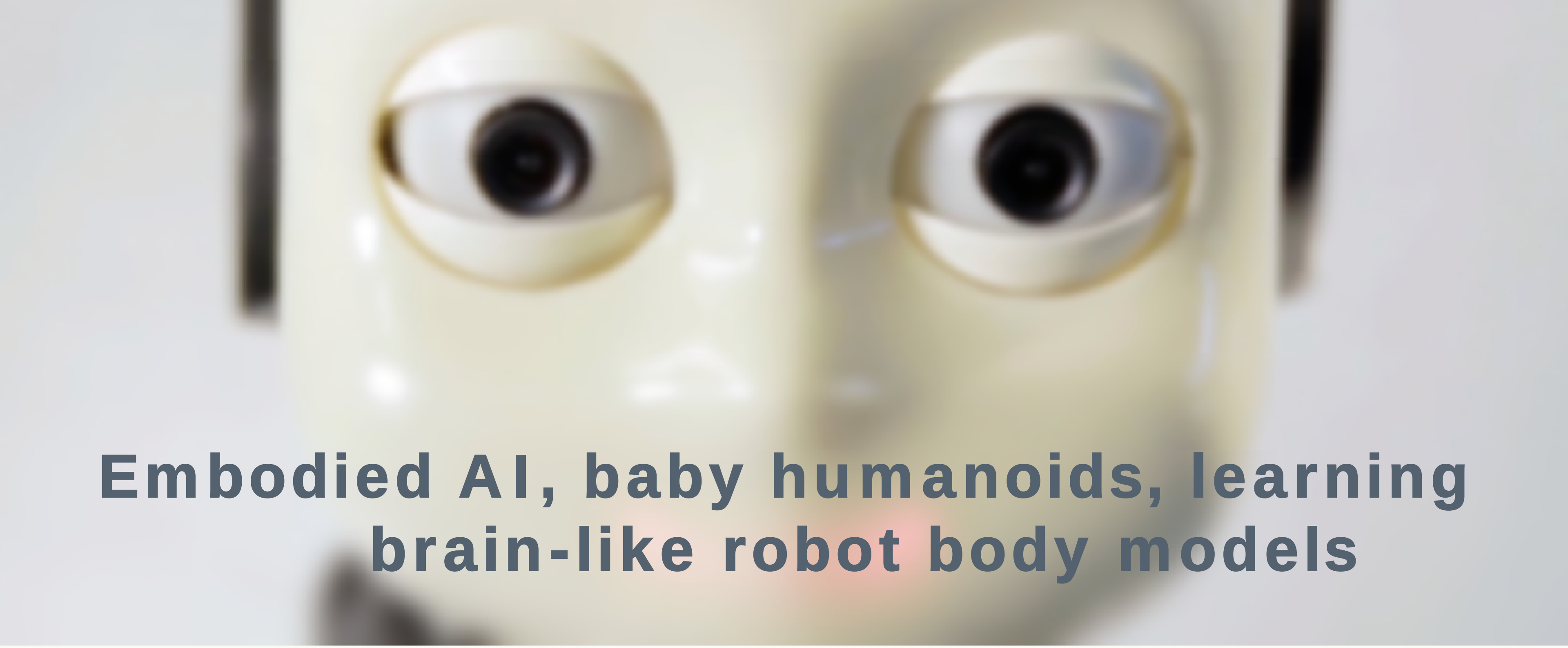


Embodied AI, baby humanoids, learning brain-like robot body models

Matěj Hoffmann, Ph.D.

Department of Cybernetics, Faculty of Electrical Engineering

Czech Technical University in Prague

matej.hoffmann@fel.cvut.cz

https://sites.google.com/site/matejhof

https://cyber.felk.cvut.cz/research/groups-teams/humanoids/

Humanoid and cognitive robotics

Department of Cybernetics
Faculty of Electrical Engineering, CTU Prague
Center for Machine Perception
Vision for Robotics and Autonomous Systems

Coordinator

Matej Hoffmann

Postdocs

Sergiu Tcaci Popescu

Valentin Marcel

https://cyber.felk.cvut.cz/research/groups-teams/humanoids/

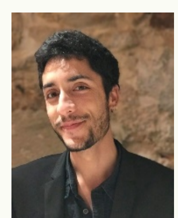
PhD students

Zdeněk Straka

Petr Švarný

Filipe Gama

Shubhan Patni



Jason Khoury

Jakub Rozlivek

Lukáš Rustler

Humanoids

iCub

Naos (1 with “iCub skin”)

Pepper

Cobots

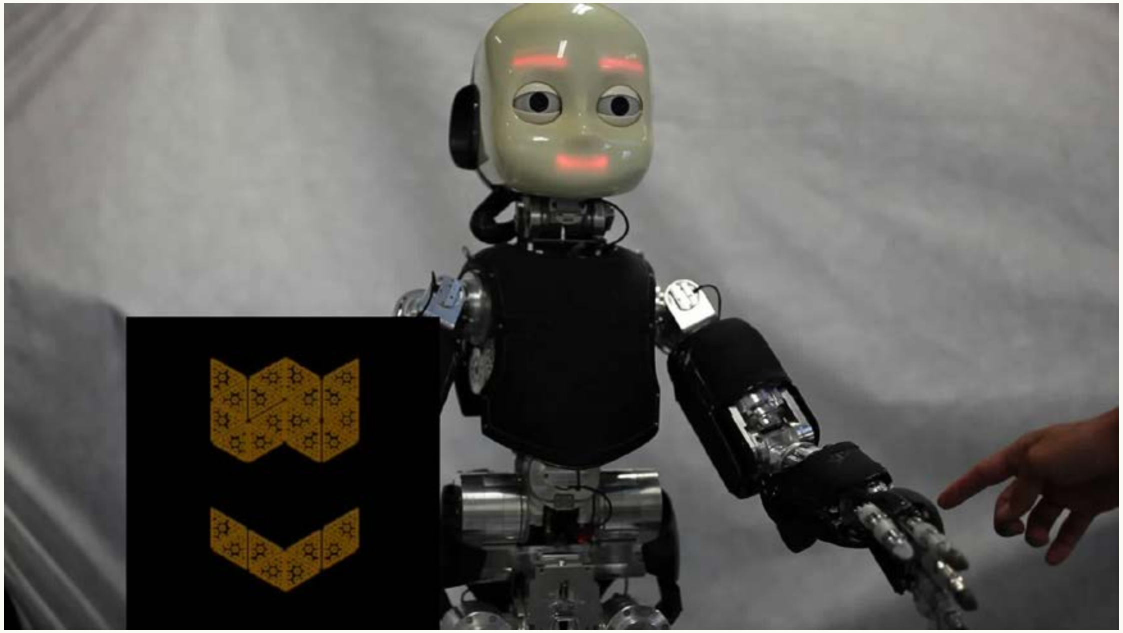
KUKA LBR iiwa

Kinova Gen3

UR10e + Airskin

Motivation

Hoffmann, M.; Chinn, L. K.; Somogyi, E.; Heed, T.; Fagard, J.; Lockman, J. J. & O'Regan, J. K. (2017), Development of reaching to the body in early infancy: From experiments to robotic models, *in 'Joint IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL-EpiRob)', pp. 112-119.*

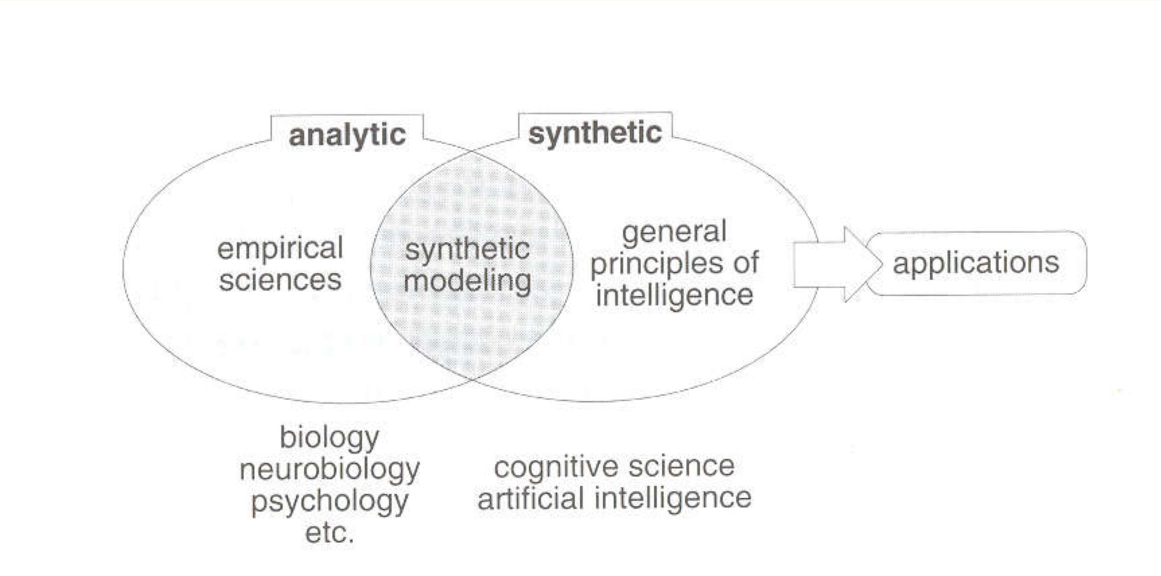


Roncone, A.; Hoffmann, M.; Pattacini, U. & Metta, G. (2014), Automatic kinematic chain calibration using artificial skin: self-touch in the iCub humanoid robot, *in* 'Proc. IEEE Int. Conf. Robotics and Automation (ICRA)'.

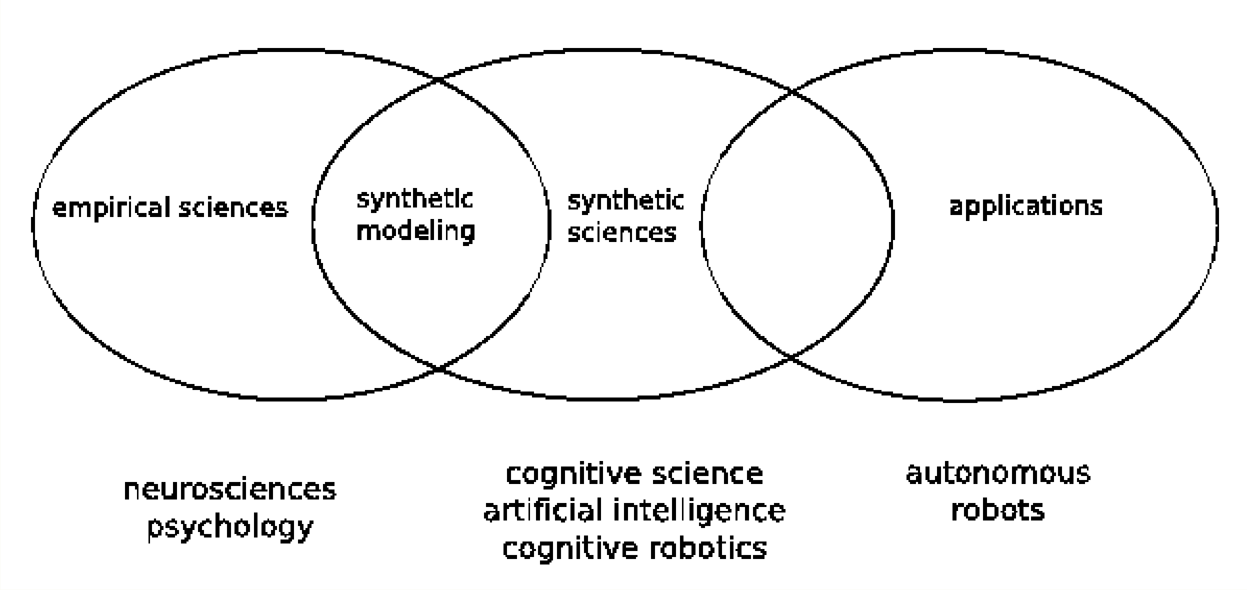
Outline

- Synthetic methodology ~ “understanding by building”
- Classical AI – intelligence as computation
- Embodied AI
  - Morphology facilitating control
    - Body design simplifying task
    - Behavior emergent from simple sensory-motor loops
  - Morphology facilitating perception
- Robot body models
- Robots learning brain-like body models

Synthetic methodology ~ understanding by building



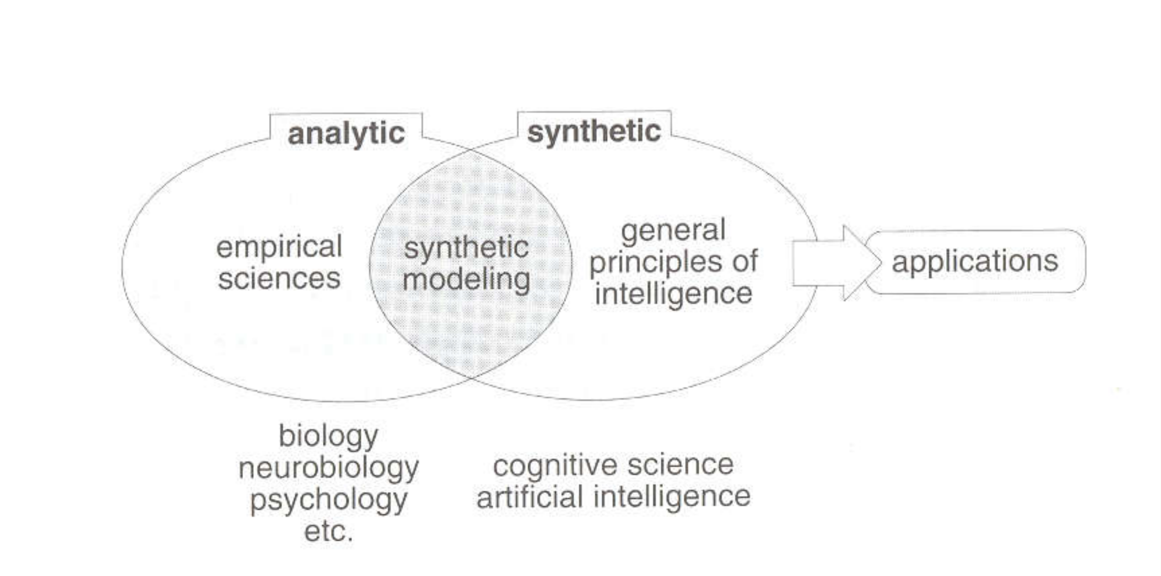
Pfeifer & Scheier (2001): Understanding intelligence

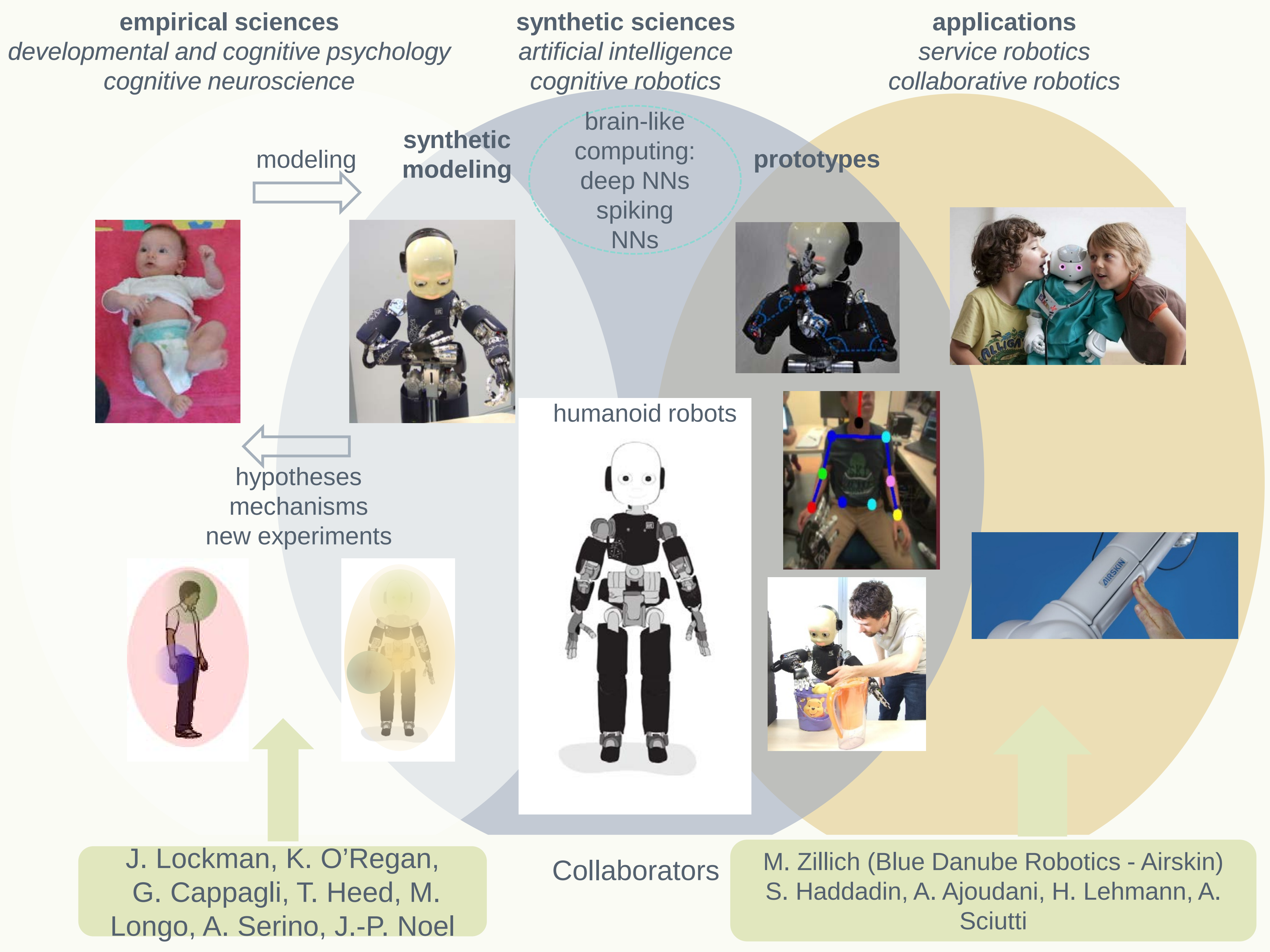


Goals

[Pfeifer and Bongard, 2007, Chapter 3]:

1. understanding natural forms of intelligence
2. abstracting general principles of intelligent behavior
3. building intelligent artifacts





empirical sciences
developmental and cognitive psychology
cognitive neuroscience
synthetic sciences
artificial intelligence
cognitive robotics
applications
service robotics
collaborative robotics
modeling
synthetic modeling
brain-like computing: deep NNs spiking NNs
prototypes
humanoid robots
hypotheses
mechanisms
new experiments
J. Lockman, K. O'Regan, G. Cappagli, T. Heed, M. Longo, A. Serino, J.-P. Noel
Collaborators
M. Zillich (Blue Danube Robotics - Airskin)
S. Haddadin, A. Ajoudani, H. Lehmann, A. Sciutti

All synthetic, yet different…

Is walking intelligent?

What it takes to walk?

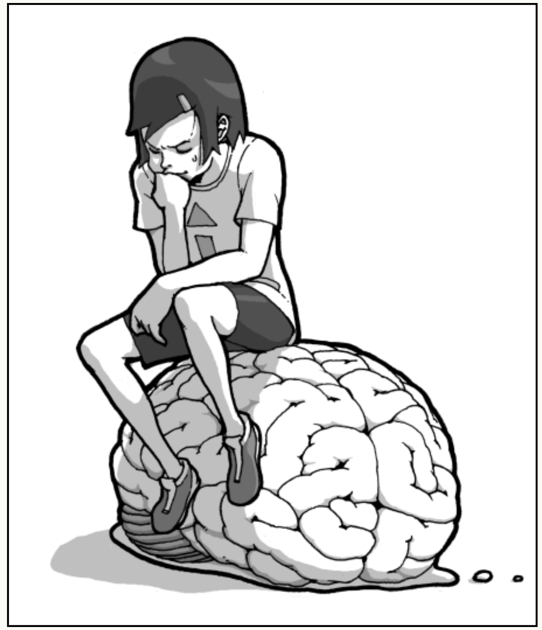
Honda Asimo (2018)
https://youtu.be/1urL_X_vp7w

Is playing chess intelligent?

Passive Dynamic Walker – Tad McGeer (1990)
https://youtu.be/WOPED7I5Lac

Outline

- Synthetic methodology ~ “understanding by building”
- Classical AI – intelligence as computation
- Embodied AI
  - – Morphology facilitating control
    - Body design simplifying task
    - Behavior emergent from simple sensory-motor loops
  - – Morphology facilitating perception
- Robot body models
- Robots learning brain-like body models



Classical:
"intelligence as computation"

Illustration: Shun Iwasawa, from Pfeifer, R: How the body shapes the way we think, 2007

Birth of Artificial Intelligence

- 1956 - onwards: Artificial Intelligence
  - 1956 Dartmouth Conference / McCarthy coins term “artificial intelligence” / first running AI program (Logic Theorist)
  - from middle ‘50s to late ’80s : ‘**Classical AI**’ (e.g. Newell, Simon, McCarthy)
    - human cognition = a set of ‘rational activities’ (reasoning, language, formal games…);
    - intelligent artifacts = programs for computers

Classical AI = modelling “high level” capabilities (mainly) through computer programs detached from robotic bodies

Slide source: Hagen Lehmann

Classical AI – theoretical positions

Intelligence ~ abstract symbol processing

Functionalism

- Algorithm / software matters
- Hardware (on which it runs) does not matter

Physical Symbol Systems Hypothesis (Newell and Simon)

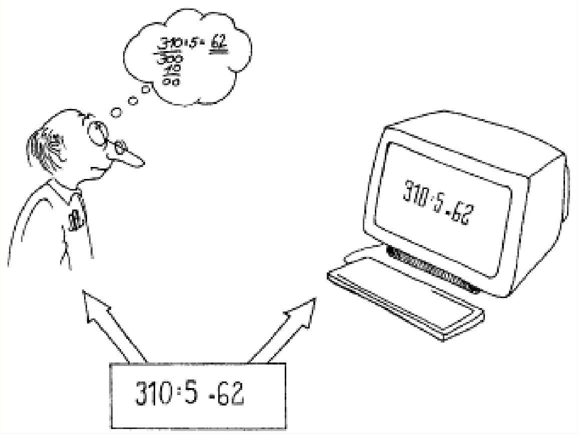


Fig. 2.4 from Pfeifer & Scheier 1999

Digital computer

- Key tool
- Metaphor for the mind!

Nicknamed GOFAI – Good Old-Fashioned Artificial Intelligence (Haugeland 1985)

Where it works nicely… search

IBM Deep Blue chess computer, 1997

Google Deep Mind AlphaGo, 2016

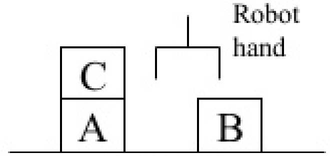
- formally precisely defined discrete state space
- program has access to complete information (fully observable)
- deterministic state evolution
- not real-time (or soft real time)

- Premiere methods – e.g.: **search**, deep reinforcement learning

Where it works nicely… planning

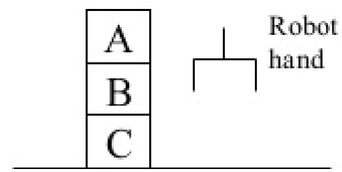
Example : Blocks World

•STRIPS : A planning system – Has rules with precondition deletion list and addition list



START

on(B, table)
on(A, table)
on(C, A)
hand empty
clear(C)
clear(B)



GOAL

on(C, table)
on(B, C)
on(A, B)
hand empty
clear(A)

Connecting to the real world - representation

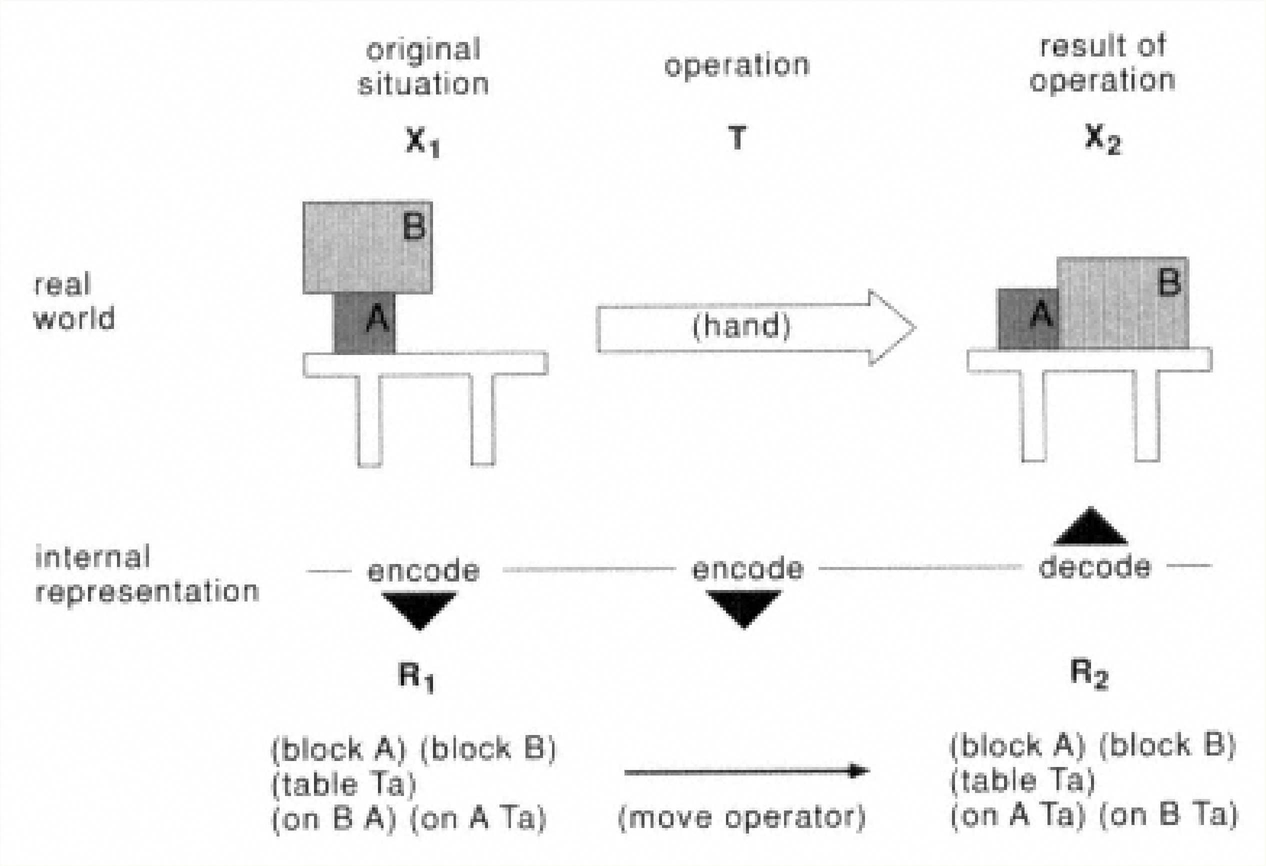
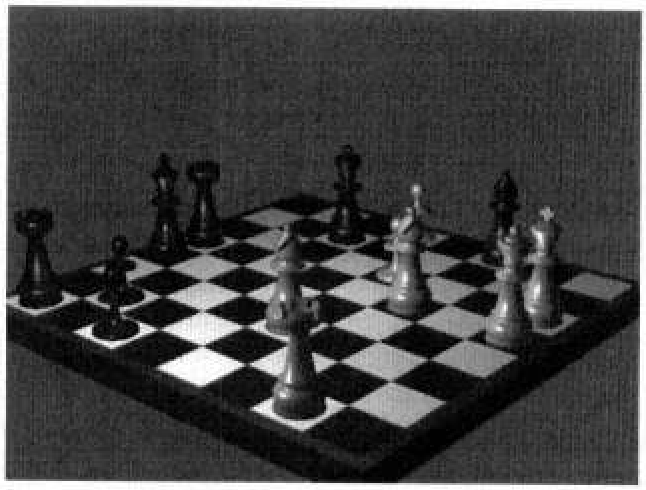


Fig. 2.5 from Pfeifer & Scheier 1999

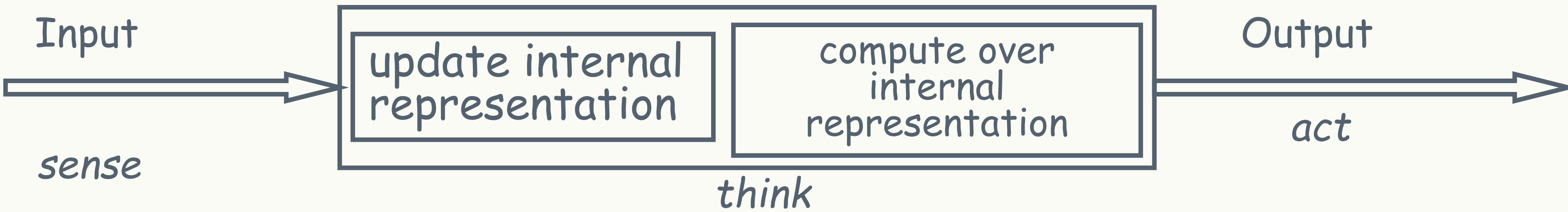
From formal world to real world

Chess

Soccer

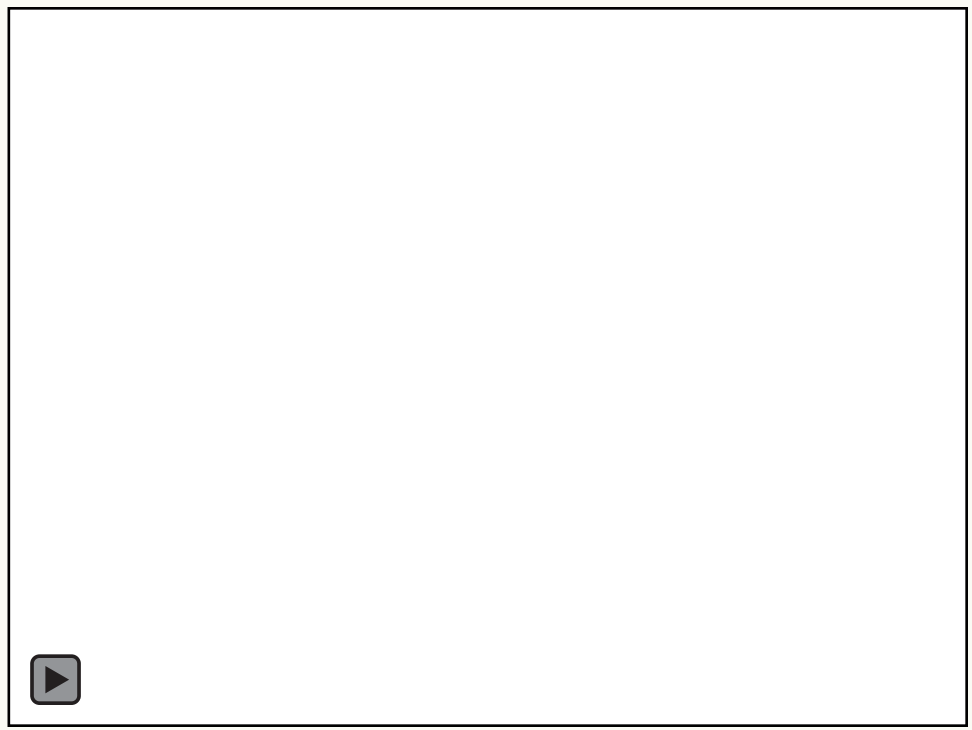


From formal world to real world



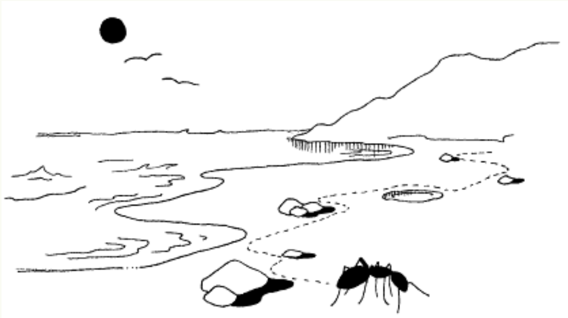
Ancient times:

Stanford Cart, 1975



GOFAI fundamental problems

- Frame problem
  - How can a model of a continuously changing environment be kept in tune with the real world?
- Symbol grounding problem (Harnad, 1990)
- Frame of reference problem
  - Ant on the beach (Herbert A. Simon)
  - simple behavioral rules
  - complexity in interaction, not in brain



GOFAI problems viewed today

Some problems have been mitigated through

- New algorithms
  - Probabilistic reasoning (e.g. Thrun et al. 2005)
  - Learning
    - Reinforcement learning
    - “Deep” neural networks
- Higher computational power

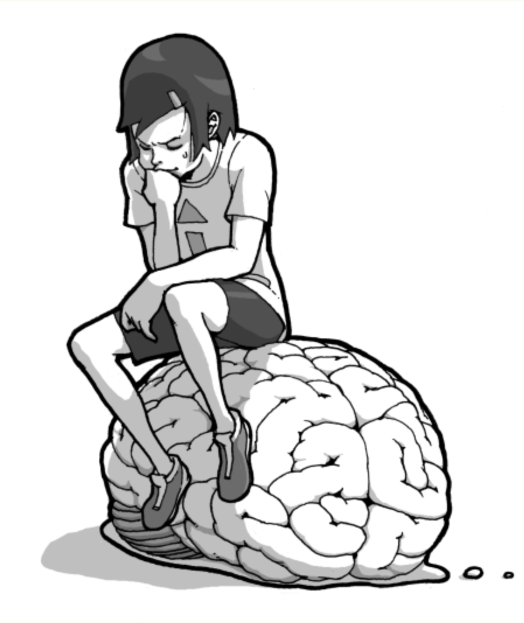
=> real-time operation in real world is possible

Stanley, 2006

Google self-driving car today

What remains?

AI still heavily biased toward representation and computation.



vs. natural (also human) intelligence:

- embodied
- emergent from sensory-motor and interaction processes

Research questions

Classical AI

- Thinking, reasoning, abstract problem solving

Embodied AI

- Movement, physical interaction with the real world

"Why do plants not have brains? The answer is actually quite simple: they don't have to move."

Lewis Wolpert, UCL

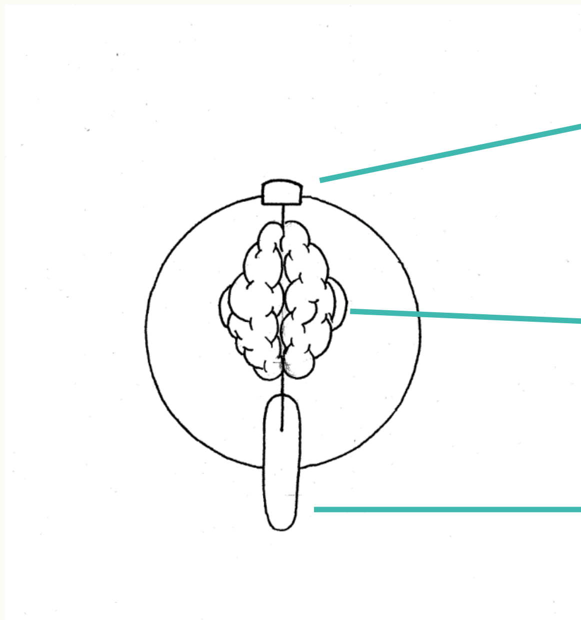
Outline

- Synthetic methodology ~ “understanding by building”
- Classical AI – intelligence as computation
- Embodied AI
  – Morphology facilitating control
    • Body design simplifying task
    • Behavior emergent from simple sensory-motor loops
  – Morphology facilitating perception
- Robot body models
- Robots learning brain-like body models

Embodiment

- “intelligence requires a body”
- Interplay / task distribution
  - Brain
  - Body (morphology – shape, materials, ...)
  - Environment
- Principal of ecological balance
  - match in complexity of sensory, motor, and neural system

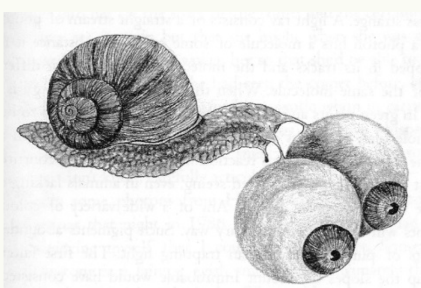
Ecologically unbalanced systems



sensor for one quality (e.g. temperature, light)

very large brain

one motor



Physical implications of embodiment

~ morphology facilitating control

Is brain/computation needed for walking?

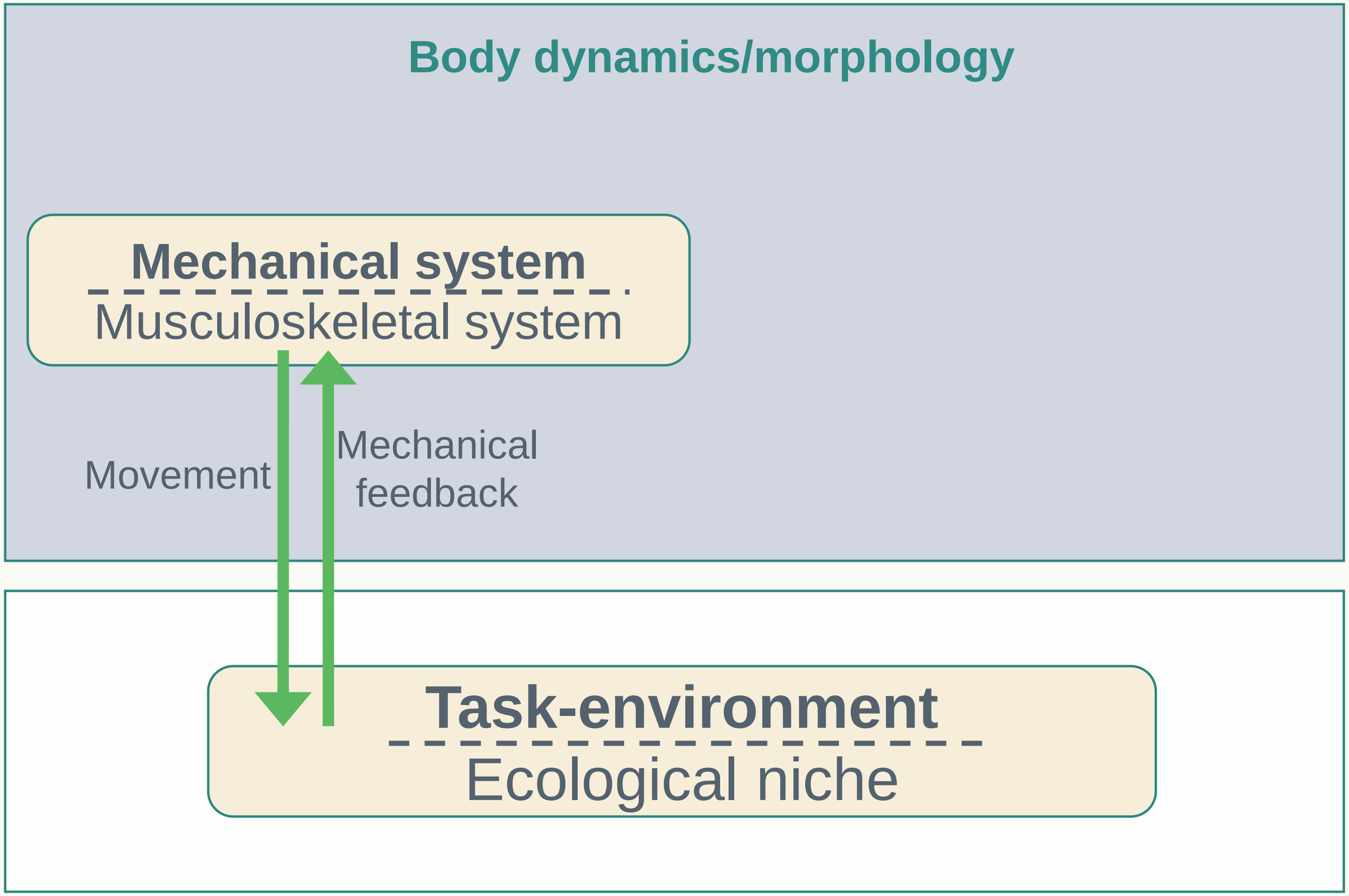
Passive dynamic walkers (McGeer 1990)

- "pure physics walking"
- no computer
- no motors
- no sensors

Morphology:
- shape of feet
- counterswing of arms
- friction on bottom of feet

Cornell PDW with arms, Collins et al. 2001

Steve Collins, Passive dynamic walker



Schematics based on Pfeifer et al., Science 2007

Self-stabilization

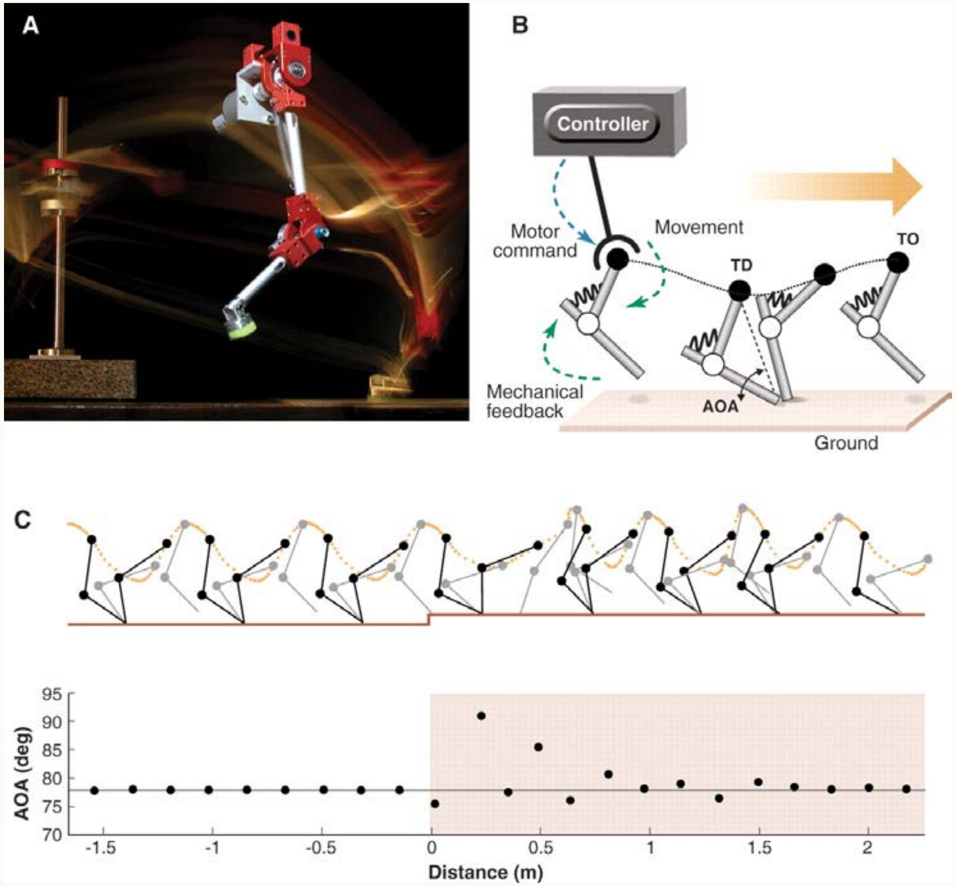
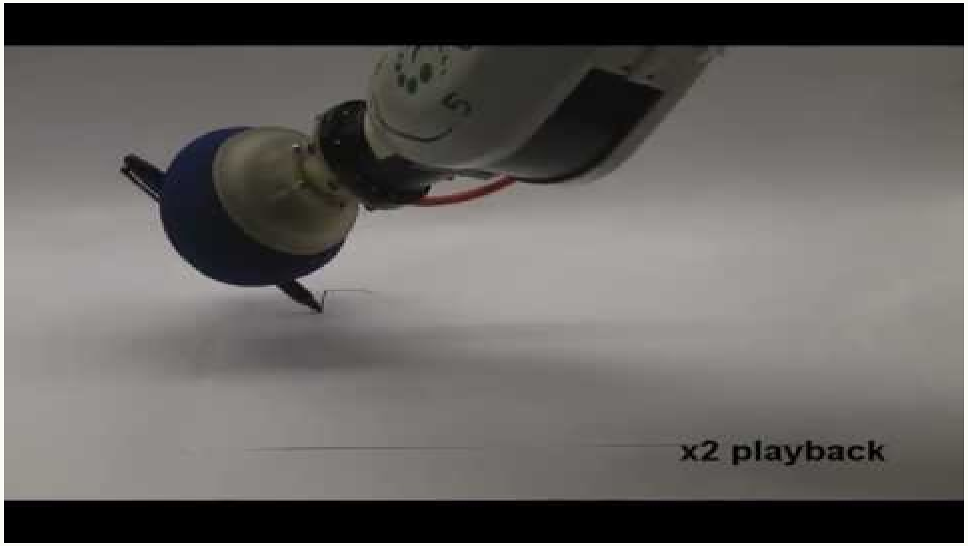


Fig. adapted from Blickhan et al. 2007

https://youtu.be/Zt7J0dly70M

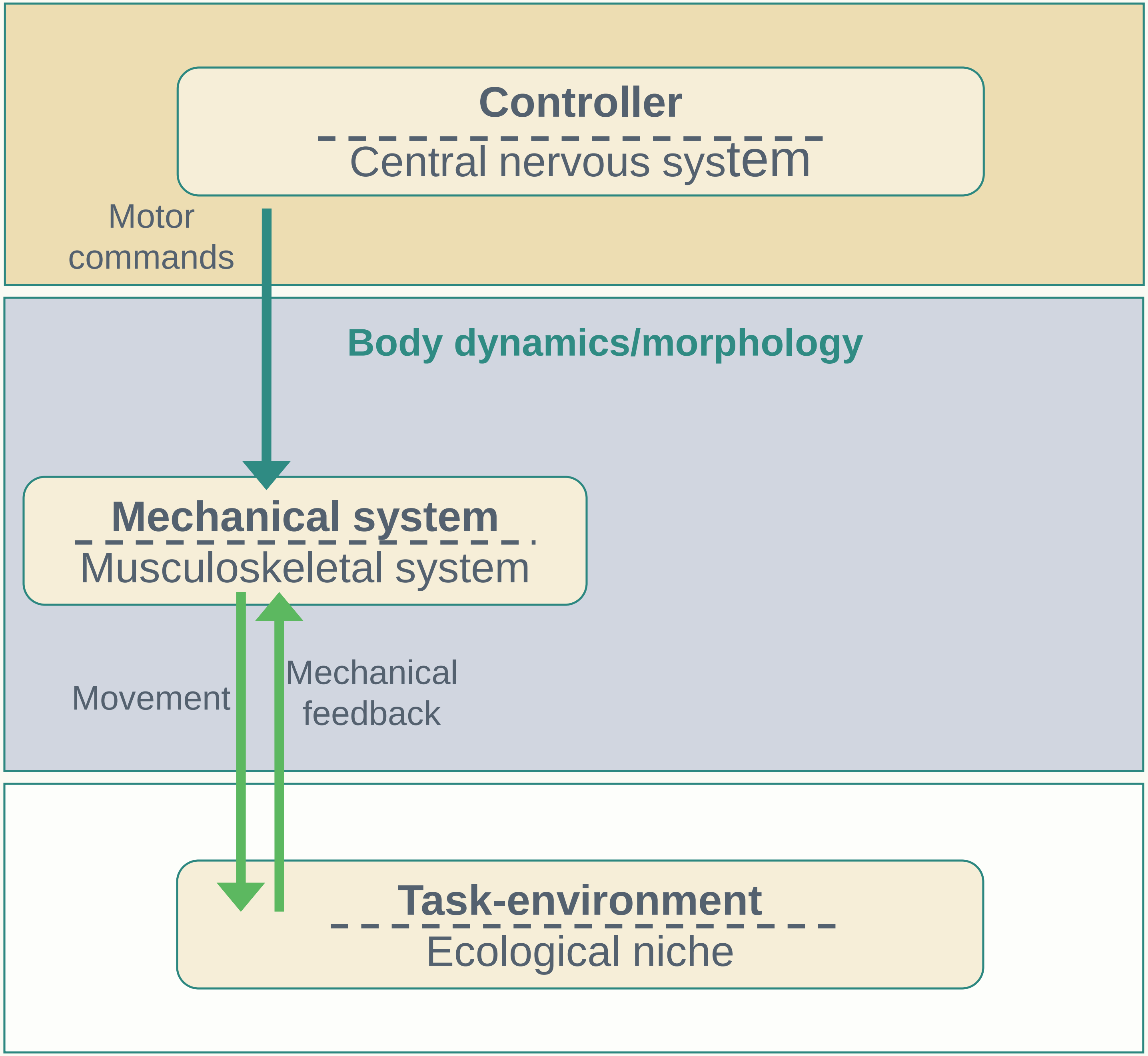
Grasping with coffee balloon grippers

Image: John Amend (jra224@cornell.edu)



https://youtu.be/ZKOI_lVDPpw

Brown et al. 2010



Controller
Central nervous system
Motor commands
Body dynamics/morphology
Mechanical system
Musculoskeletal system
Movement
Mechanical feedback
Task-environment
Ecological niche

Outline

Synthetic methodology ~ “understanding by building”

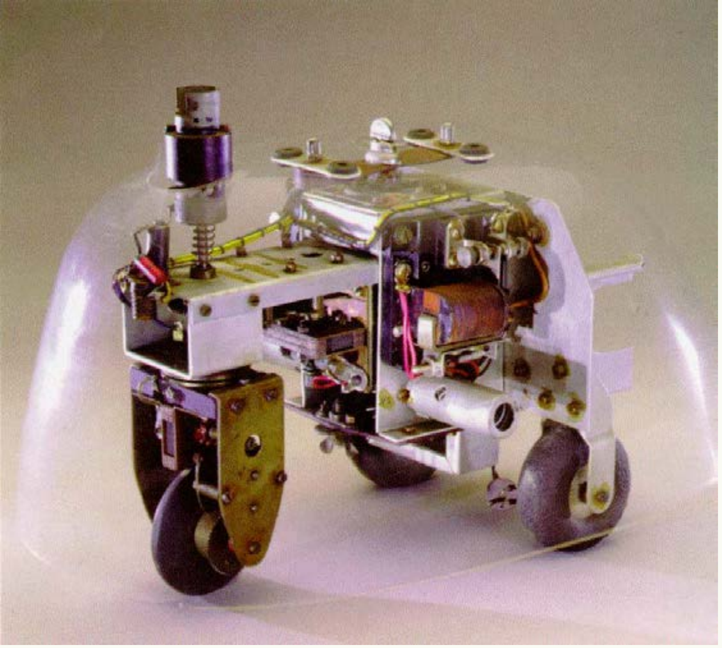
Classical AI – intelligence as computation

Embodied AI

- Morphology facilitating control
  - Body design simplifying task
  - Behavior emergent from simple sensory-motor loops
- Morphology facilitating perception

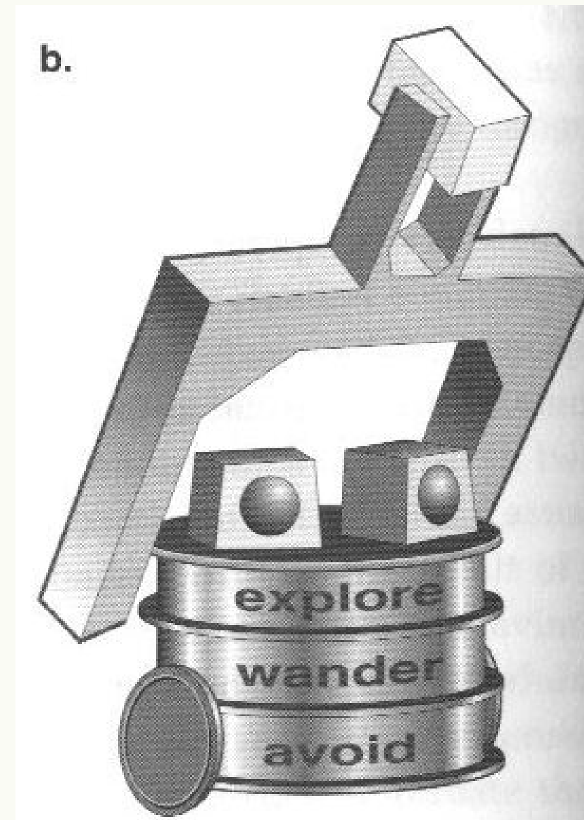
Robot body models

Robots learning brain-like body models



Grey Walter
Turtle, 1940s

V. Breitenberg, 1980s

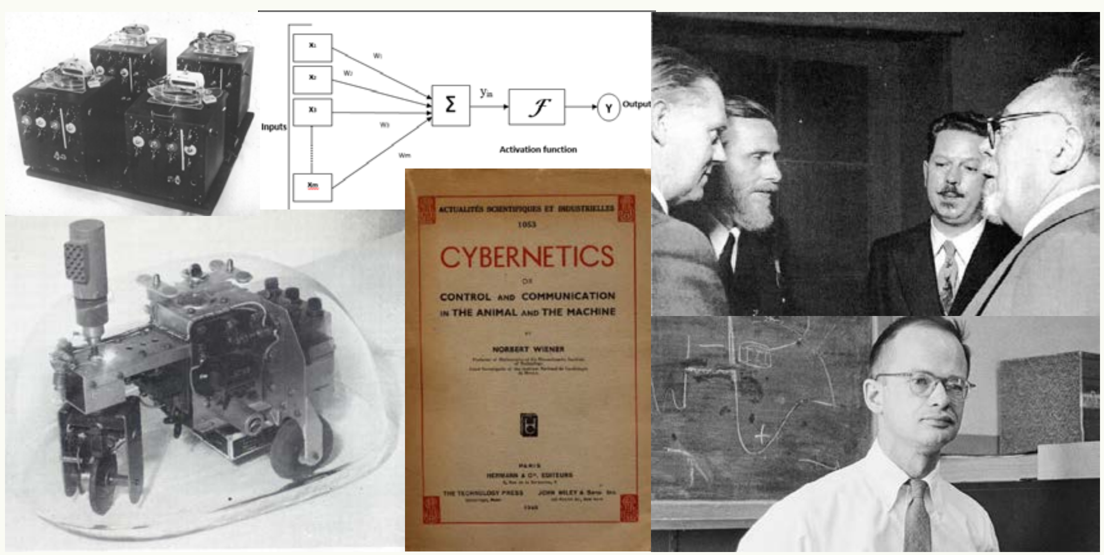


R. Brooks, 1980s
subsumption architecture

Middle ’40s: Cybernetics - modelling intelligence through machines (Wiener 1948, von Neumann 1948)

Beginnings

- early ideas of embodiment and modeling neurophysiological processes in the 1940s (McCulloch, Pitts 1946 - formal neuron; Ross Ashby - Homeostat; Grey Walter - tortoise robots)
- 1946 - 1953 Macy Conferences on Cybernetics



Slide source: Hagen Lehmann

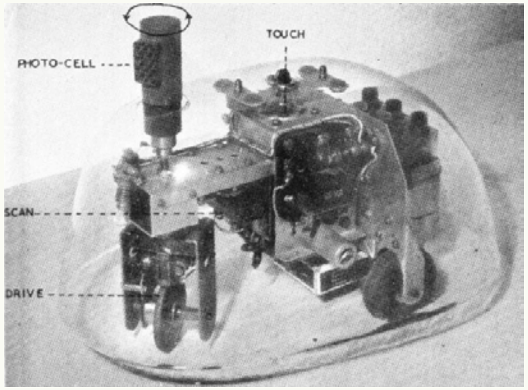
William Grey Walter (1910-1977)

English neurophysiologist and roboticist

Work on EEG, conditioning, etc.

“Robotic tortoises” (1948-49)

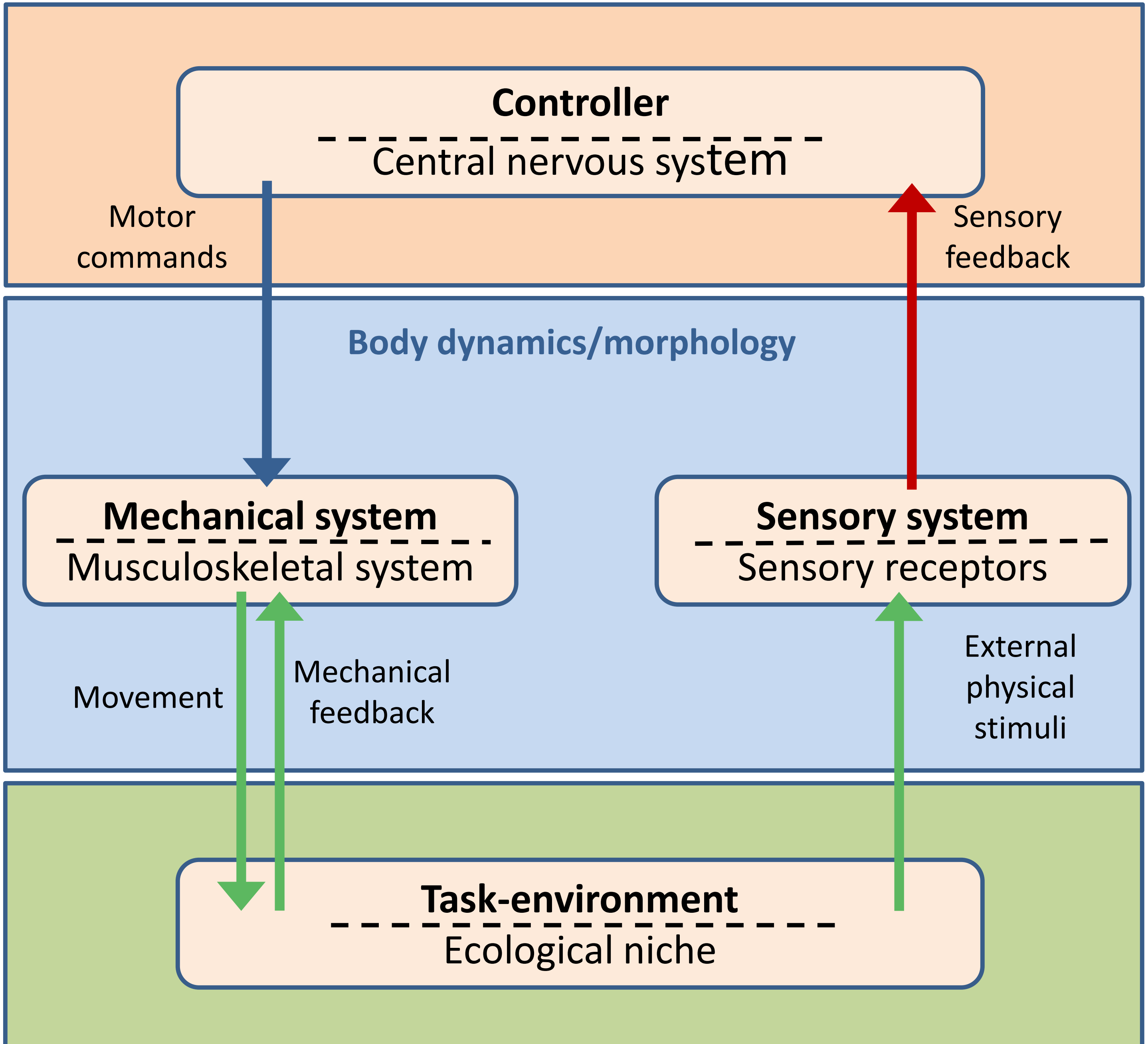
- Autonomous robots with touch and light sensors
- Simple “brain” (2 “neurons”)
- “tortoises” influenced a number of roboticists (Hans Moravec, Rodney Brooks, etc.)
- “descendants”: robotic vacuum cleaners



Slide source: Miloš Železný

Grey Walter's tortoises

Breitenberg vehicle


Controller
Central nervous system
Motor commands
Sensory feedback
Body dynamics/morphology
Mechanical system
Musculoskeletal system
Sensory system
Sensory receptors
Movement
Mechanical feedback
External physical stimuli
Task-environment
Ecological niche

Behavior-based robotics manifestos

Intelligence without representation*

Rodney A. Brooks

MIT Artificial Intelligence Laboratory, 545 Technology Square, Rm. 836, Cambridge, MA 02139, USA

Received September 1987

Brooks, R.A., Intelligence without representation, Artificial Intelligence 47 (1991), 139–159.

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
ARTIFICIAL INTELLIGENCE LABORATORY

A.I. Memo No. 1293 April, 1991

Intelligence Without Reason

Rodney A. Brooks

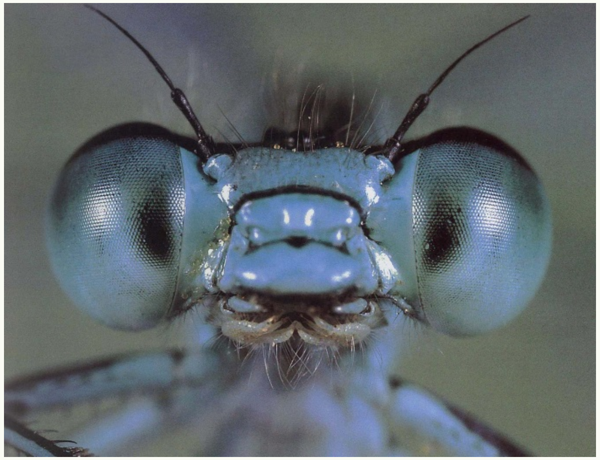
Prepared for *Computers and Thought*, IJCAI-91

Outline

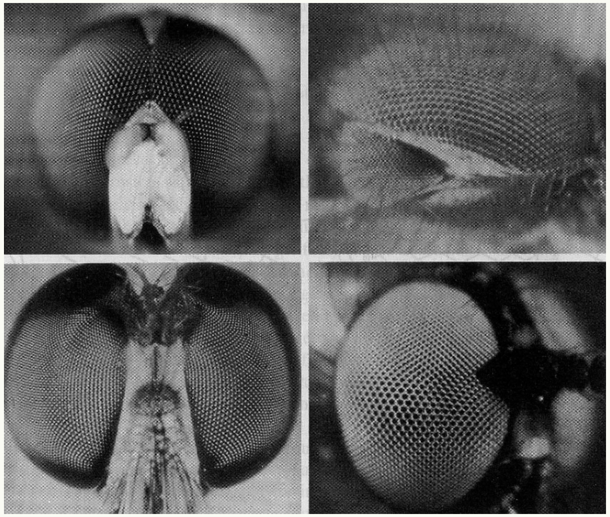
- Synthetic methodology ~ “understanding by building”
- Classical AI – intelligence as computation
- Embodied AI
  - Morphology facilitating control
    - Body design simplifying task
    - Behavior emergent from simple sensory-motor loops
  - Morphology facilitating perception
- Robot body models
- Robots learning brain-like body models

Insect eye morphology

Different species of insects have evolved different non-homogeneous arrangements of the light-sensitive cells in their eyes, providing an advantageous nonlinear transformation of the input for a particular task



horsefly

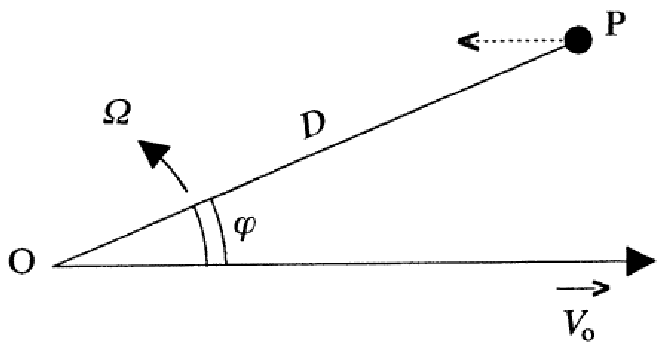


honeybee

Obstacle avoidance

exploiting ego-motion together with motion parallax

Franceschini et al. 1992

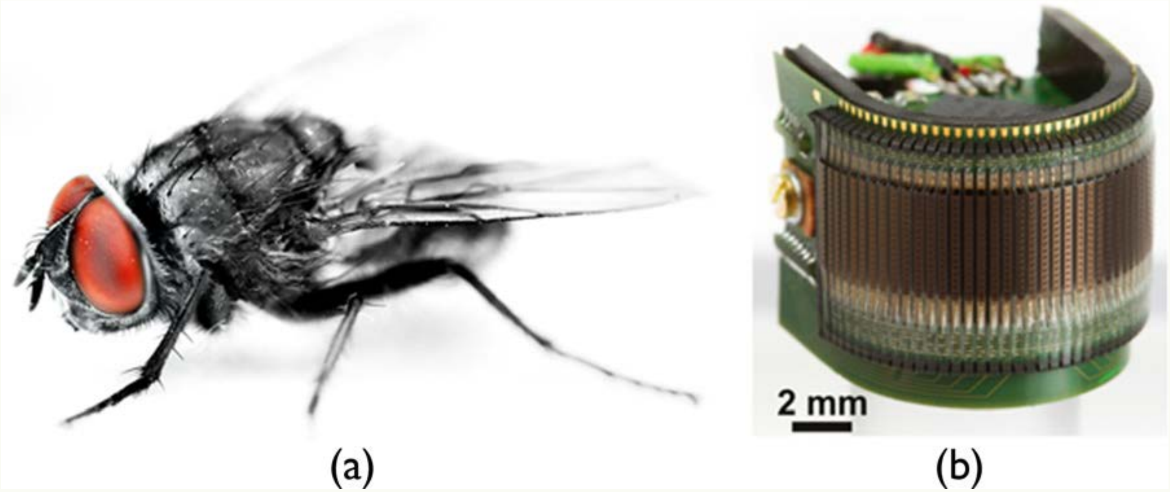


$$\Omega = \frac{V_o}{D} \cdot \sin\varphi$$

Figure 6. Principle of motion parallax. Any agent (fly, human, robot, etc.) translating at speed V_0 can gauge the distance to a contrast point P located at azimuth φ if it is equipped with a passive sensor able to measure the angular speed Ω of P when this point crosses its visual field due to the agent's own movement.

Nonuniform distribution & elementary motion detectors

The distribution of the cells is nonuniform and follows a sine gradient in the interommatidial angle, such that sampling of the visual space is finer towards the front than laterally. This effectively compensates for the sine relationship in the formula and allows uniform motion detection circuitry to be used everywhere.



CurvACE – artificial compound eye - image courtesy of Dario Floreano

Message to remember: embodiment

behavior is not in the brain

(or cell, molecule...)

it is in the interaction

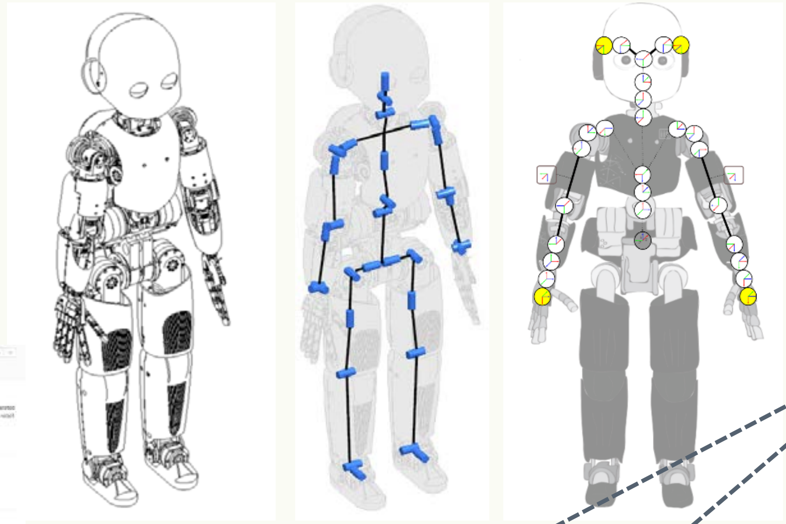
(vs. "all behavior is a result of brain function" – Eric R. Kandel, Ch. 1: The Brain and Behavior, in Kandel, E.R., Schwartz, J.H. and Jessell, T.M. eds., 2000. *Principles of neural science* (Vol. 4, pp. 1227-1246). New York: McGraw-hill.

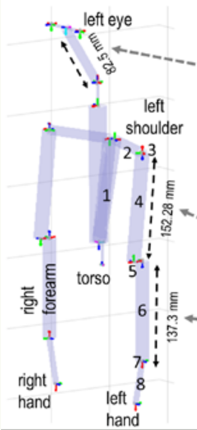
Illustrations: Shun Iwasawa, from R. Pfeifer & J. Bongard: How the body shapes the way we think, 2007

Outline

- Synthetic methodology ~ "understanding by building"
- Classical AI – intelligence as computation
- Embodied AI
  - Morphology facilitating control
    - Body design simplifying task
    - Behavior emergent from simple sensory-motor loops
  - Morphology facilitating perception
- Robot body models
- Robots learning brain-like body models

How we make robots do things – the traditional way



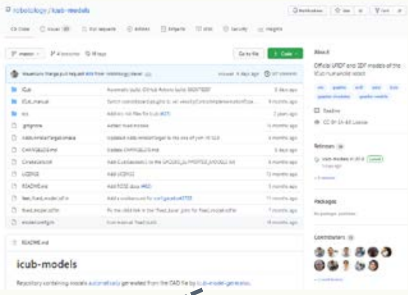


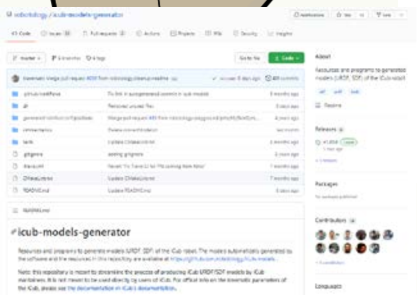
Link(i)	a(i) [mm]	d(i) [mm]	α [rad]	o [rad]
1	2.31	- 193.3	$-\pi/2$	$\pi/4$
2	33	0	$\pi/2$	$\pi/4$
3	0	1	$-\pi/2$	$\pi/4$
4	- 54	82.5	$-\pi/2$	$\pi/4$
5	0	- 34	$-\pi/2$	0
6	0	0	$\pi/2$	$-\pi/4$

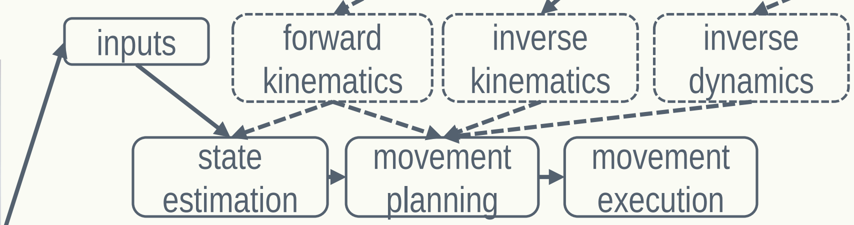
TABLE I
DH PARAMETERS – HEAD AND LEFT EYE

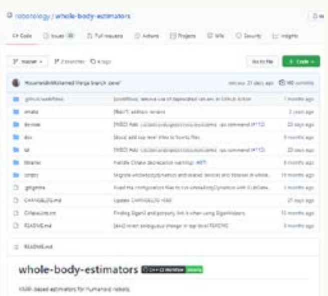
Link(i)	a(i) [mm]	d(i) [mm]	α [rad]	o [rad]
1	23.36	143.3	$\pi/2$	$105 * \pi/180$
2	0	107.74	$-\pi/2$	$\pi/2$
3	0	0	$\pi/2$	$-\pi/2$
4	15	152.28	$-\pi/2$	$75 * \pi/180$
5	-15	0	$\pi/2$	0
6	0	137.3	$\pi/2$	$-\pi/2$
7	0	0	$\pi/2$	$\pi/2$
8	62.5	-16	0	0

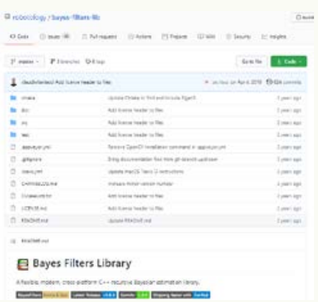
TABLE II
DH PARAMETERS – LEFT ARM

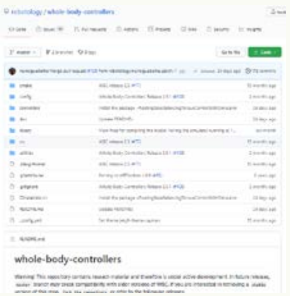




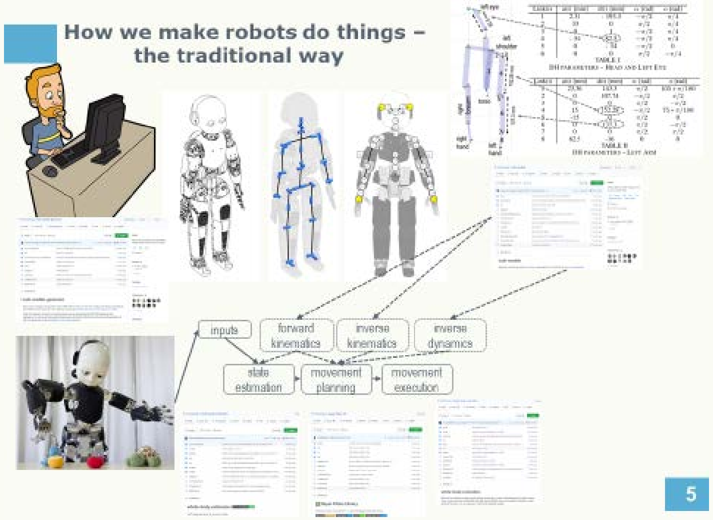








Engineering way – pros and cons



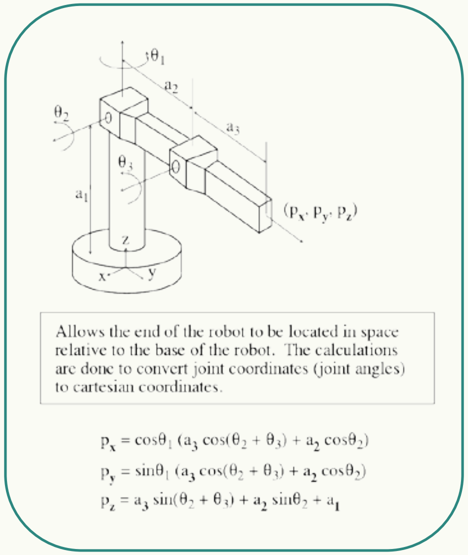
Pros

- very neat... ☺
- mathematics and physics
  - ➢ extrapolation...
- veridical representation
  - ➢ we understand the model
  - ➢ accuracy can be measured
- modularity
  - ➢ maintenance

Cons

- lot of man-hours
- model typically fixed
  - ➢ external calibration procedures...
- no redundancy
  - ➢ fragility

Robot body models and calibration

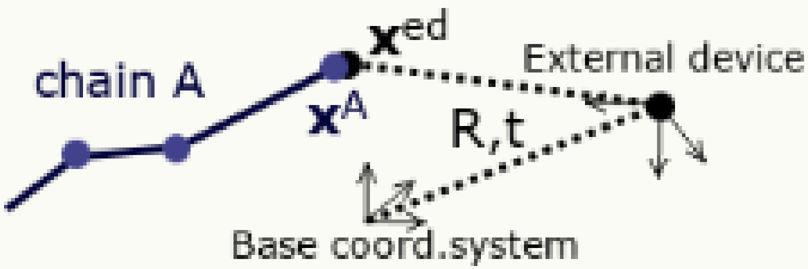


- Robotic models tend to be
  - fixed
  - centralized
  - explicit
  - rely on minimal sensory info
  - start from significant prior knowledge
- Calibration is typically performed using external metrology (e.g., calibration chambers).
- Calibration ~ fine-tuning of parameters

Traditional kinematic calibration

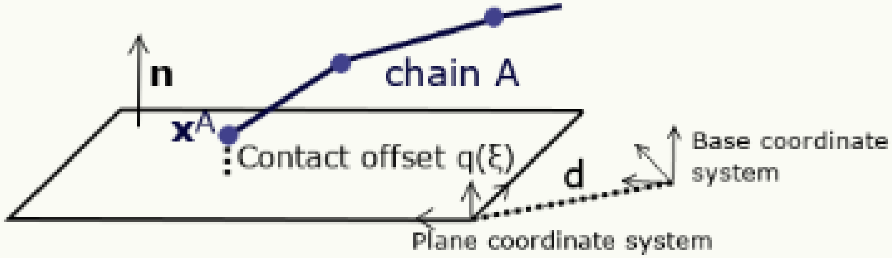
open-loop calibration

- utilizes an external metrology system to measure the pose components
- manipulator not in contact with environment



closed-loop calibration

- utilizes physical constraints on the end link pose to substitute for measurements



Hollerbach, J., Khalil, W., & Gautier, M. (2016). Model identification. In *Springer handbook of robotics* (pp. 113-138). Springer, Cham.

Automatic self-contained robot calibration - motivation

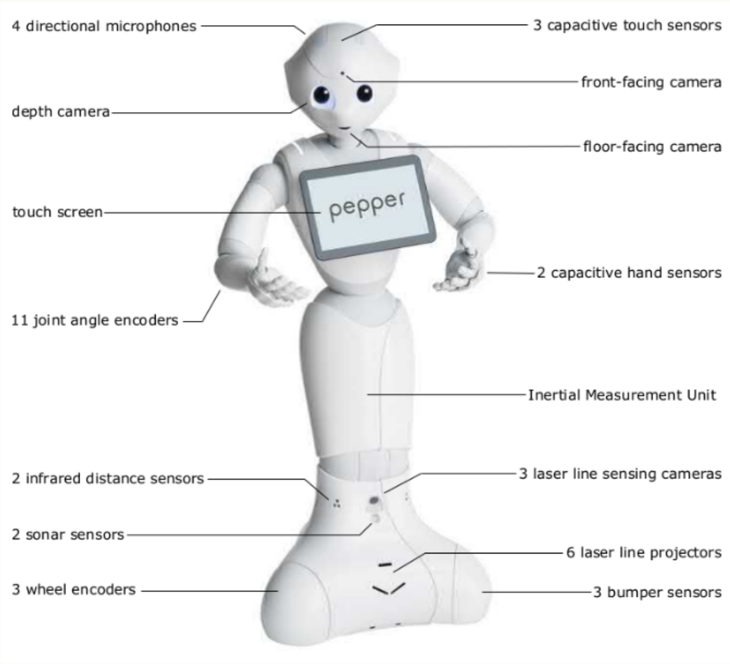
Current robots:

- cheaper and more elastic materials
- set of affordable but increasingly accurate

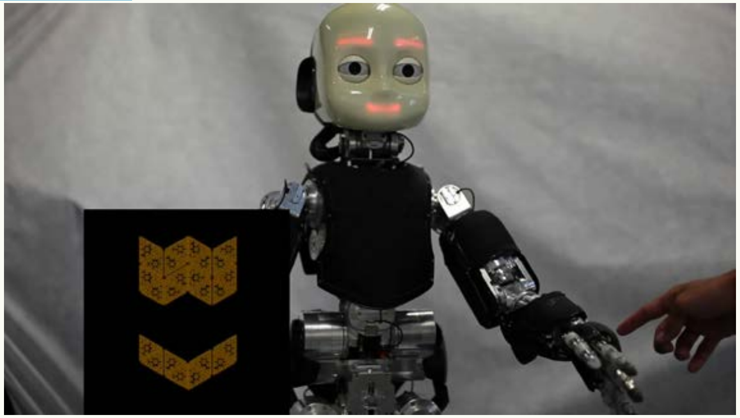
  sensors (e.g. RGB-D cameras, tactile, force,

  or inertial sensors, etc.)

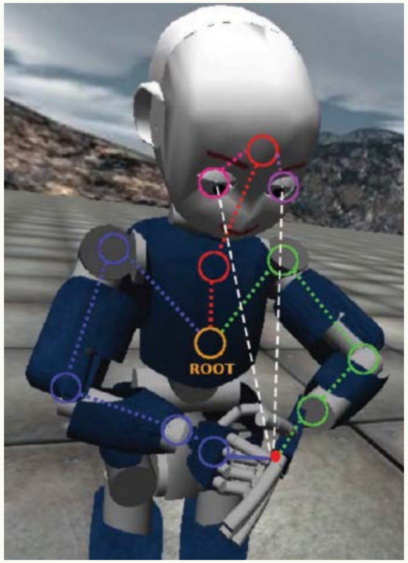
=> Necessity and opportunity for autonomous continuous (re-)calibration

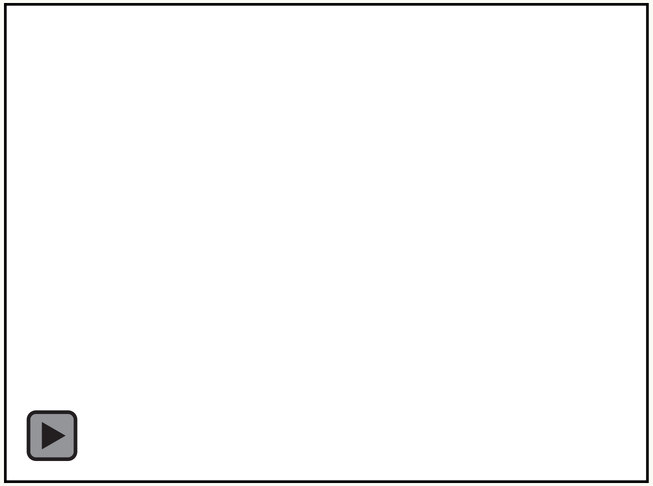


Multisensorial self-contained robot calibration

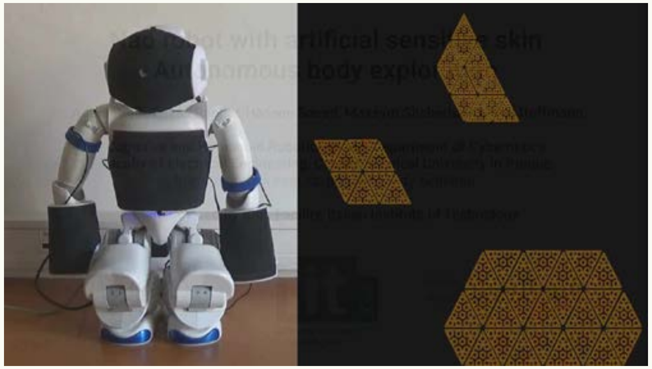


Roncone, A.; Hoffmann, M.; Pattacini, U. & Metta, G. (2014), Automatic kinematic chain calibration using artificial skin: self-touch in the iCub humanoid robot, *in* 'Proc. IEEE Int. Conf. Robotics and Automation (ICRA)'.





Stepanova, K.; Pajdla, T. & Hoffmann, M. (2019), 'Robot self-calibration using multiple kinematic chains – a simulation study on the iCub humanoid robot', *IEEE Robotics and Automation Letters* **4**(2), 1900-1907.



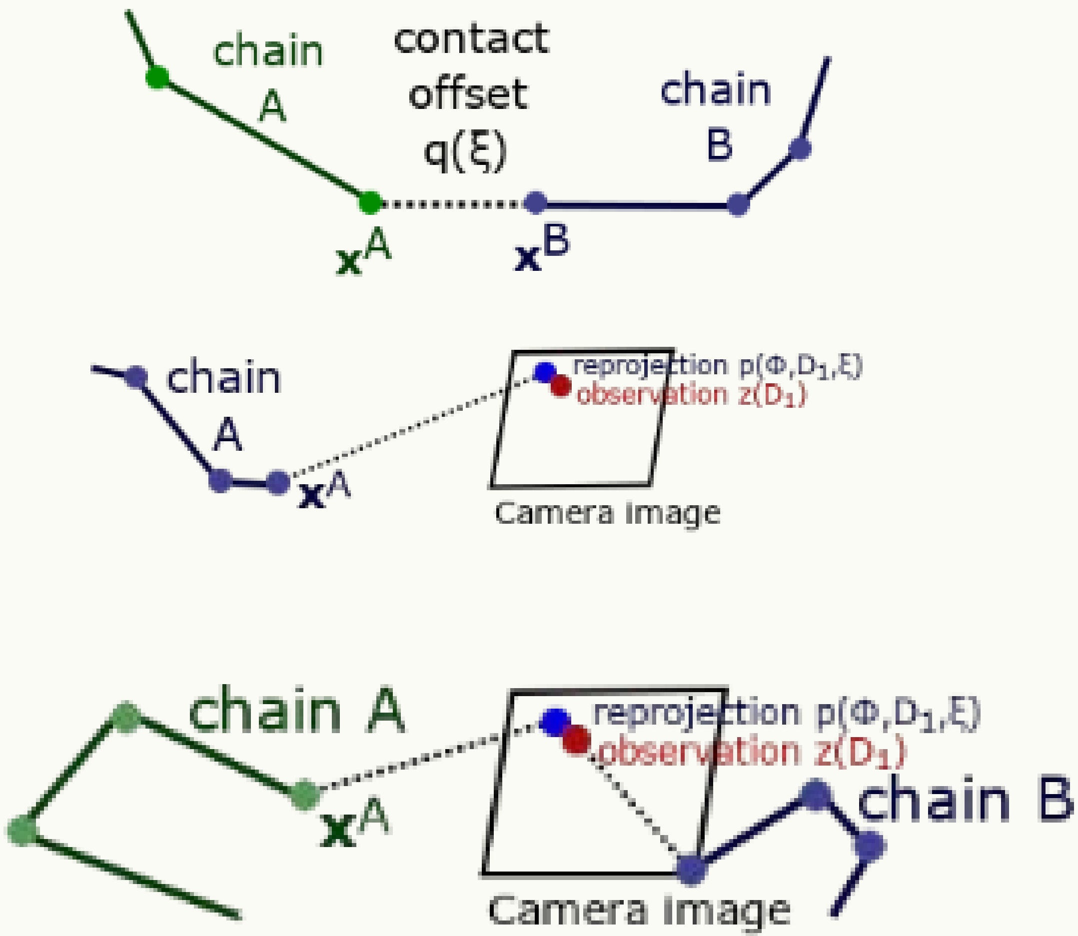
Rustler, L.; Potocna, B.; Polic, M.; Stepanova, K. & Hoffmann, M. (2021), Spatial calibration of whole-body artificial skin on a humanoid robot: comparing self-contact, 3D reconstruction, and CAD-based calibration, in 'Humanoid Robots (Humanoids), IEEE-RAS International Conference on'.

https://github.com/ctu-vras/multirobot-calibration

Rozlivek, J.; Rustler, L.; Stepanova, K. & Hoffmann, M. (2021), Multisensorial robot calibration framework and toolbox, *in* 'Humanoid Robots (Humanoids), IEEE-RAS International Conference on'.

Stepanova, K.; Rozlivek, J.; Puciow, F.; Krsek, P.; Pajdla, T. & Hoffmann, M. (2022), 'Automatic self-contained calibration of an industrial dual-arm robot with cameras using self-contact, planar constraints, and self-observation', *Robotics and Computer-Integrated Manufacturing* 73, 102250.

Self-contact and self-observation



Rozlivek, J.; Rustler, L.; Stepanova, K. & Hoffmann, M. (2021), Multisensorial robot calibration framework and toolbox, *in* 'Humanoid Robots (Humanoids), IEEE-RAS International Conference on'.

Multi-chain robot calibration

Estimate parameter vector:

$$\boldsymbol{\phi} = \{[a_1, \ldots, a_n], [d_1, \ldots, d_n], [\alpha_1, \ldots, \alpha_n], [o_1, \ldots, o_n]\} \text{ with } k \in N$$

$N = \{1, \ldots, n\}$ is a set of indices identifying individual links; a_k, d_k and α_k are the first three parameters of the DH formulation of link k; o_k is the offset that specifies the positioning of the encoders on the joints with respect to the DH representation.

$$\boldsymbol{\phi}^* = \arg\min_{\boldsymbol{\phi}} \boldsymbol{f}(\boldsymbol{\phi}, \boldsymbol{D}, \boldsymbol{\zeta}),$$

$$\boldsymbol{f}(\boldsymbol{\phi}, \boldsymbol{D}, \boldsymbol{\zeta}) = \|\boxed{\boldsymbol{g}(\boldsymbol{\phi}, \boldsymbol{D}, \boldsymbol{\zeta})}\|^2 = \sum_{i=1}^{M'} g(\boldsymbol{\phi}, \boldsymbol{D}_i, \boldsymbol{\zeta})^2$$

$$\boldsymbol{D} \subset \boldsymbol{D}^{whole}$$

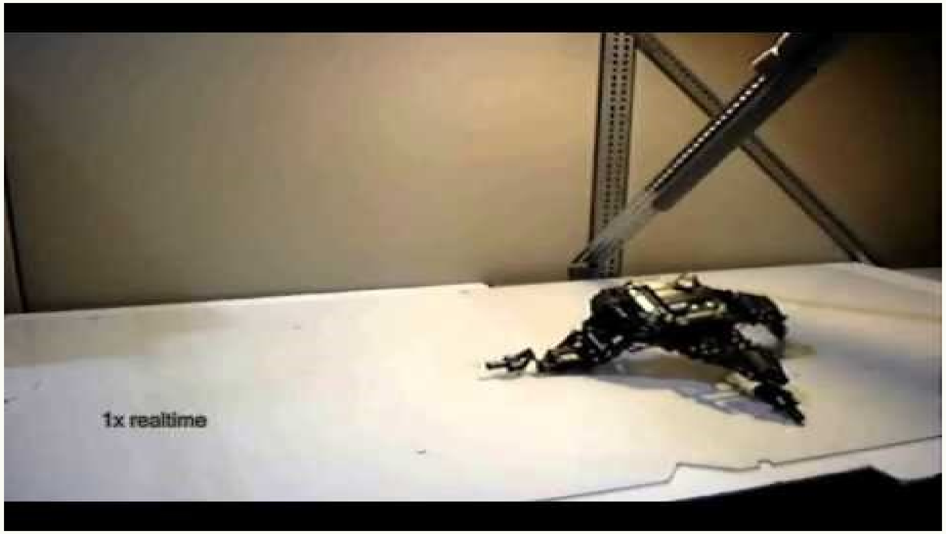
$$\boldsymbol{D}_i = [m_i, c_i, \boldsymbol{u}_i, \boldsymbol{\theta}_i]$$

~ Reprojection error (camera chains)
~ Distance of real (observed) and estimated end effector positions (other chains)

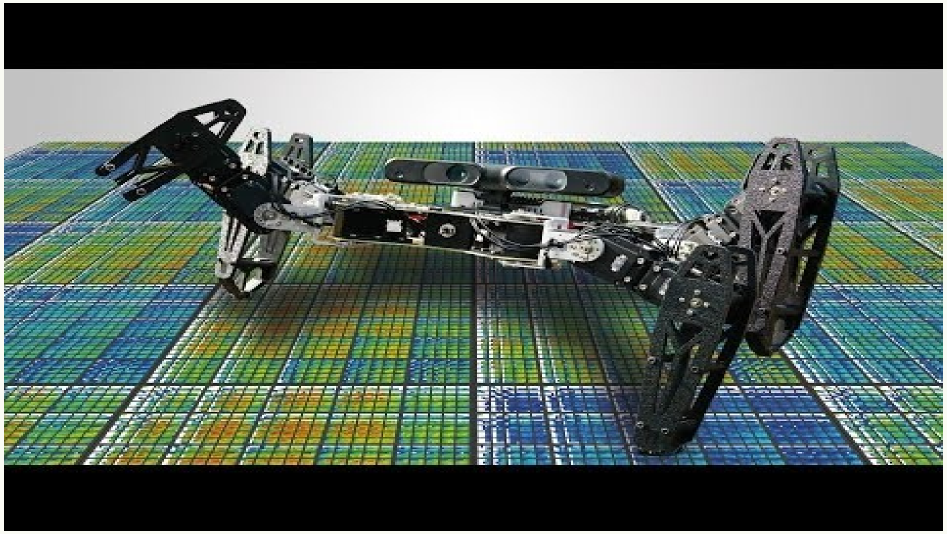
It works, but…

- Still quite laborious.
- Local optimization methods => good initial guess of parameters is needed.
- Will not cope with dramatic changes.

Resilient robots

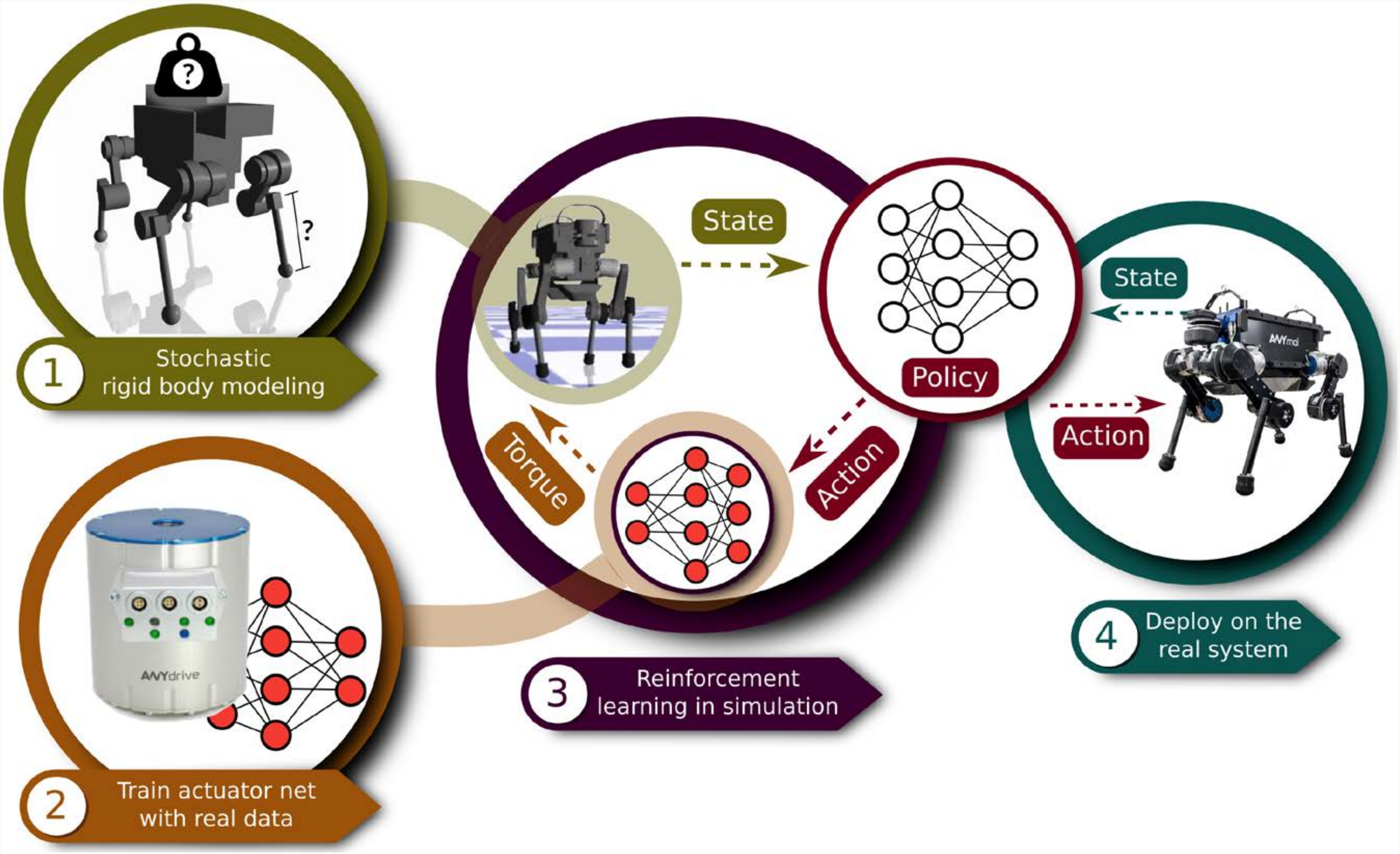


https://youtu.be/x579QKA6fkY
Bongard, J., Zykov, V., & Lipson, H. (2006). Resilient machines through continuous self-modeling. *Science*, *314*(5802), 1118-1121.



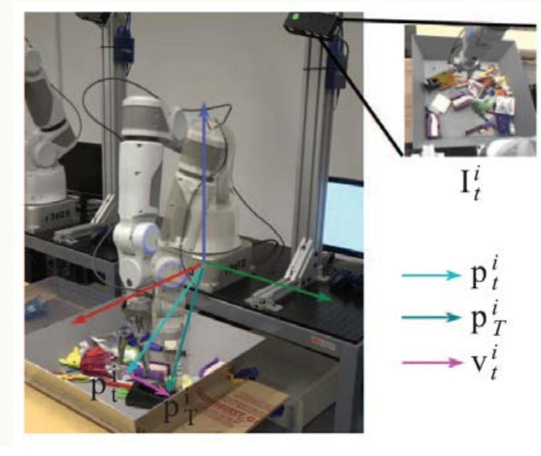
https://youtu.be/T-c17RKh3uE
Cully, A., Clune, J., Tarapore, D., & Mouret, J. B. (2015). Robots that can adapt like animals. Nature, 521(7553), 503-507.

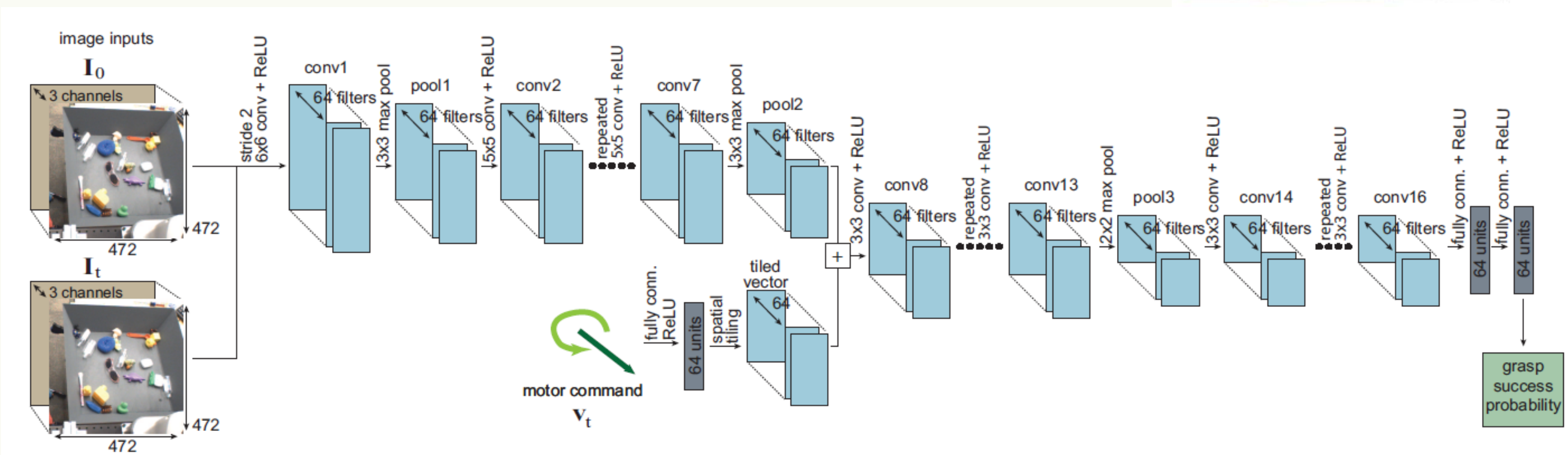
Beyond the white-box (body) model



Hwangbo, J., Lee, J., Dosovitskiy, A., Bellicoso, D., Tsounis, V., Koltun, V., & Hutter, M. (2019). Learning agile and dynamic motor skills for legged robots. *Science Robotics*, *4*(26).

Let’s forget about the body model

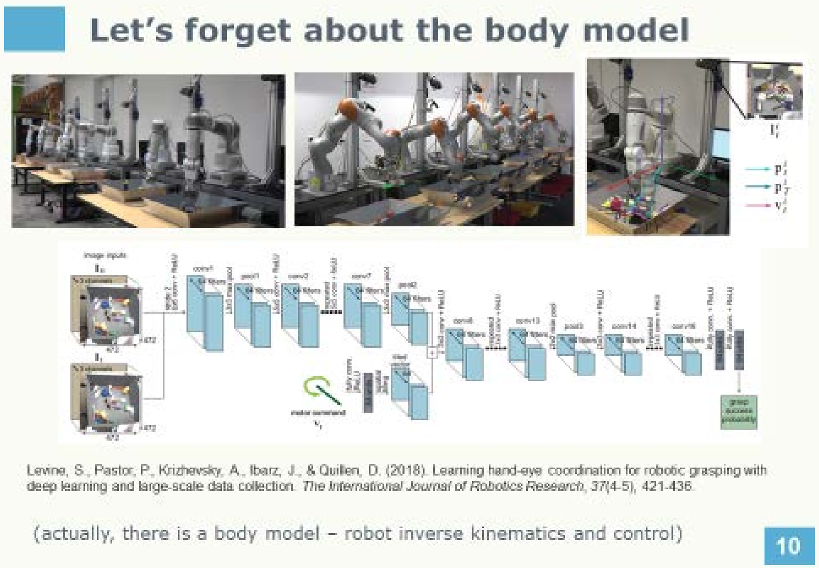




Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *The International Journal of Robotics Research*, *37*(4-5), 421-436.

(actually, there is a body model – robot inverse kinematics and control)

End-to-end / deep / RL way – pros and cons



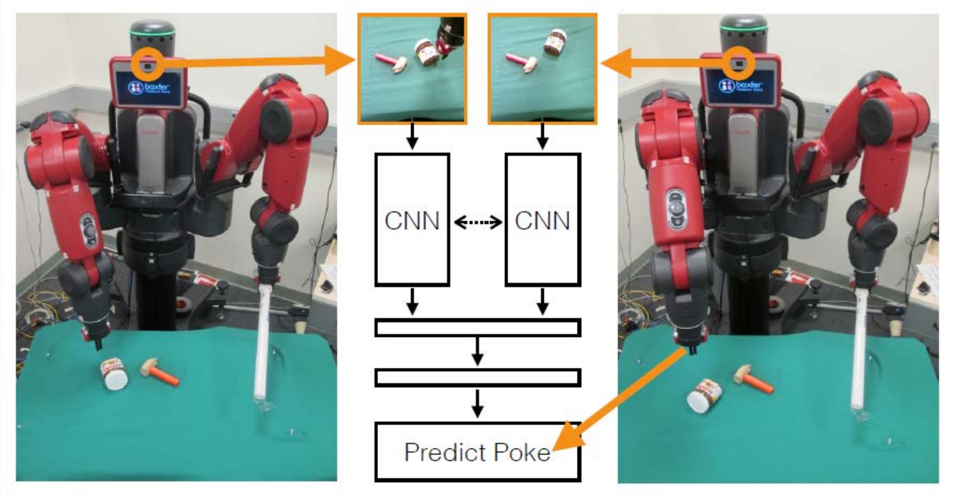
Pros

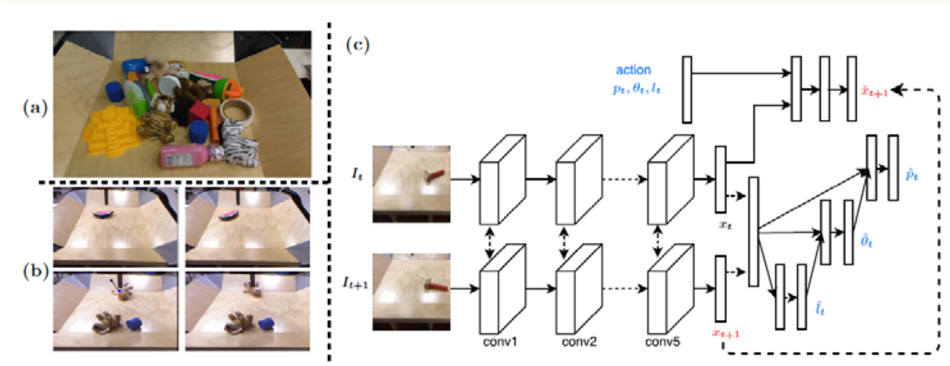
- it is learned ☺
  - ➢ adaptive (possibly)
- fewer man-hours
  - unless hand-labeling is needed

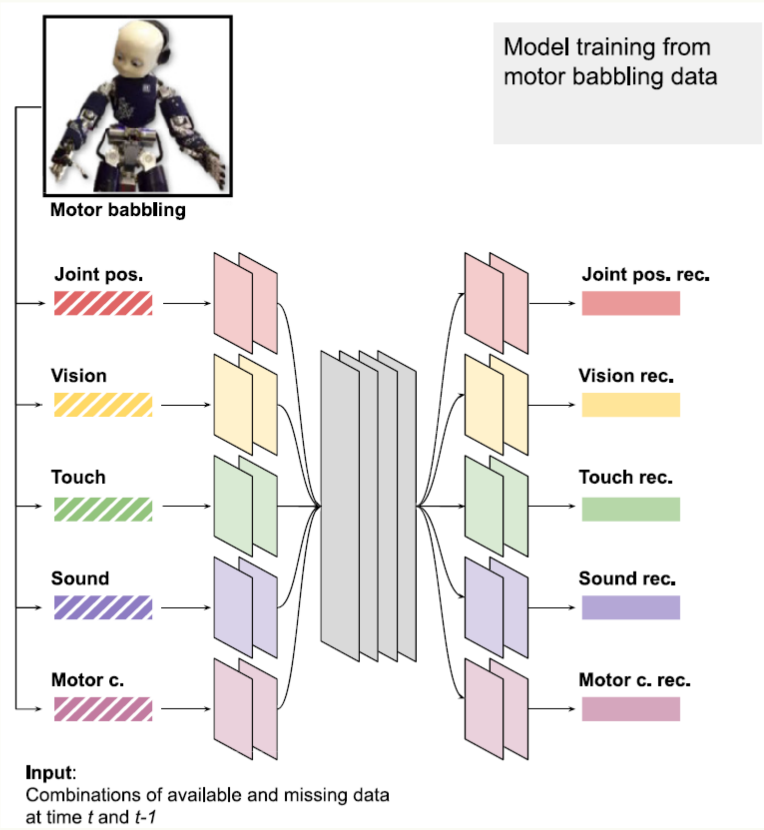
Cons

- one task only
- black-box
  - ➢ fragility / danger of overfitting
  - ➢ interpolation only
  - ➢ limited understanding of the model
  - ➢ difficult maintenance
- many simulator/robot and GPU hours

Making black-box models generalize







Agrawal P, Nair AV, Abbeel P, Malik J, Levine S (2016) Learning to poke by poking: Experiential learning of intuitive physics. In: Advances in neural information processing systems, pp 5074–5082

Zambelli, M., Cully, A., & Demiris, Y. (2020). Multimodal representation models for prediction and control from partial information. Robotics and Autonomous Systems, 123, 103312.

“regularization” by simultaneous learning of forward and inverse model

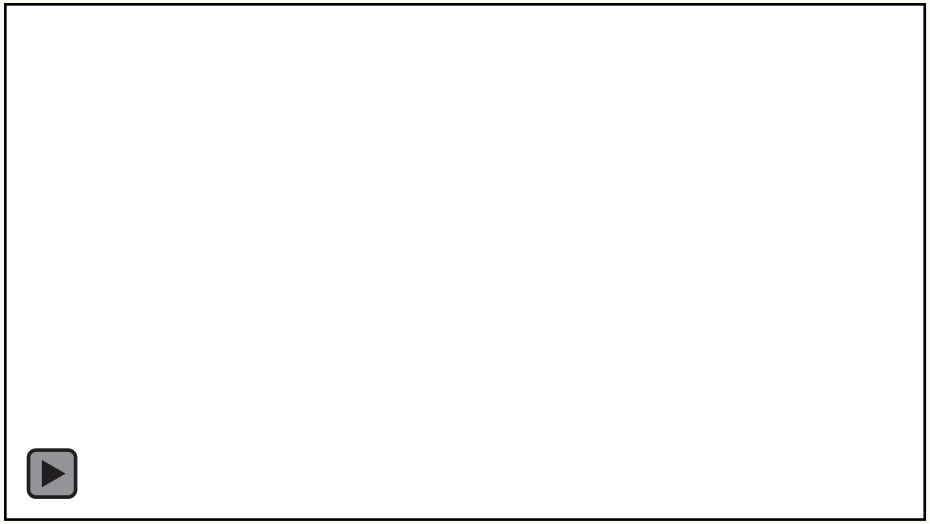
learning sensory-motor mappings (~ body schema) rather than a task

Robots failing…

https://youtu.be/g0TaYhjpOfo

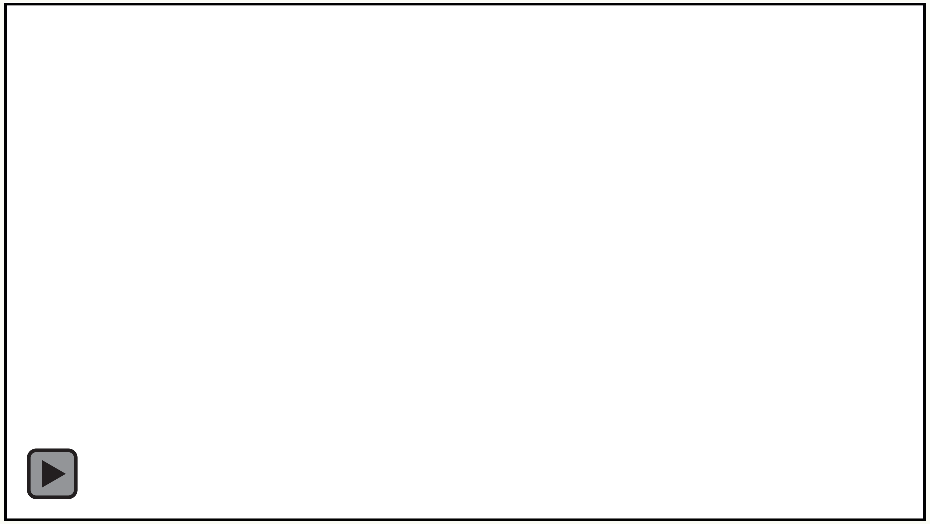
Let’s look at animals and brains….

Body awareness and body schema plasticity



tool-using and tool-making crows
https://youtu.be/UZM9GpLXepU

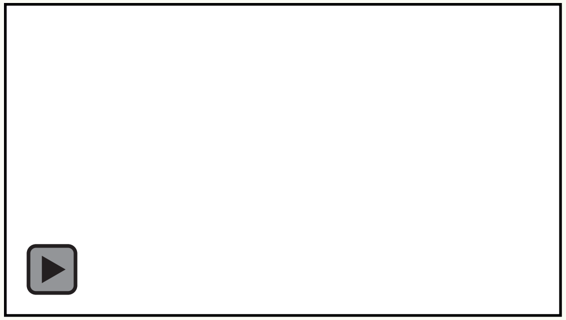
- tool use
- body extension



dogs that never give up
https://youtu.be/B2f58Khnohk

- adaptation to injury
- resilience

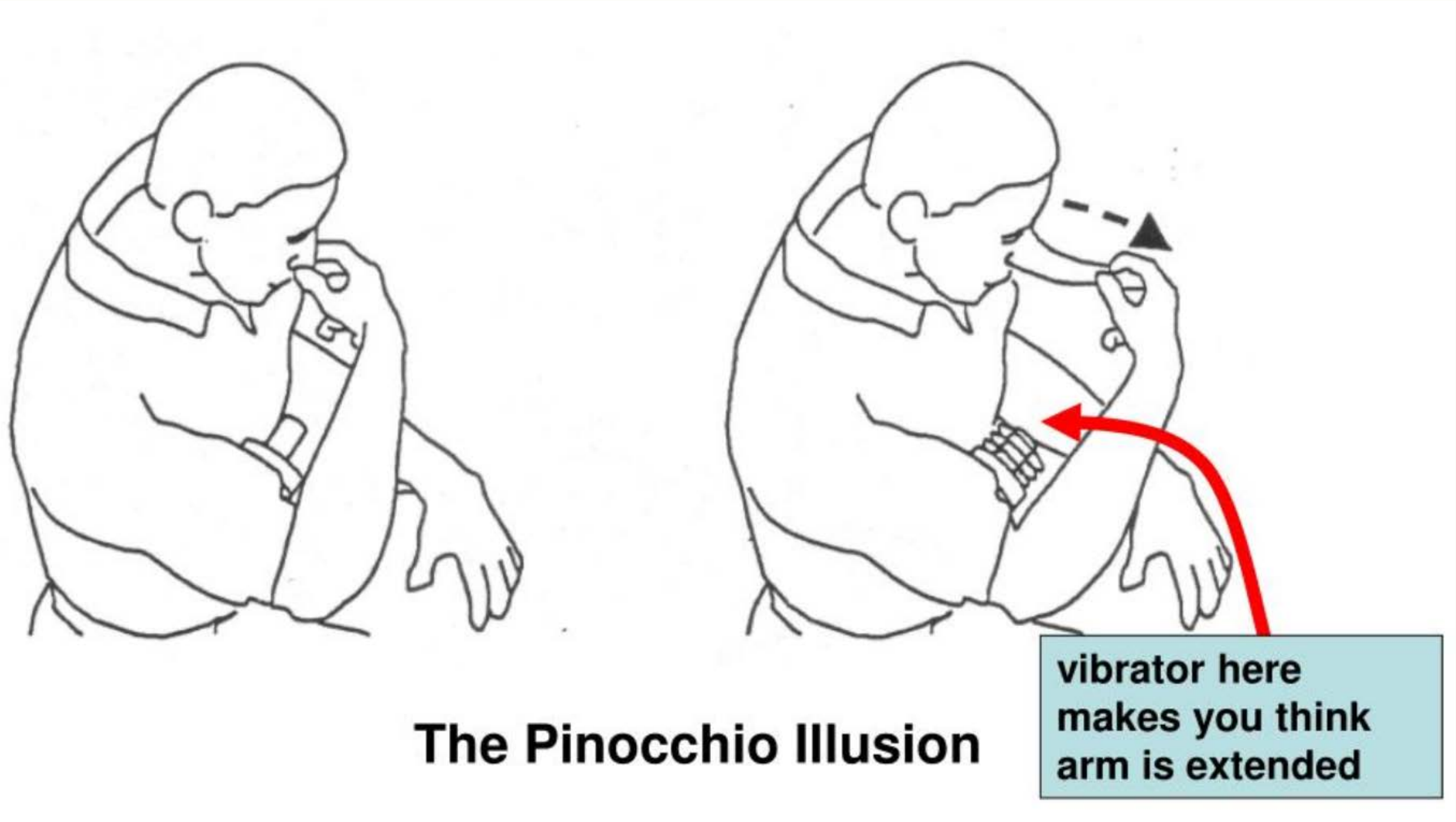
- awareness of body in space



https://youtu.be/akjDRRgeUoI

Let's look at animals and brains….

Lesson 1 – there is a lot of plasticity (adaptivity) and few constraints.



The Pinocchio Illusion

https://www.slideserve.com/amal/the-pinocchio-illusion

The octopus

https://youtu.be/APdRR2bL_Z0

https://youtu.be/Y0o4Wuf1Nt4

Levy, G., Flash, T., & Hochner, B. (2015). Arm coordination in octopus crawling involves unique motor control strategies. Current Biology, 25(9), 1195-1200.

Yekutieli et al. (2005b) speculate that the octopus reaches toward a target using the following strategy:

1. Initiating a bend in the arm so that the suckers point outward.
2. Orienting the base of the arm in the direction of the target or just above it.
3. Propagating the bend along the arm at the desired speed by a wave of muscle activation that equally activates all muscles along the arm.
4. Terminating the reaching movement when the suckers touch the target by stopping the bend propagation and thus catching the target.

3 kinematic control parameters (two angles for arm base orientation and one for movement speed) and 1 dynamic control parameter (~ muscle force).

Yekutieli, Y., Sagiv-Zohar, R., Hochner, B., & Flash, T. (2005). Dynamic model of the octopus arm. II. Control of reaching movements. *Journal of neurophysiology*, *94*(2), 1459-1468.

... there is no octopunculus...

Let’s look at animals and brains….

Lesson 2 – use the body directly whenever you can

The world is its own best model

3

Elephants Don't Play Chess

Rodney A. Brooks
MIT Artificial Intelligence Laboratory, Cambridge, MA 02139, USA

There is an alternative route to Artificial Intelligence that diverges from the directions pursued under that banner for the last thirty some years. The traditional approach has emphasized the abstract manipulation of symbols, whose grounding in physical reality has rarely been achieved. We explore a research methodology which emphasizes ongoing physical interaction with the environment as the primary source of constraint on the design of intelligent systems. We show how this methodology has recently had significant successes on a par with the most successful classical efforts. We outline plausible future work along these lines which can lead to vastly more ambitious systems.

Keywords: Situated activity; Mobile robots; Planning; Subsumption architecture; Artificial Intelligence.

Rodney A. Brooks was born in Adelaide, Australia. He studied Mathematics at the Flinders University of South Australia and received a Ph.D. from Stanford in Computer Science in 1981. Since then he has held research associate positions at Carnegie Mellon University and the Massachusetts Institute of Technology and faculty positions at Stanford and M.I.T. He is currently an Associate Professor of Electrical Engineering and Computer Science at M.I.T. and a member of the Artificial Intelligence Laboratory where he leads the mobile robot group. He has authored two books, numerous scientific papers, and is the editor of the *International Journal of Computer Vision*.

North-Holland
Robotics and Autonomous Systems 6 (1990) 3–15

1. Introduction

Artificial Intelligence research has foundered in a sea of incrementalism. No one is quite sure where to go save improving on earlier demonstrations of techniques in symbolic manipulation of ungrounded representations. At the same time, small AI companies are folding, and attendance is well down at national and international Artificial Intelligence conferences. While it is true that the use of AI is prospering in many large companies, it is primarily through the application to novel domains of long developed techniques that have become passé in the research community.

What has gone wrong? (And how is this book the answer?!!)

In this paper we argue that the *it symbol system hypothesis* upon which *it classical AI* is based is fundamentally flawed, and as such imposes severe limitations on the fitness of its progeny. Further, we argue that the dogma of the symbol system hypothesis implicitly includes a number of largely unfounded great leaps of faith when called upon to provide a plausible path to the digital equivalent of human level intelligence. It is the chasms to be crossed by these leaps which now impede classical AI research.

But there is an alternative view, or dogma, variously called *it nouvelle AI*, *it fundamentalist AI*, or in a weaker form *it situated activity* [1]. *It is based on the it physical grounding hypothesis.* It provides a different methodology for building intelligent systems than that pursued for the last thirty years. The traditional methodology bases its decomposition of intelligence into functional information processing modules whose combinations provide overall system behavior. The new methodology bases its decomposition of intelligence into individual behavior generating mod-

[1] Note that what is discussed in this paper is completely unrelated to what is popularly known as *it Neural Networks*. That given, there are nevertheless a number of aspects of nouvelle AI approaches which may be of interest to people working in classical neuroscience.

Intelligence without representation*

Rodney A. Brooks

MIT Artificial Intelligence Laboratory, 545 Technology Square, Rm. 836, Cambridge, MA 02139, USA

Received September 1987

Brooks, R.A., Intelligence without representation, Artificial Intelligence 47 (1991), 139–159.

"When we examine very simple level intelligence we find that explicit representations and models of the world simply get in the way. It turns out to be better to use the world as its own model."

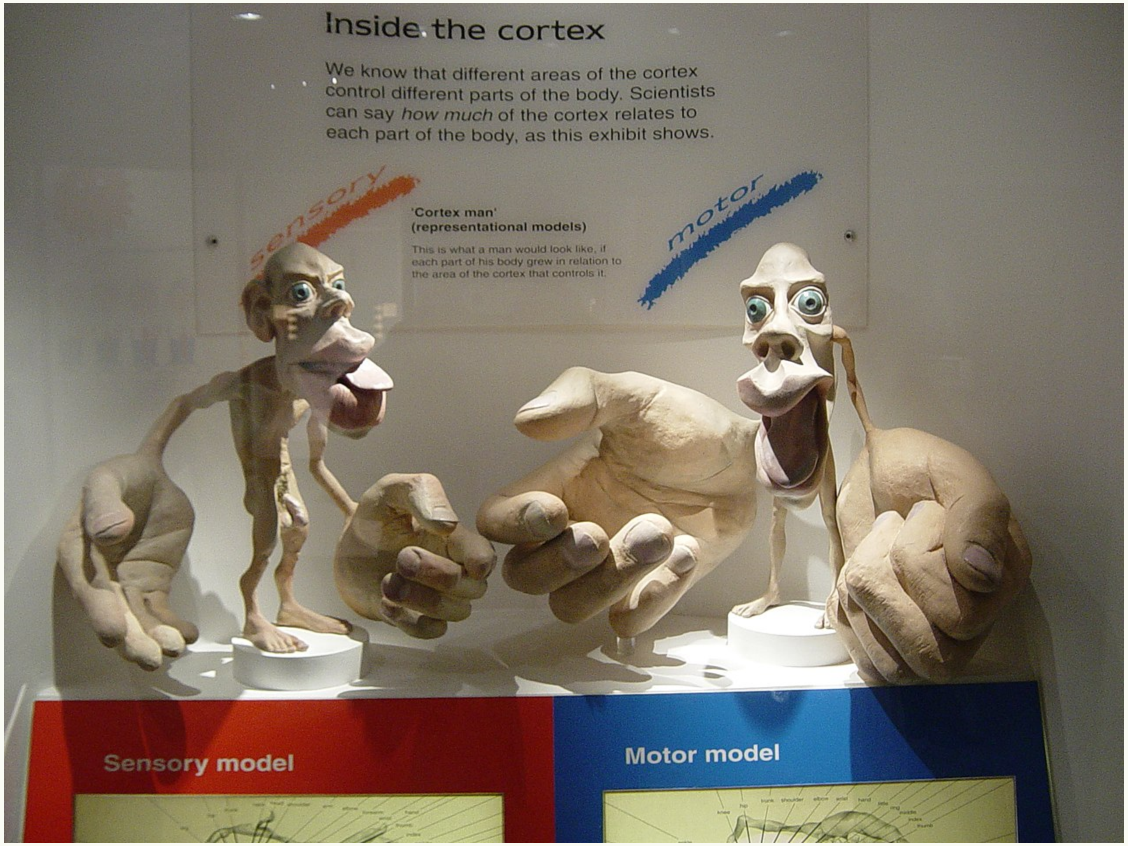
"The key observation is that the world is its own best model. It is always exactly up to date. It always contains every detail there is to be known. The trick is to sense it appropriately and often enough."

Ghenghis robot
https://youtu.be/K2xUHYFcYKI

How about the body?

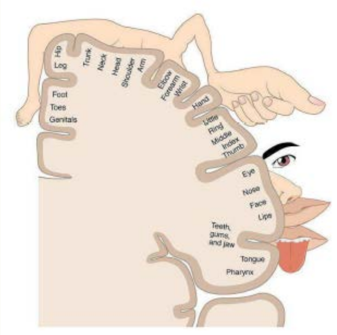
It is also (and even more) always there!

So do we need to model it?



https://en.wikipedia.org/wiki/Cortical_homunculus#/media/File:Sensory_and_motor_homunculi.jpg

“body maps” in the human brain



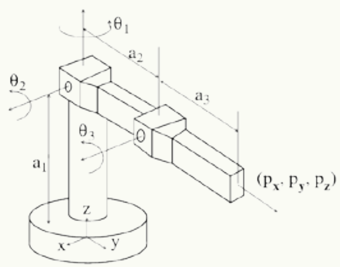
- From sensory and motor homunculi to ...
- **Body schema** – “for action”
  - ~ sensorimotor representation of body for action
  - neural representation of the body [Head & Holmes, 1911]
- **Body image** – “for perception”
  - **body structural description** [Schwoebel & Coslett 2005]
  - **body semantics** [Schwoebel & Coslett 2005]
- **Hierarchies** – primary somatosensory repr., body form representation, postural repr. [Medina & Coslett 2010]
- **...**
- **=> “chaotic state of affairs”** [Berlucchi and Aglioti 2000]

- Our focus: *body representations that mediate implicit knowledge related to the body, its parts, and their posture relevant in the context of sensorimotor coordination ~ “sensorimotor self”*

Characteristics of body models

multisensorial

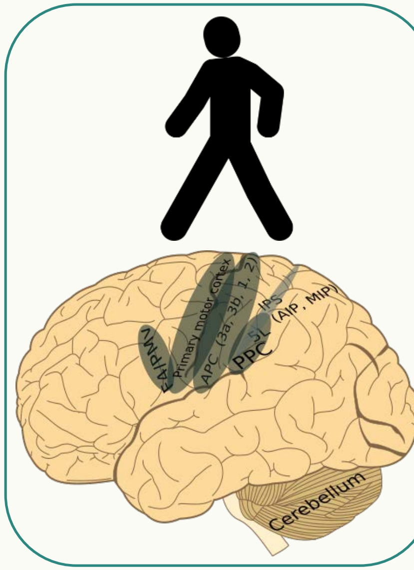
amodal/unimodal



Allows the end of the robot to be located in space relative to the base of the robot. The calculations are done to convert joint coordinates (joint angles) to cartesian coordinates.

$$p_x = \cos\theta_1\,(a_3 \cos(\theta_2 + \theta_3) + a_2 \cos\theta_2)$$
$$p_y = \sin\theta_1\,(a_3 \cos(\theta_2 + \theta_3) + a_2 \cos\theta_2)$$
$$p_z = a_3 \sin(\theta_2 + \theta_3) + a_2 \sin\theta_2 + a_1$$

Modeling mechanisms of biological body representations



Better performance of robots – autonomy, robustness, safety

fixed

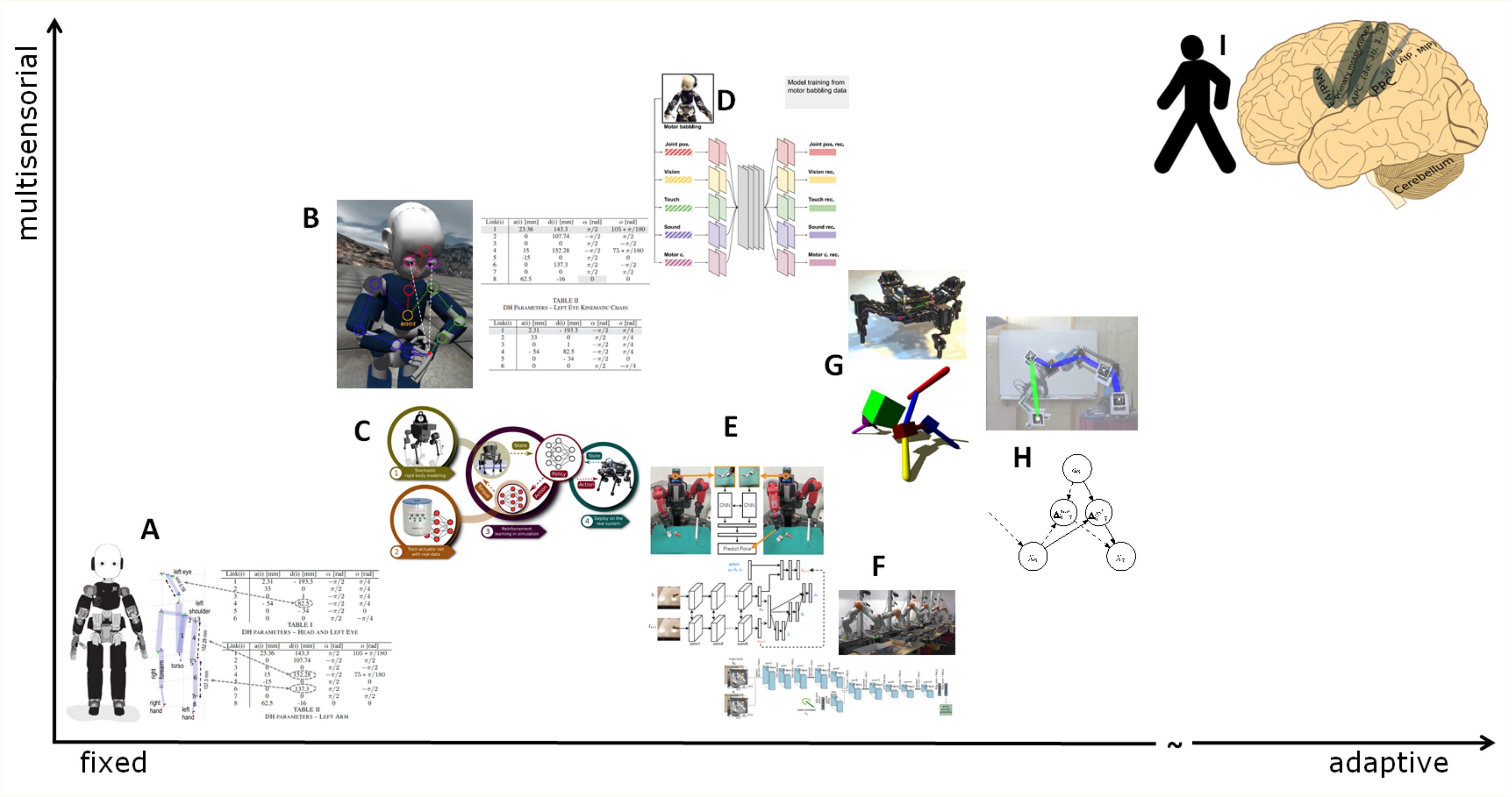
adaptive

explicit

implicit

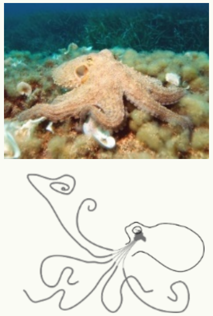
Hoffmann, M. & Pfeifer, R. (2018), Robots as Powerful Allies for the Study of Embodied Cognition from the Bottom Up, *in* Albert Newen; Leon de Bruin & Shaun Gallagher, ed., 'The Oxford Handbook 4e Cognition', Oxford University Press, pp. 841-862.
Hoffmann, M.; Marques, H.; Hernandez Arieta, A.; Sumioka, H.; Lungarella, M. & Pfeifer, R. (2010), 'Body Schema in Robotics: A Review', *Autonomous Mental Development, IEEE Transactions on* **2**(4), 304-324.

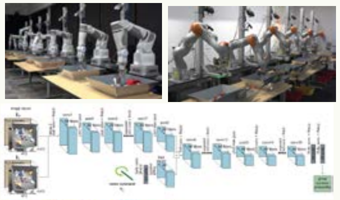
Plasticity, multimodality

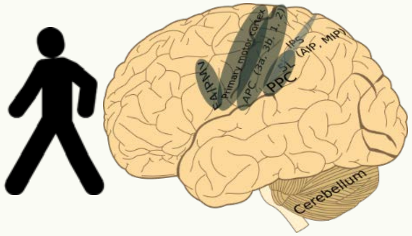


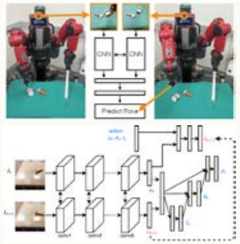
Hoffmann, M. (2022), Biologically inspired robot body models and self-calibration, *in* Marcelo Ang; Oussama Khatib & Bruno Siciliano, ed., 'Encyclopedia of Robotics', Springer.

distributed & specialized

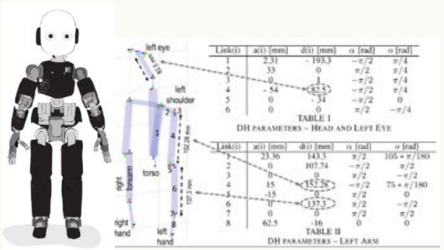


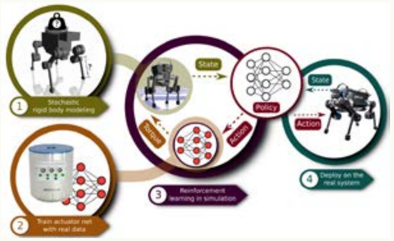


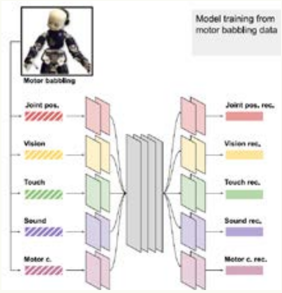




centralized & universal





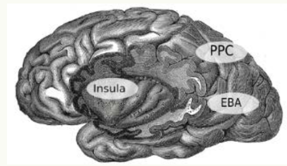


modular

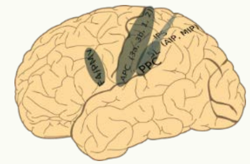
end-to-end / holistic

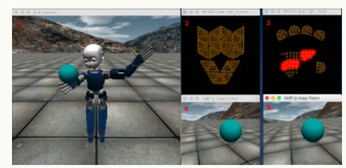
parallel & recurrent

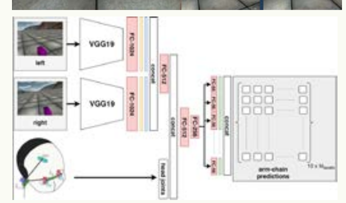
body image



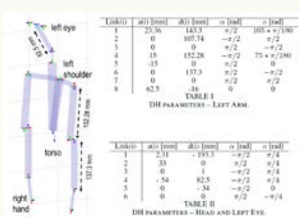
body schema







serial



explicit / veridical

implicit / embodied

Hoffmann, M. (2021), Body models in humans, animals, and robots, *in* Yochai Ataria; Shogo Tanaka & Shaun Gallagher, ed., 'Body Schema and Body Image: New Directions', Oxford University Press.

Are robots like Ian Waterman?

Ian's Story

Click the thumbnails below to see the full image and caption.

At the age of 19, Ian had a bout of severe gastric flu. During this his body produced antibodies to the infection which then attacked his nerves. Though still able to feel temperature and pain and with normal movement or motor nerves, he lost – permanently – all touch and sense of movement and position sense below the neck. Without seeing where his body was he had no idea where it was. And without peripheral feedback from the limbs, his movement brain could not coordinate movement. He could not move in a controlled way at all, and was effectively paralysed not by weakness but by an absence of any ability to make an ordered movement.

He learnt after a few weeks that if he looked at, say, his arm and thought about moving it then it could move, but that the mental effort to do this was huge. He spent the next 17 months as an inpatient learning to think about movement again. Subsequently he

http://www.thearticulatehand.com/ian.html

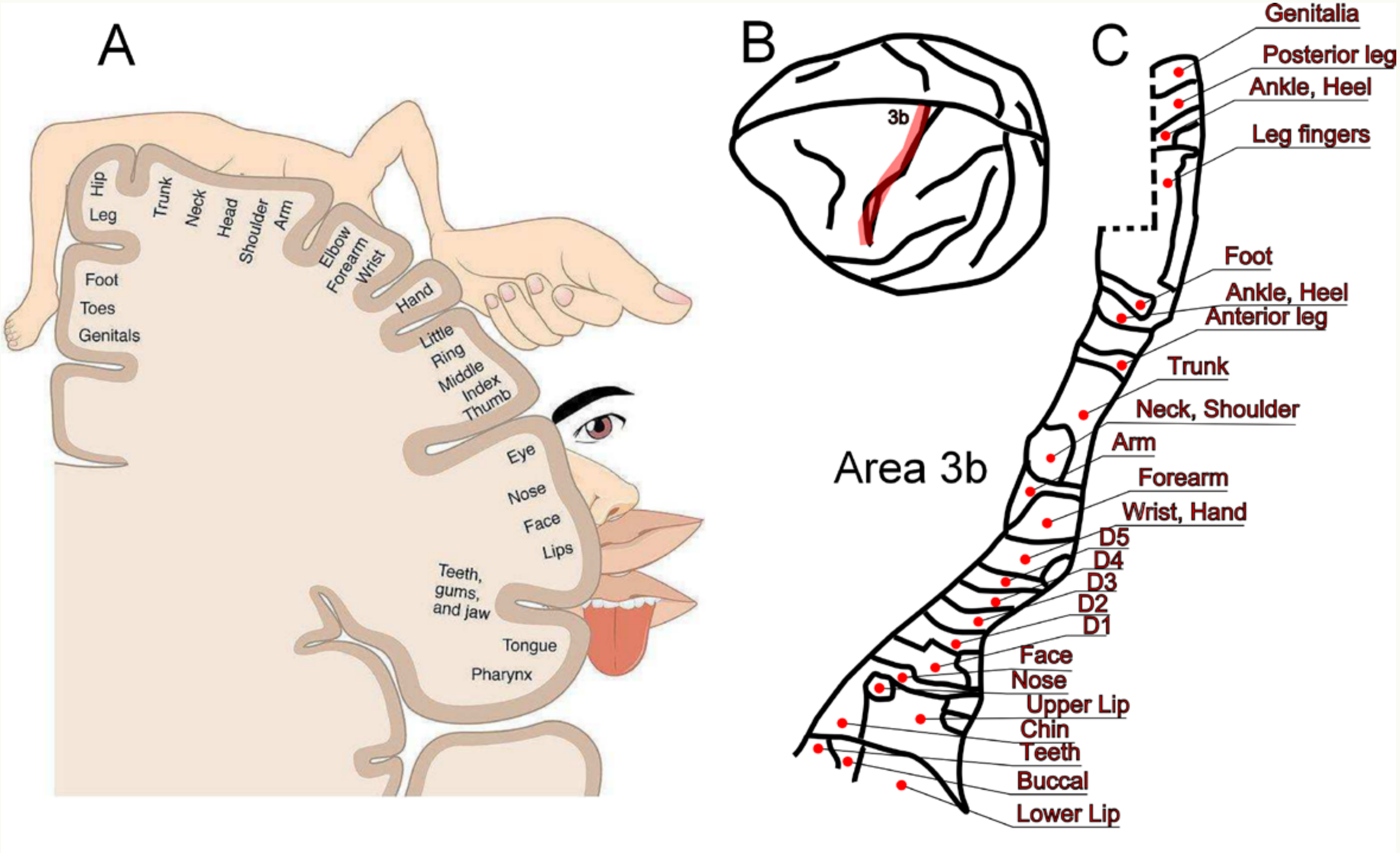
McNeill, D., Quaeghebeur, L., & Duncan, S. (2010). IW-“The man who lost his body”. In *Handbook of phenomenology and cognitive science* (pp. 519-543). Springer, Dordrecht.

Hoffmann, M. (2021), Body models in humans, animals, and robots, *in* Yochai Ataria; Shogo Tanaka & Shaun Gallagher, ed., 'Body Schema and Body Image: New Directions', Oxford University Press.

Outline

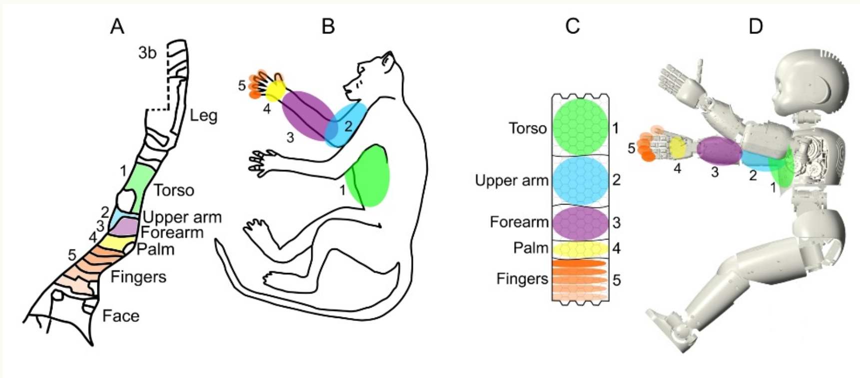
- Synthetic methodology ~ "understanding by building"
- Classical AI – intelligence as computation
- Embodied AI
  - Morphology facilitating control
    - Body design simplifying task
    - Behavior emergent from simple sensory-motor loops
  - Morphology facilitating perception
- Robot body models
- Robots learning brain-like body models

Robots learning brain-like body models

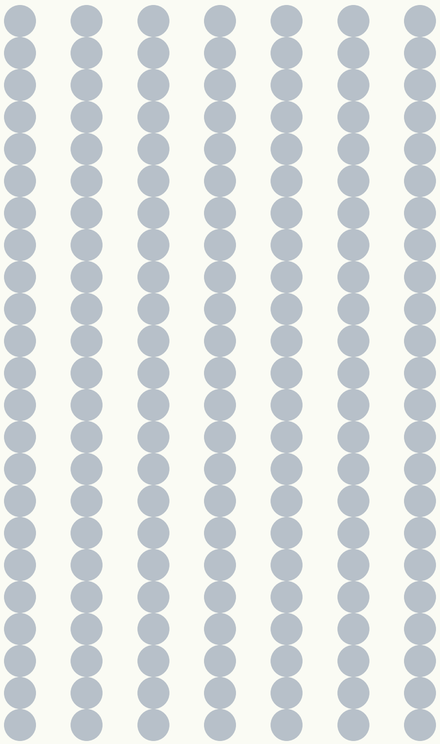


(A) Penfield W., Rasmussen T.: The cerebral cortex of man; a clinical study of localization of function, 1950. (pic from OpenStax College)
(B,C) Organization of the representations of body surface in area 3b of the cynomolgus macaque. (after Nelson 1980)

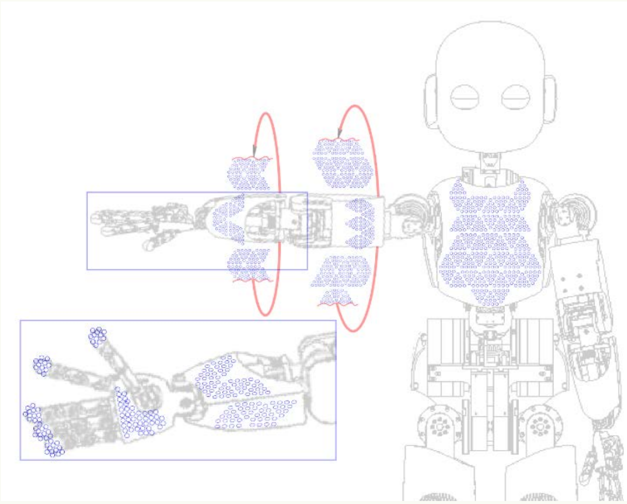
Learning using Self-Organizing (Kohonen) map (SOM)

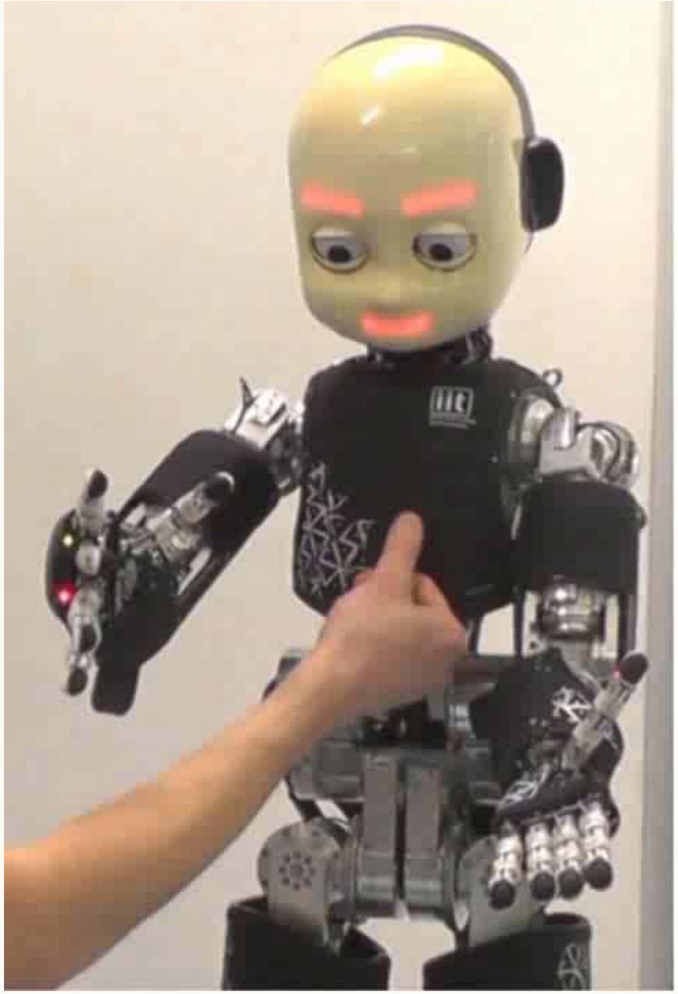


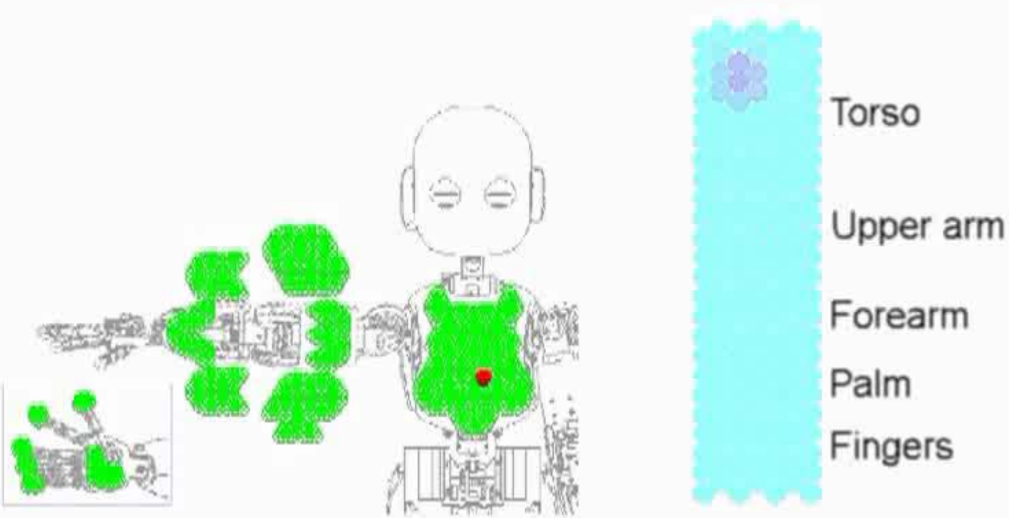
Output layer: 7 x 24 neurons



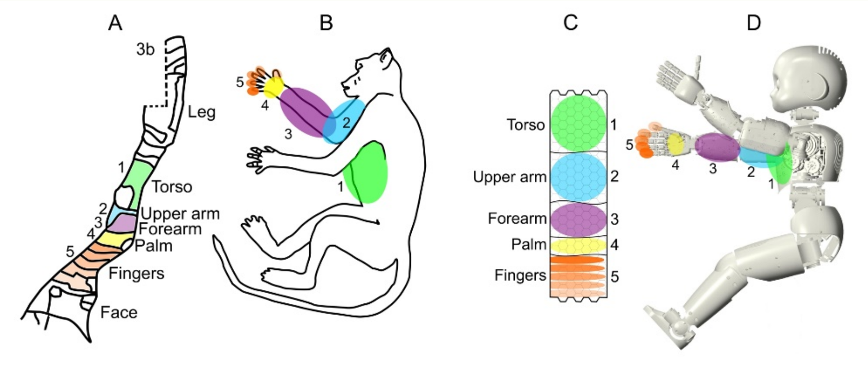
input layer: 1154 taxels



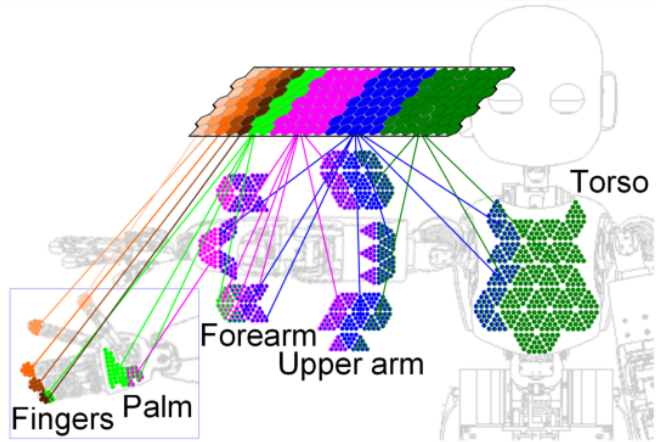




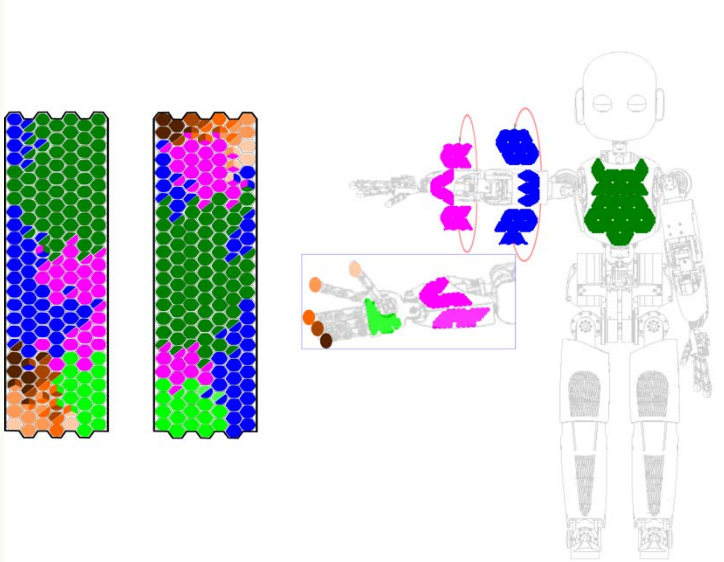
Hoffmann, M.; Straka, Z.; Farkas, I.; Vavrecka, M. & Metta, G. (2018), 'Robotic homunculus: Learning of artificial skin representation in a humanoid robot motivated by primary somatosensory cortex', *IEEE Transactions on Cognitive and Developmental Systems* **10**(2), 163-176.

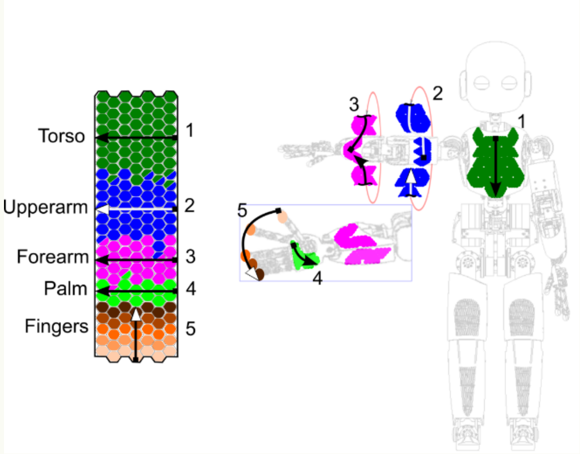


To obtain a layout similar to area 3b: sequence of body parts ensured through additional constraints – maximum receptive field size setting: **MRF-SOM**.



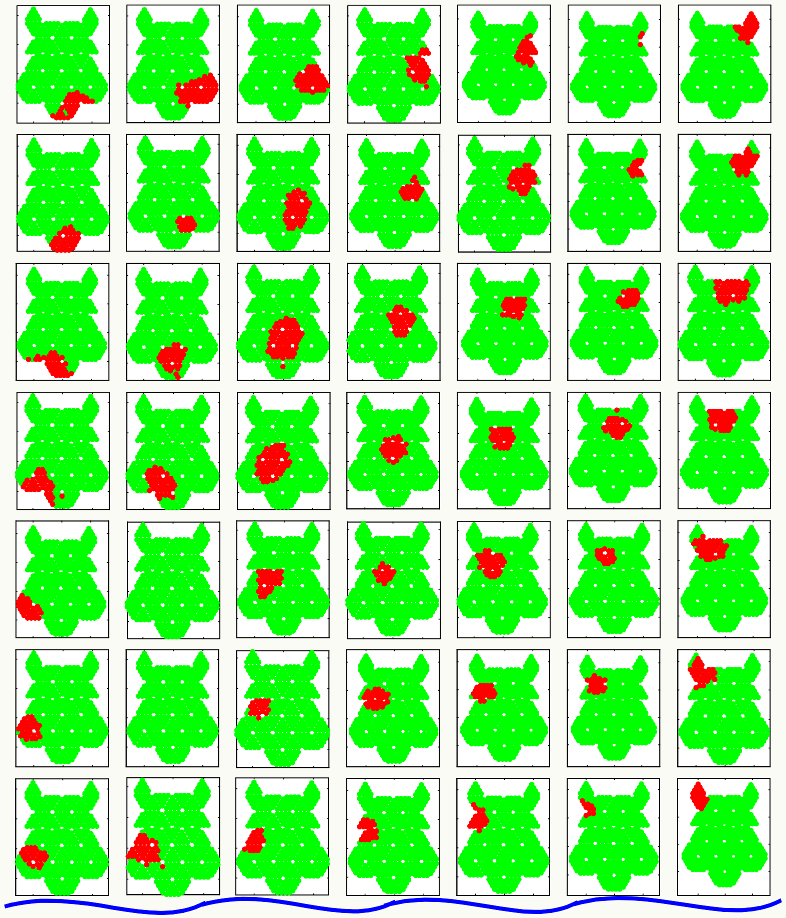
learning with standard SOM



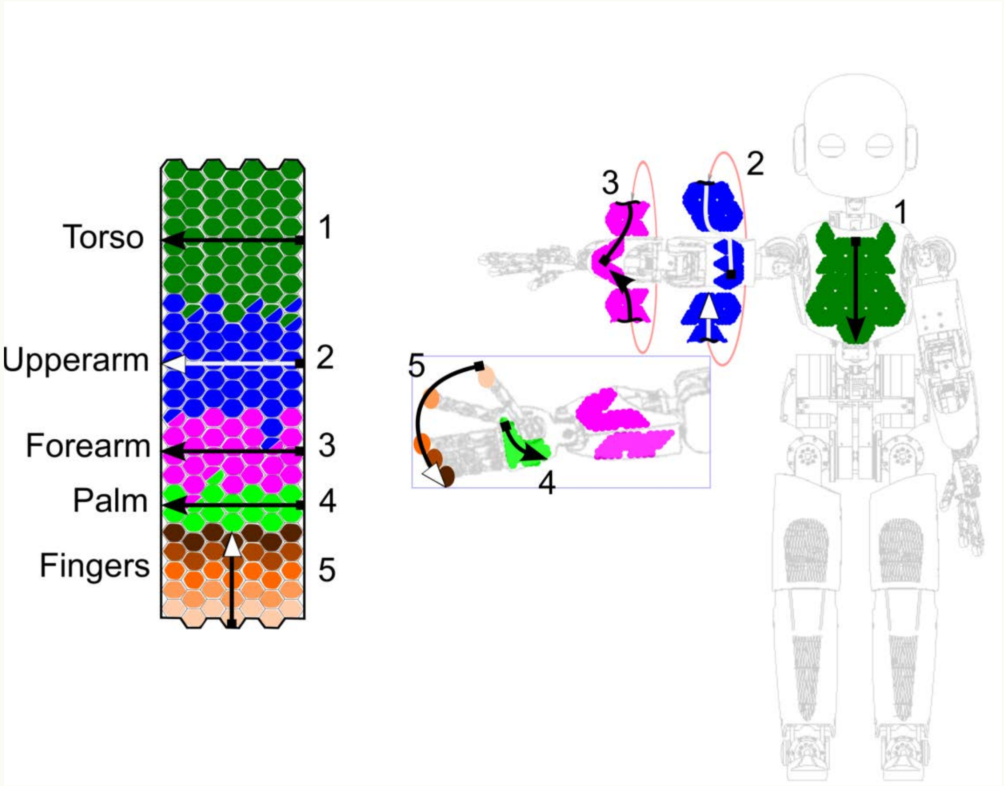


Learned SOM with maximum RF setting

RFs of neurons representing torso



repr. of indiv. skin parts on final map



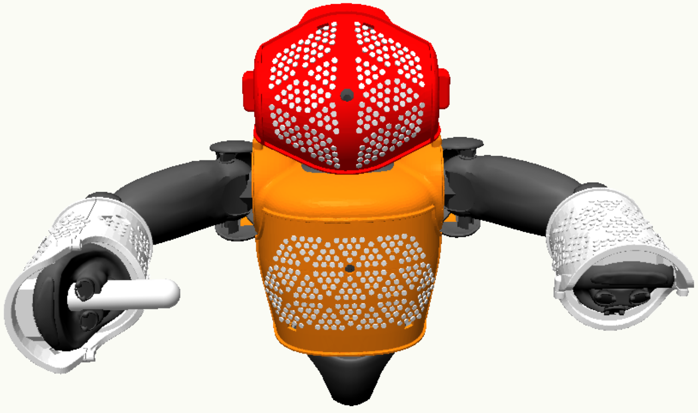
Hoffmann, M.; Straka, Z.; Farkas, I.; Vavrecka, M. & Metta, G. (2018), 'Robotic homunculus: Learning of artificial skin representation in a humanoid robot motivated by primary somatosensory cortex', *IEEE Transactions on Cognitive and Developmental Systems* **10**(2), 163-176.

Learning to reach for stimulus on the body

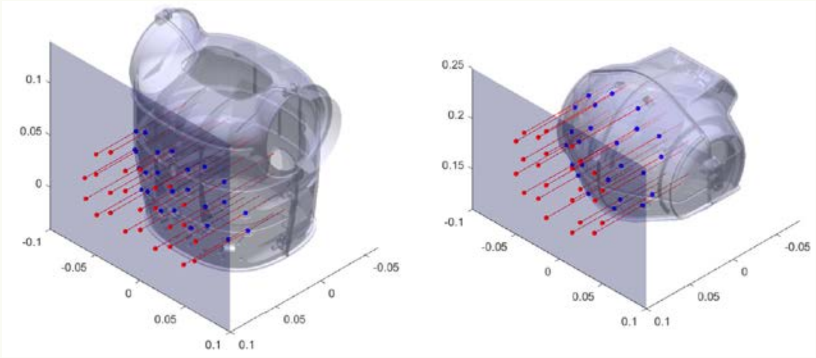
1. Spontaneous self-touch
2. Detecting motor-proprioceptive-tactile (-visual) correlations
3. "Intrinsic motivation" needed to focus exploration? Learning to recreate a stimulus (self-touch) that first occurred spontaneously?

3 months

Active exploration of "skin space"



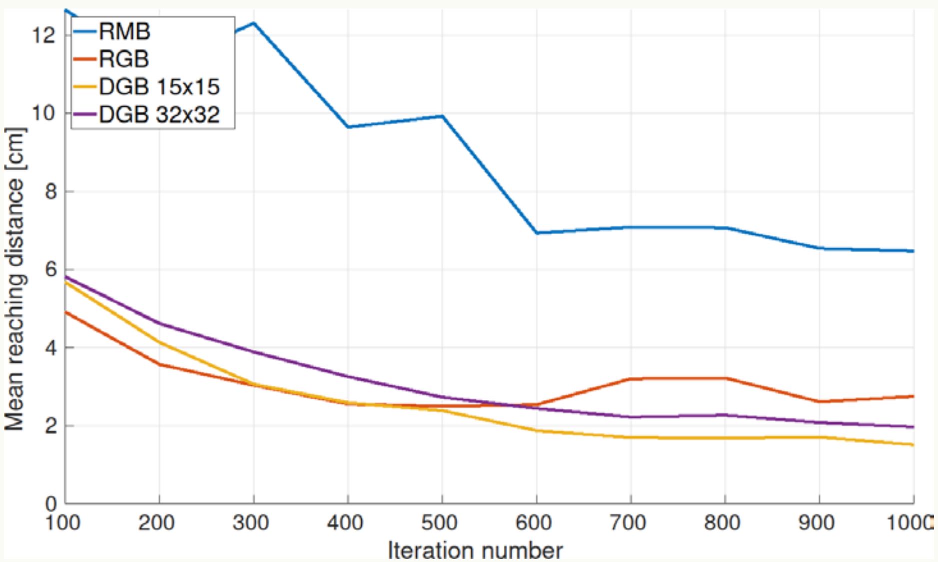
- simulated Nao robot with artificial skin
- Action space Q:
  - 5 degrees of freedom (DoF) for torso-reaching experiments ($Q \subseteq \mathbb{R}^5$)
  - 7 DoF for head-reaching experiments ($Q \subseteq \mathbb{R}^7$)
- Observation space $X \subseteq \mathbb{R}^2$
  - Planar projection of skin surface



Gama, F.; Shcherban, M.; Rolf, M. & Hoffmann, M. (2020), Active exploration for body model learning through self-touch on a humanoid robot with artificial skin, *in* 'Joint IEEE 10th International Conference on Development and Learning and Epigenetic Robotics (ICDL-EpiRob)'.
Gama, F.; Shcherban, M.; Rolf, M. & Hoffmann, M. (2021), 'Goal-directed tactile exploration for body model learning through self-touch on a humanoid robot', *IEEE Transactions on Cognitive and Developmental Systems*. [in revision]

Motor babbling vs. active goal exploration

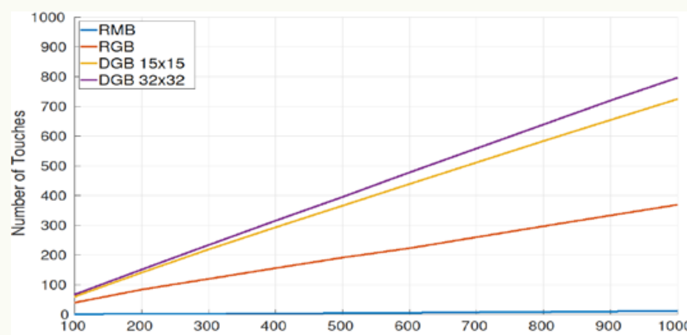
Random Motor Babbling (RMB)



mean reaching error

Discretized Goal Babbling (DGB)

- exploring goal space (skin space)
- building inverse model (from skin space to joint space)
- focusing exploration onto regions with fastest progress
- https://github.com/flowersteam/explauto



number of touches

“Sporadic touch” vs. “complex touch”

first 2 months (DiMercurio et al. 2018)

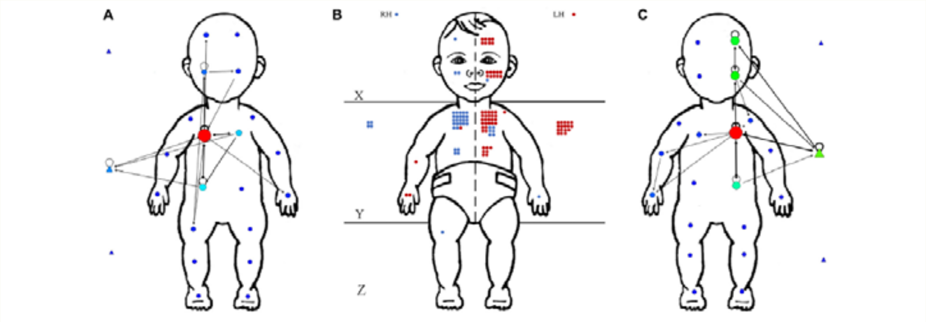
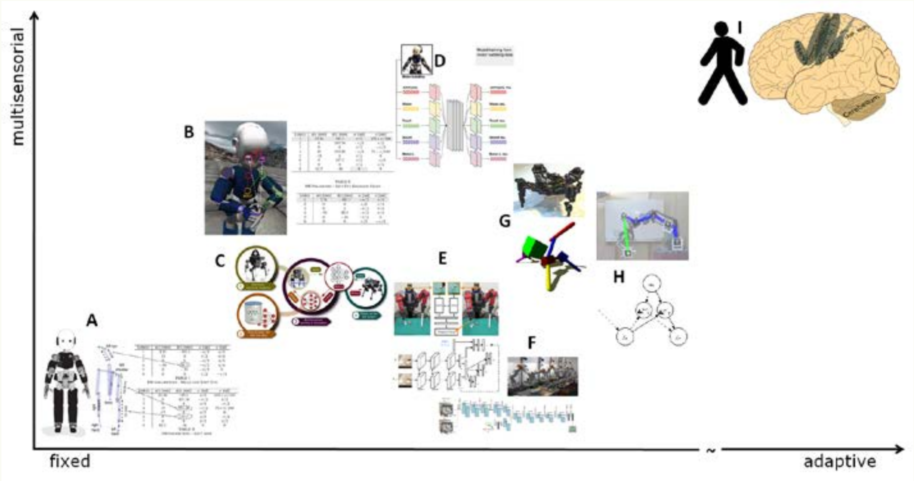


FIGURE 3 | Illustration of number of touches coded by area and body side with corresponding network maps from one condition and session (week 6) of one infant (DJ). **(A)** Network map of touches and transitions performed by the right hand. The colored dots (nodes) represent the different locations touched, their size and color indicate the frequency each were touched (warmer colors indicate more frequent touches to that area), and the arrows and their thickness indicate the direction and frequency of transitions between pairs of nodes. **(B)** Frequency of touches by area. Each dot corresponds to a coded contact to that area. The blue dots are contacts performed by the right hand, the red dots are contacts performed by the left hand. **(C)** Corresponding network map for the left hand.

Gama, F.; Shcherban, M.; Rolf, M. & Hoffmann, M. (2021), 'Goal-directed tactile exploration for body model learning through self-touch on a humanoid robot', *IEEE Transactions on Cognitive and Developmental Systems*. [in revision]

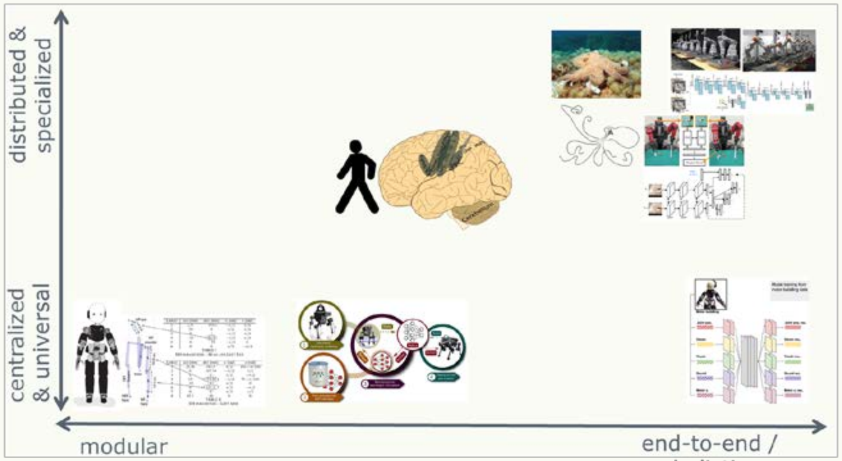
What from brain-like control / body models should robots take on board?

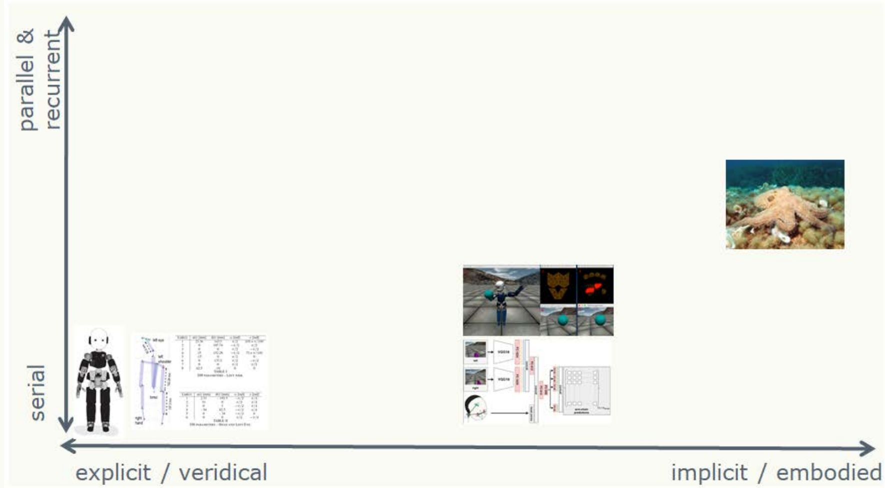
- Should we learn tasks, body models or physics (Lake et al. 2017)?
  - The human brain cannot afford an end-to-end network for every task – that's why it developed body representations...
- Some characteristics of brain-like body models should clearly be incorporated and it should be largely unproblematic.
  - *adaptivity/plasticity* (a.k.a. self-calibration) ☑
  - *multimodality* ☑



Some characteristics of brain-like body models are clearly at odds with engineering practice….

- Giving up
  - modularity? ☒
  - centralized & universal nature? ☒
  - explicit and veridical character? ☒
  - serial operation (and mindset)? ☒
- In the end, humans and animals' body models *serve action* – they don't need to be correct, but useful.
- Many suboptimal redundant solutions => robustness.





Resources and further reading

Pfeifer, R. & Scheier, C. (2001), *Understanding intelligence, MIT Press Cambridge, MA, USA.*

Pfeifer, R. & Bongard, J. C. (2007), *How the body shapes the way we think: a new view of intelligence, MIT Press, Cambridge, MA.*

Cangelosi, A., & Schlesinger, M. (2015). *Developmental robotics: From babies to robots*. MIT press.

ShanghAI lectures repository: [*http://shanghailectures.org/lectures*](http://shanghailectures.org/lectures)

Hoffmann, M. & Pfeifer, R. (2011), The implications of embodiment for behavior and cognition: animal and robotic case studies, in W. Tschacher & C. Bergomi, ed., 'The Implications of Embodiment: Cognition and Communication', Exeter: Imprint Academic, pp. 31-58.

Müller, V. C., & Hoffmann, M. (2017). What is morphological computation? On how the body contributes to cognition and control. *Artificial life*, *23*(1), 1-24.