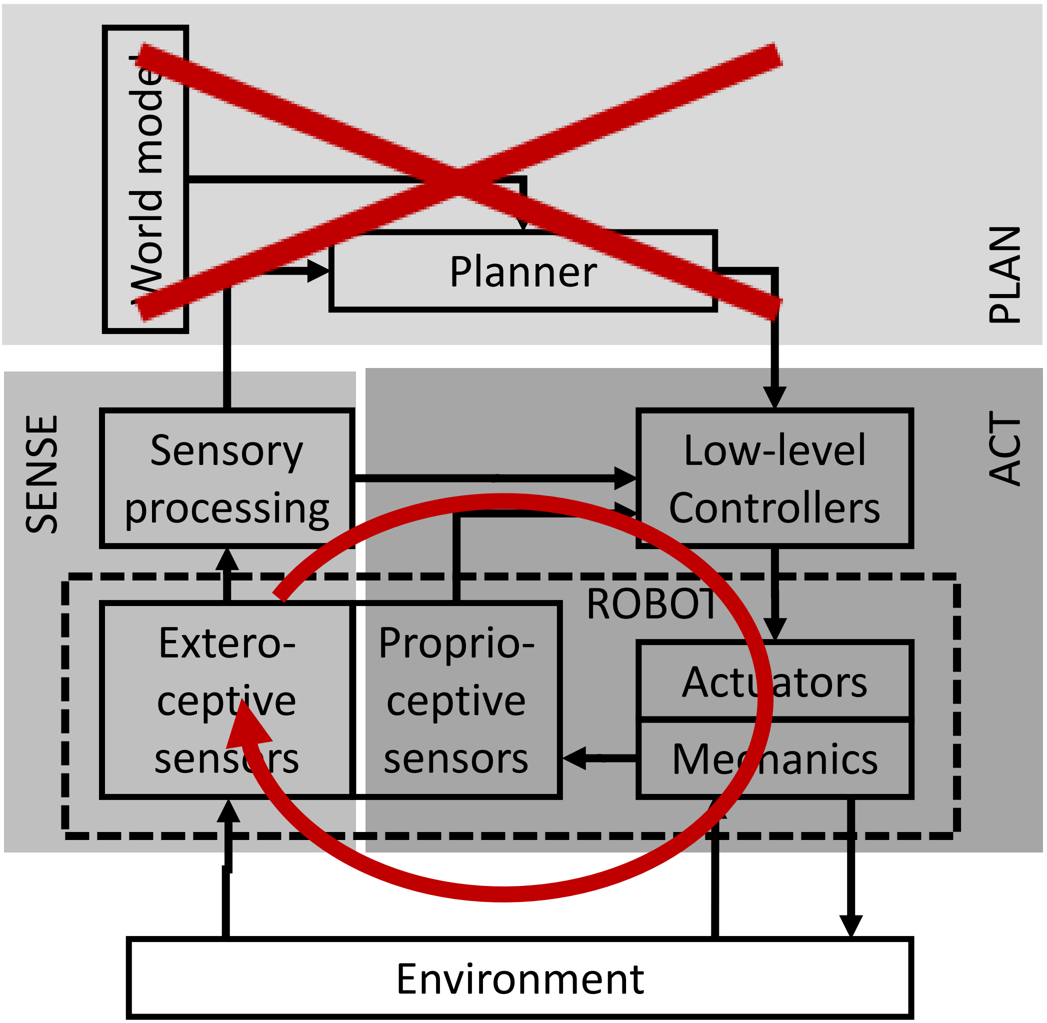


Architectures for robot sensory-motor behaviour



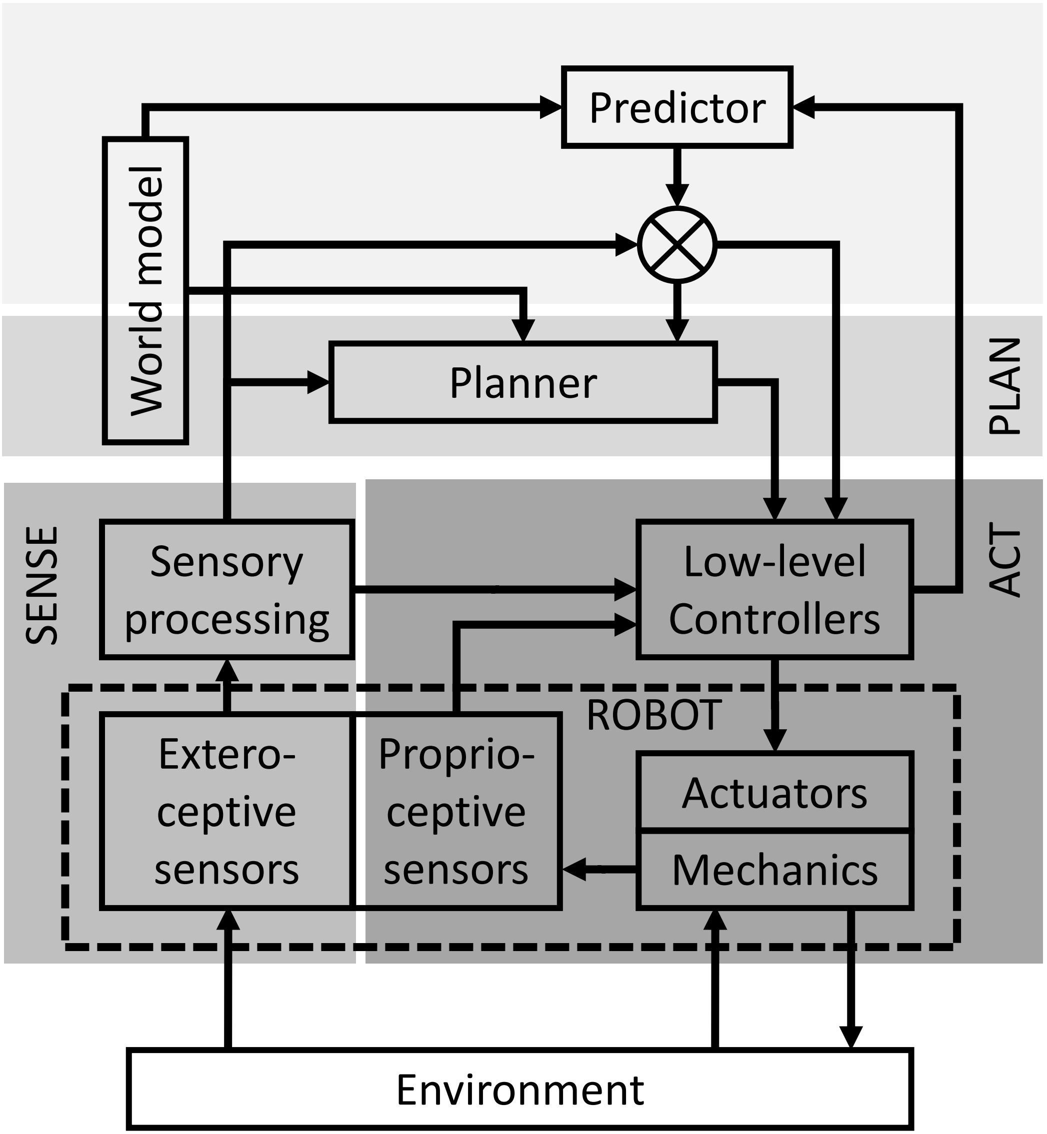
Hierarchical architectures

Architectures for robot sensory-motor behaviour



Reactive architectures

Architectures for robot sensory-motor behaviour



Predictive architectures