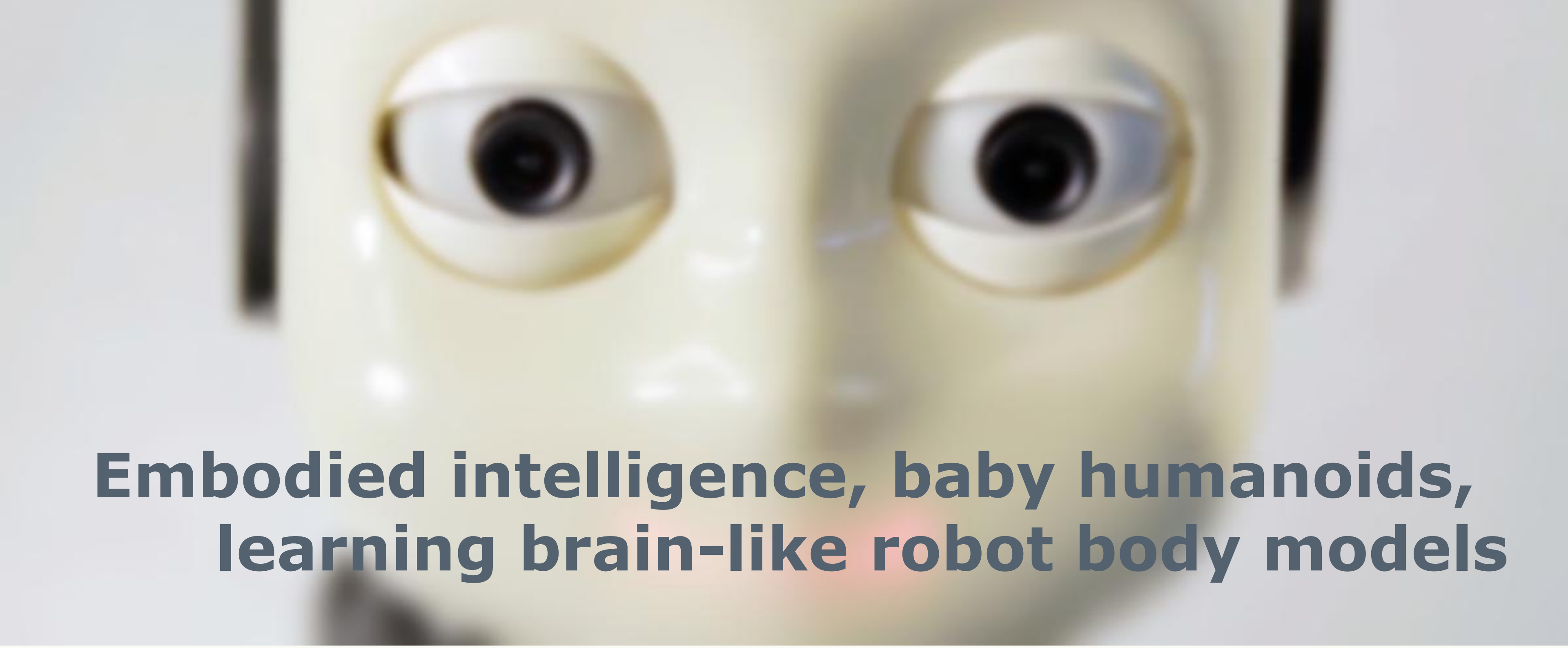

Embodied intelligence, baby humanoids, learning brain-like robot body models

Doc. Matěj Hoffmann, Ph.D.

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

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

Outline

Synthetic methodology ~ "understanding by building"

Classical AI – intelligence as computation

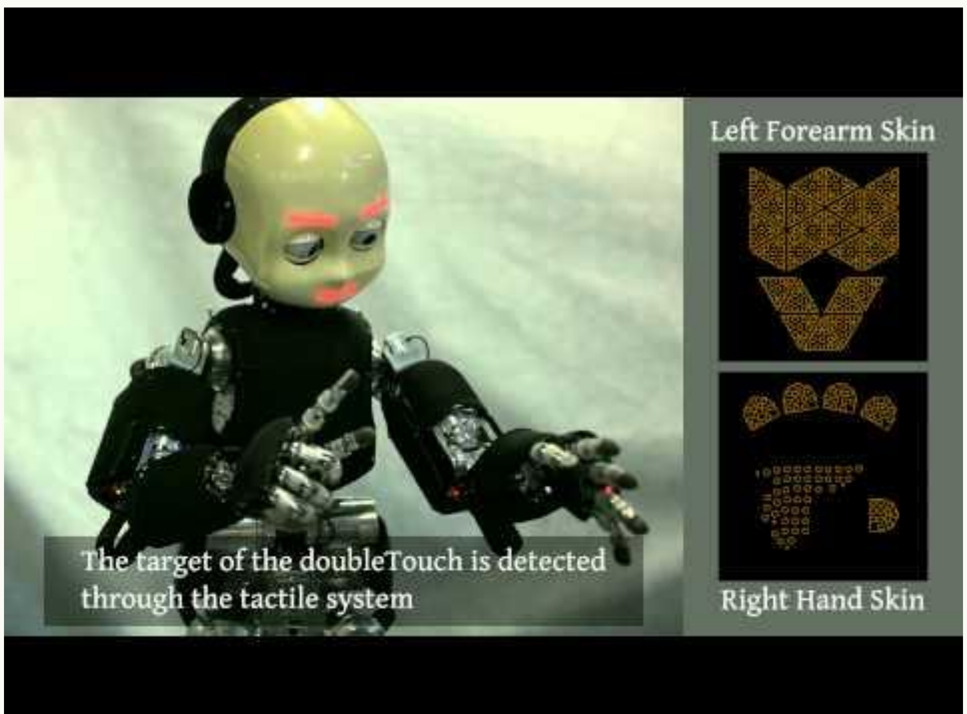
Embodied Intelligence

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

Embodied AI

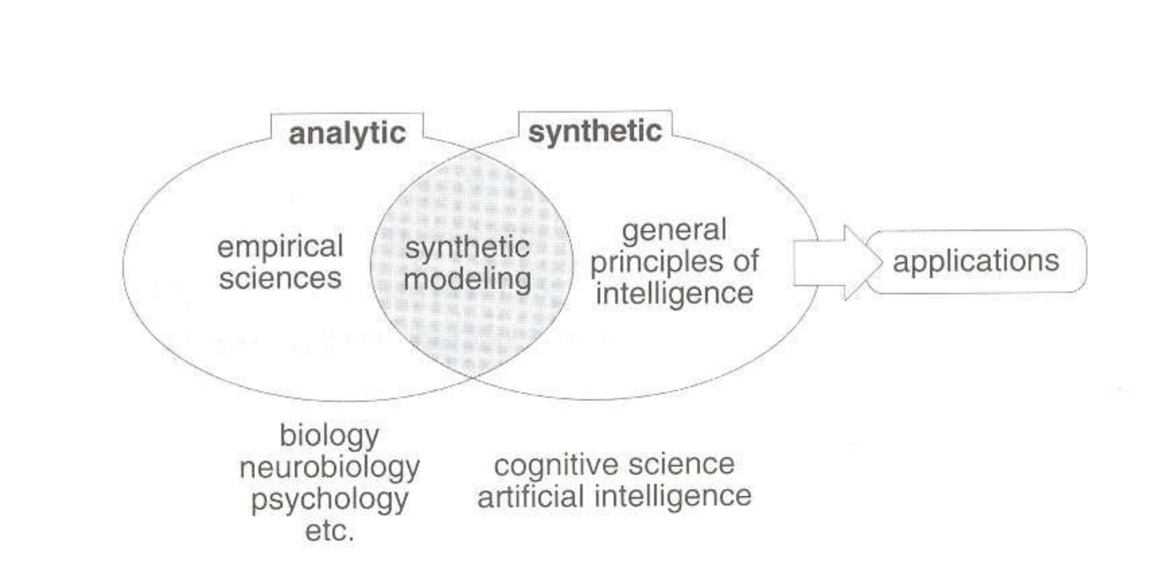
Our research examples and student projects

robots as embodied computational models of child and brain development

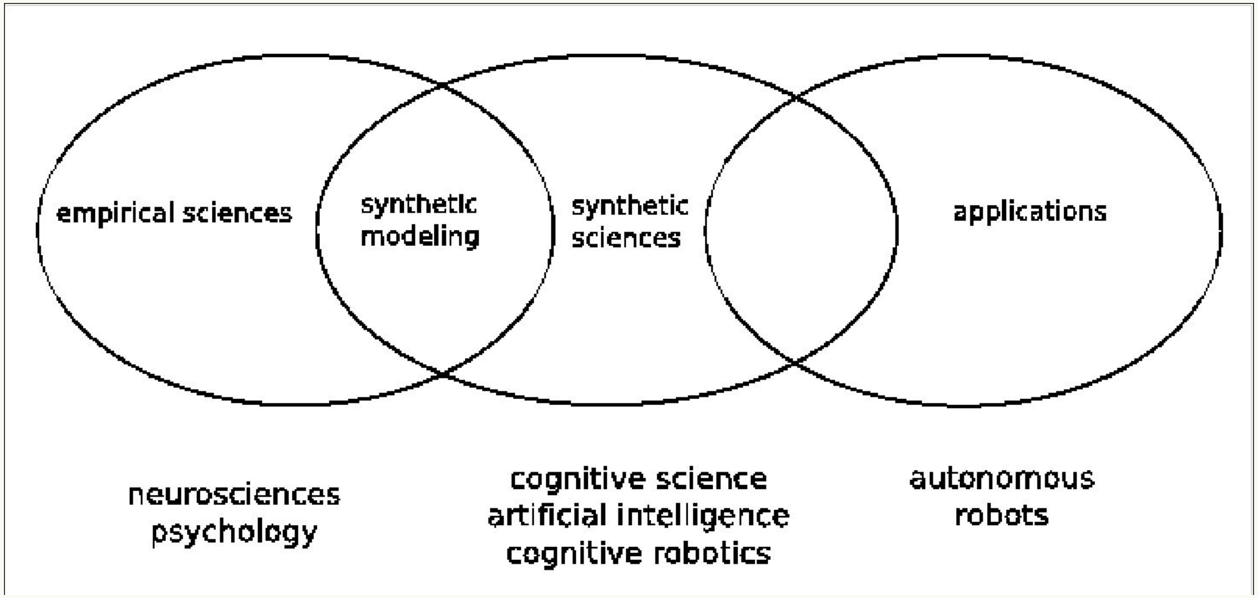


autonomous, adaptive, resilient, and self-calibrating robots

Synthetic methodology ~ understanding by building



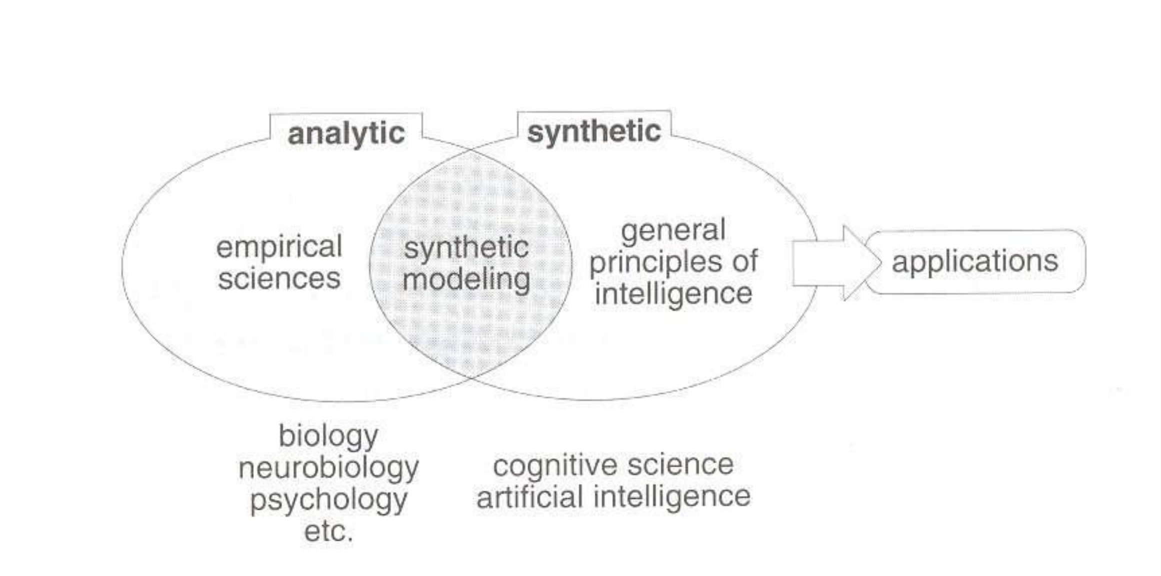
Pfeifer & Scheier (2001): Understanding intelligence

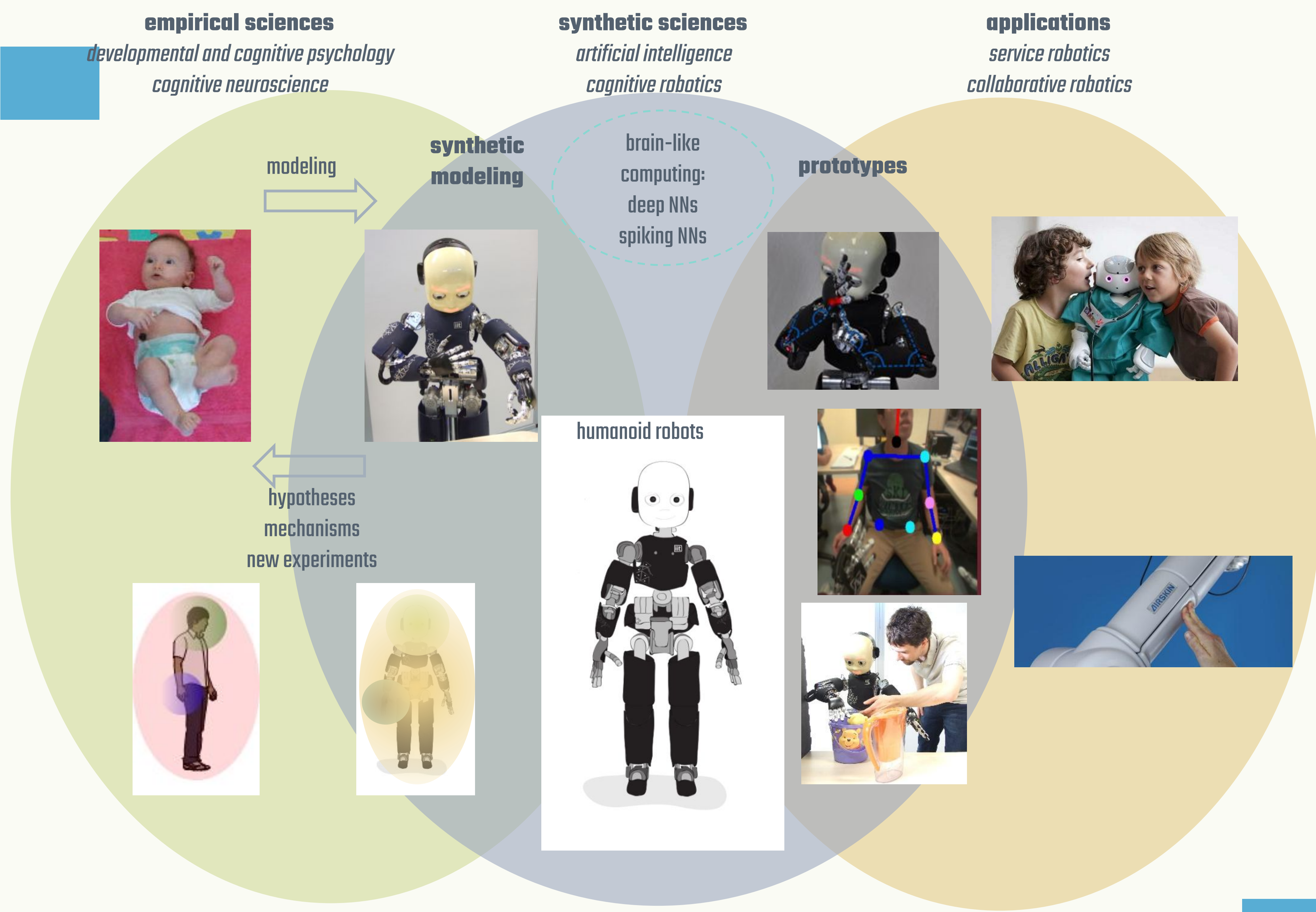


Goals

[Pfeifer and Bongard, 2007, Chapter 3]:

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

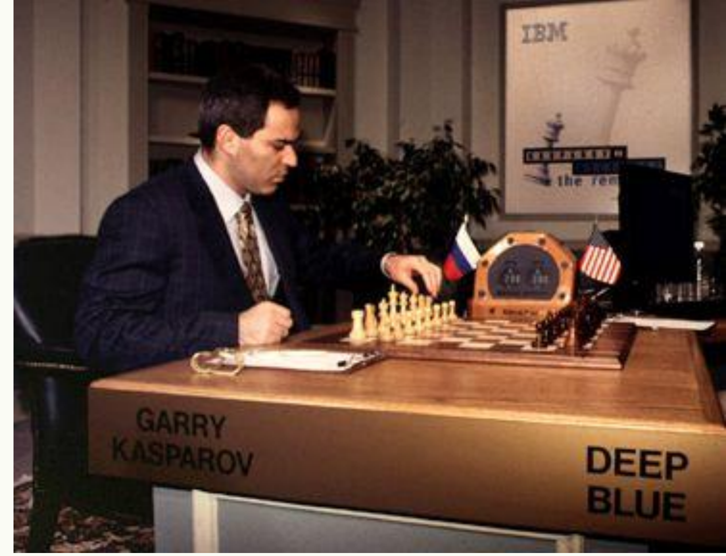



empirical sciences
developmental and cognitive psychology
cognitive neuroscience
synthetic sciences
artificial intelligence
cognitive robotics
applications
service robotics
collaborative robotics
modeling
synthetic modeling
brain-like computing:
deep NNs
spiking NNs
prototypes
humanoid robots
hypotheses
mechanisms
new experiments

All synthetic, yet different...

Is walking intelligent?

What it takes to walk?



Is playing chess intelligent?

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

Passive Dynamic Walker – Tad McGeer (1990)
https://youtu.be/W0PED7I5Lac

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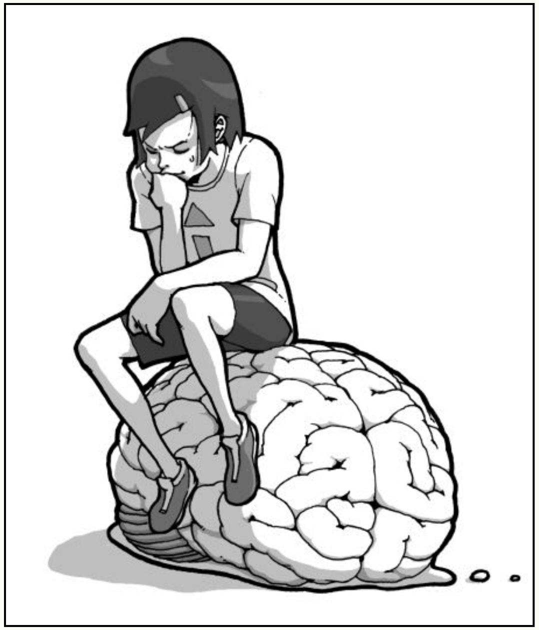
Embodied AI

Our research examples and student projects



Classical:
"intelligence as computation"

Input → ***think*** → **Output**

sense ***act***

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)

Digital computer

- Key tool
- Metaphor for the mind!

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

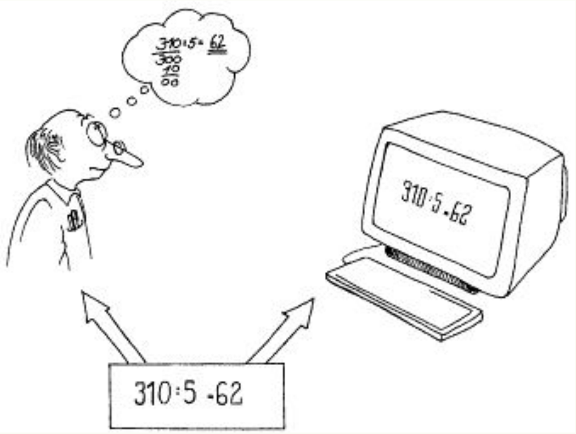
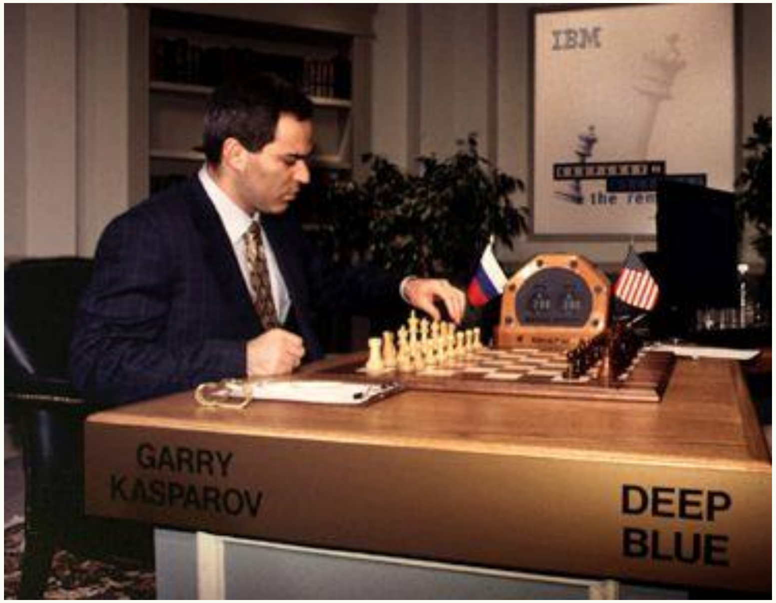


Fig. 2.4 from Pfeifer & Scheier 1999

Where it works nicely… search



IBM Deep Blue chess computer, 1997

Google Deep Mind AlphaGo, 2016

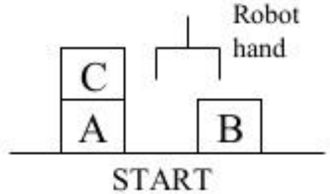
- formally precisely defined discrete state space
- program has access to complete information (fully observable)
- deterministic state evolution
- not real-time (or soft real time)

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

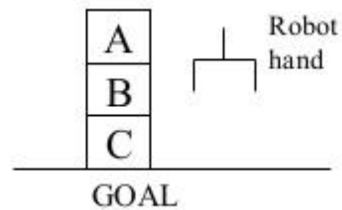
Where it works nicely… planning

Example : Blocks World

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



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



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

Connecting to the real world - representation

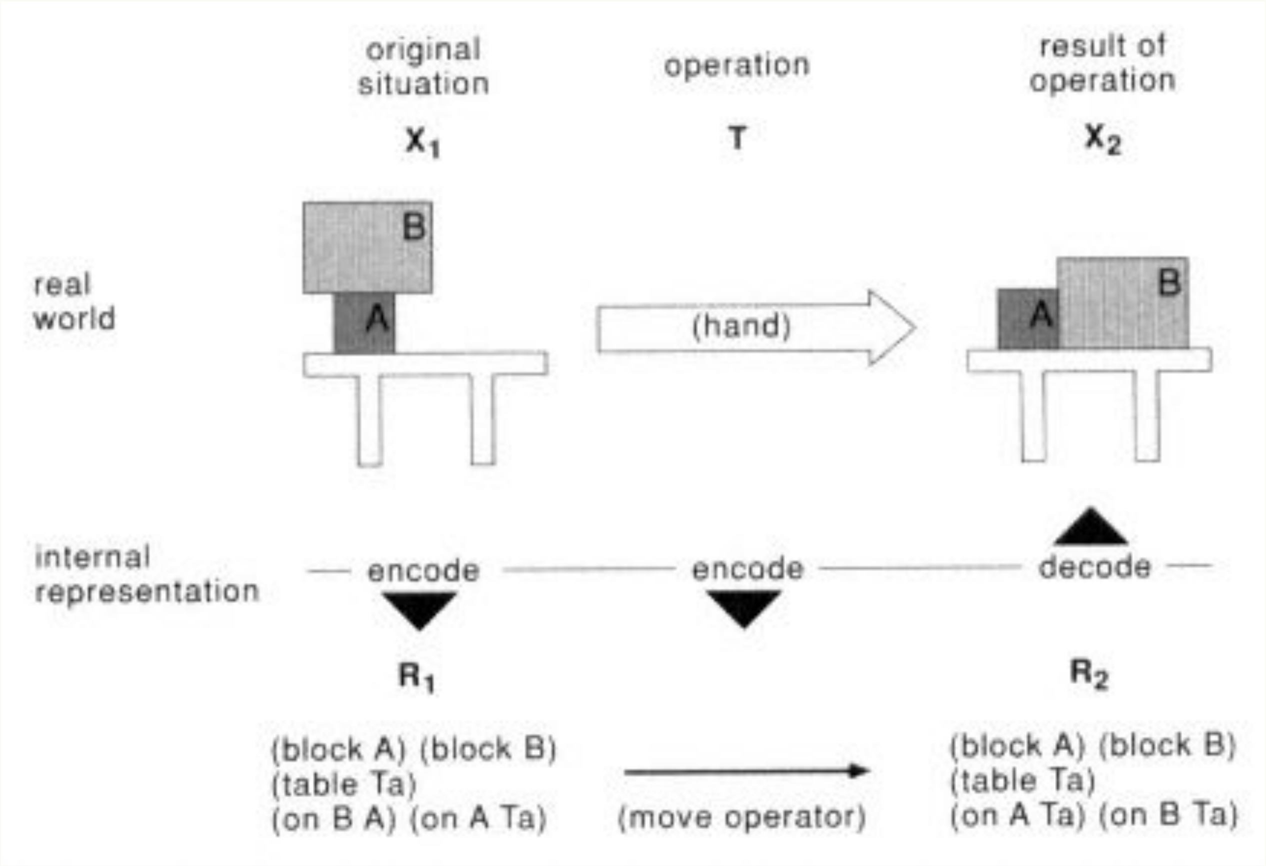
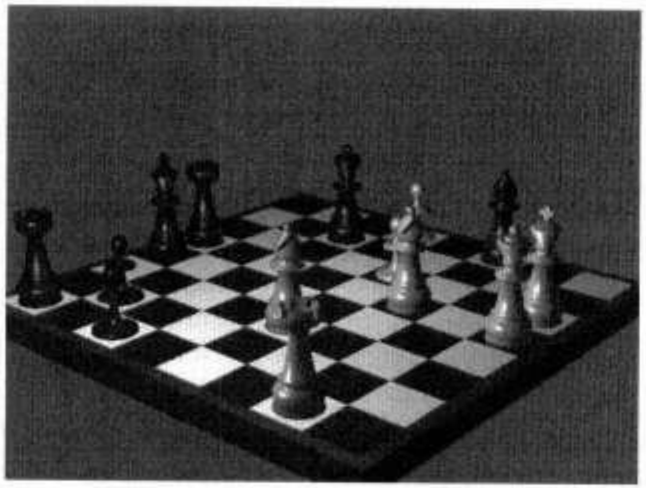


Fig. 2.5 from Pfeifer & Scheier 1999

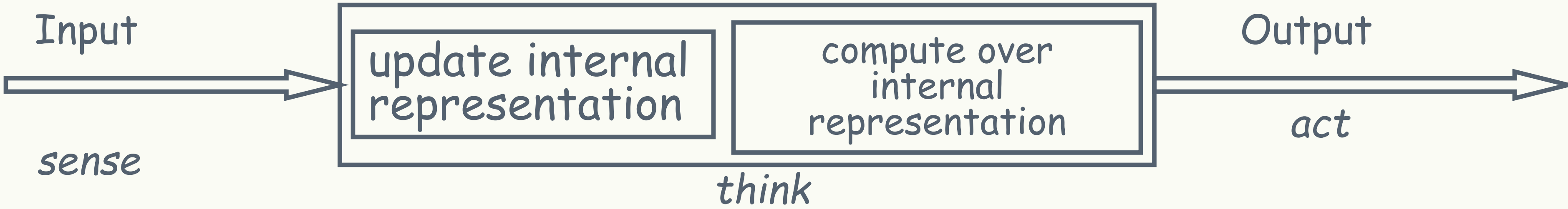
From formal world to real world

Chess



Soccer

From formal world to real world



Ancient times:

Stanford Cart, 1975

https://youtu.be/dcS6Ol5xXqY

GOFAI fundamental problems

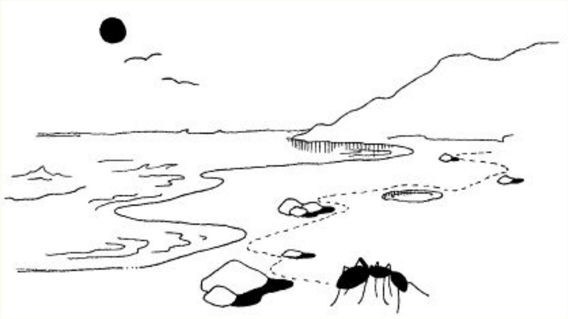
Frame problem

- 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

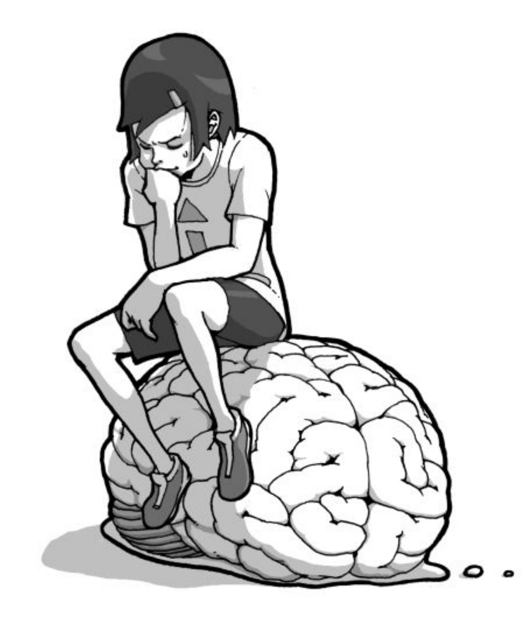
=> real-time operation in real world is possible

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 Intelligence

- 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

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Our research examples and student projects

Embodiment

"intelligence requires a body"

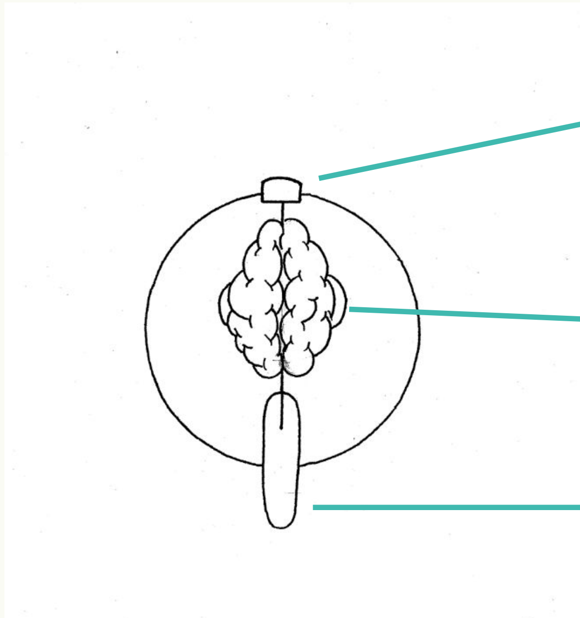
Interplay / task distribution

- Brain
- Body (morphology – shape, materials, …)
- Environment

Principal of ecological balance

- match in complexity of sensory, motor, and neural system

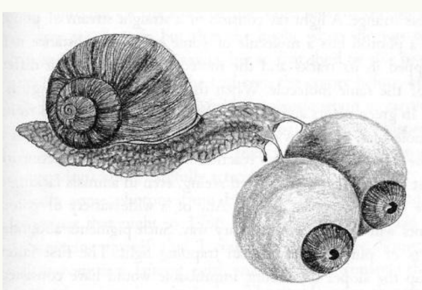
Ecologically unbalanced systems



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?

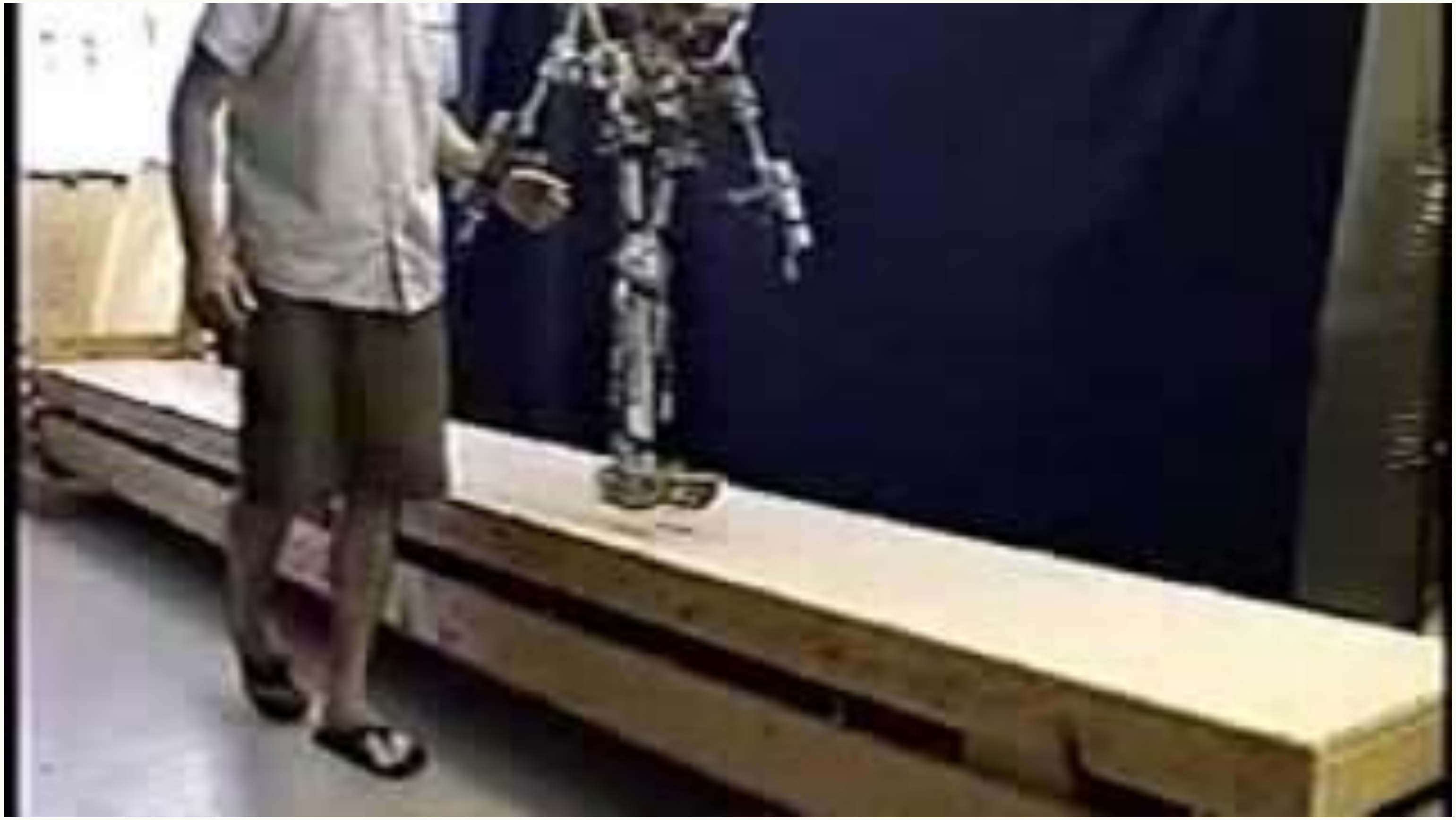
Passive dynamic walkers (McGeer 1990)

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

Morphology:

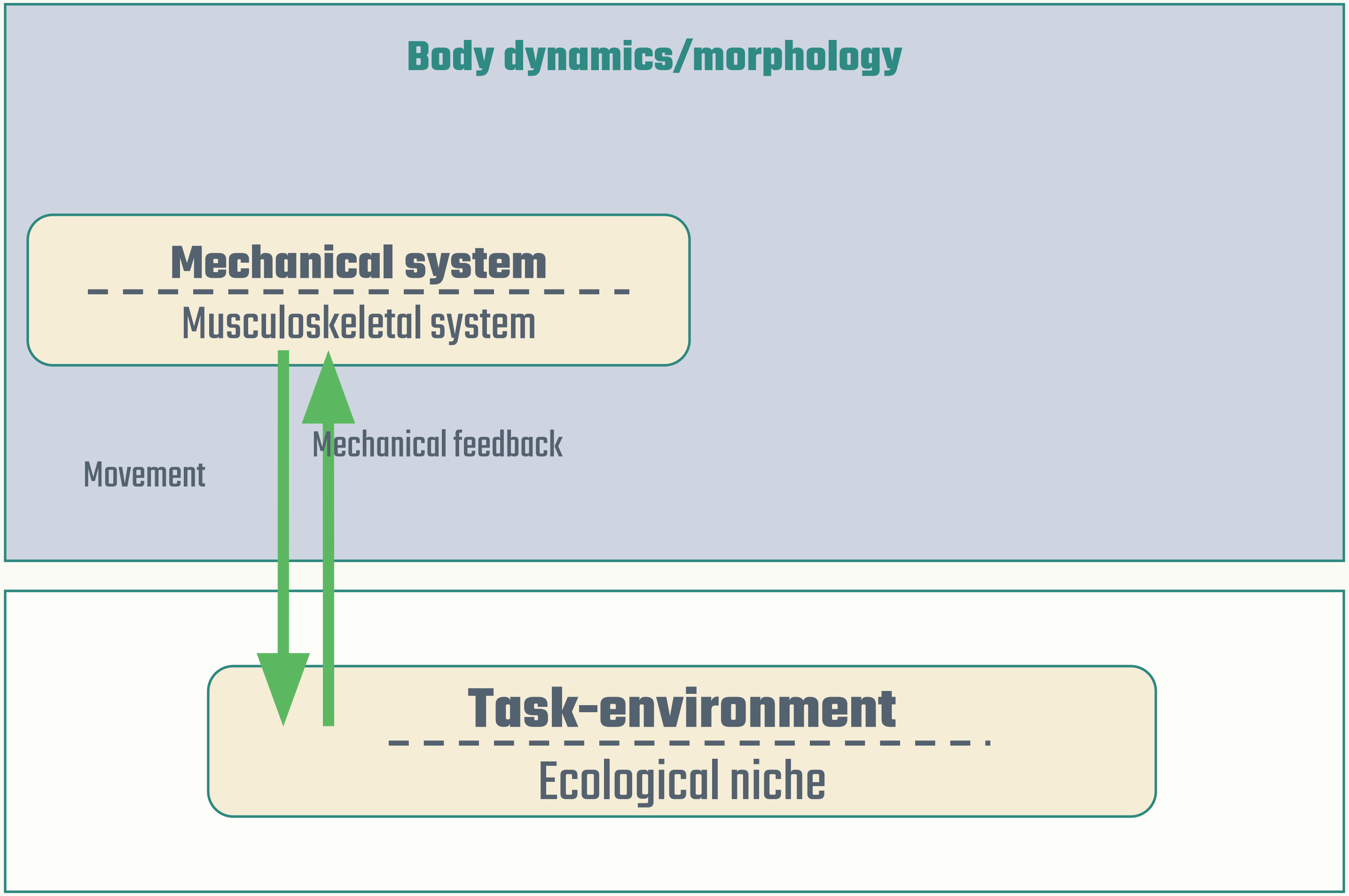
- shape of feet
- counterswing of arms
- friction on bottom of feet

Cornell PDW with arms, Collins et al. 2001



https://youtu.be/e2Q2Lx8O6Cg

Steve Collins, Passive dynamic-based walker



Schematics based on Pfeifer et al., Science 2007

Self-stabilization

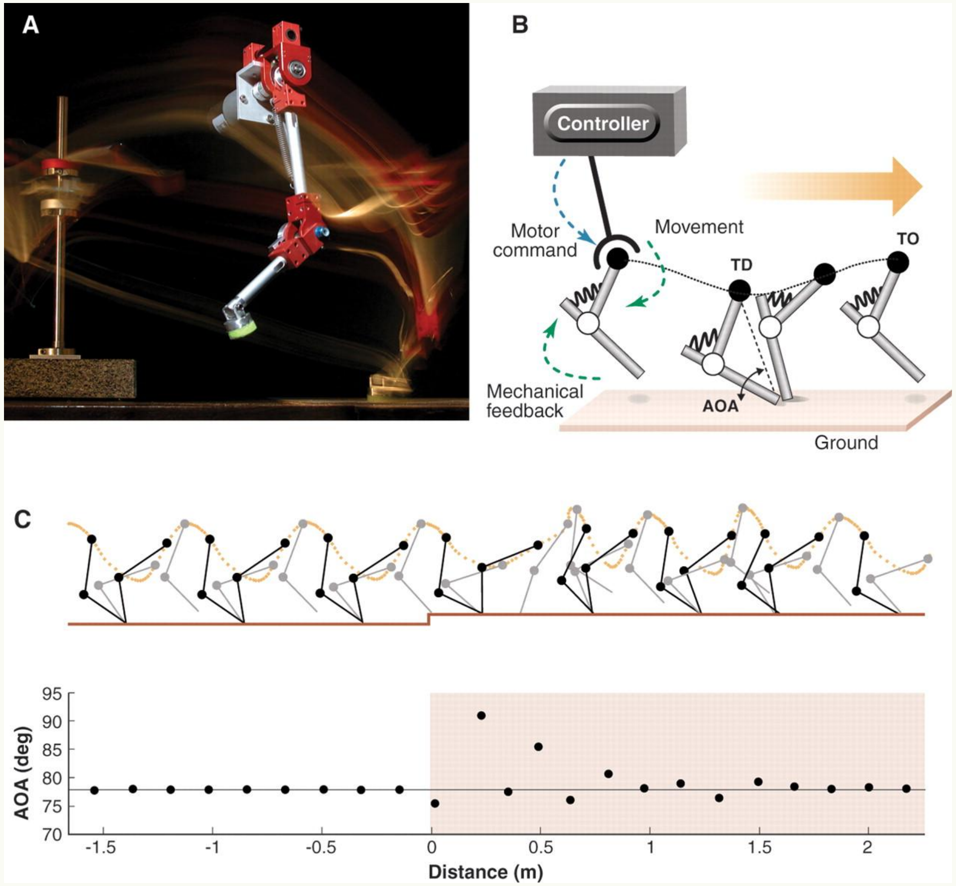
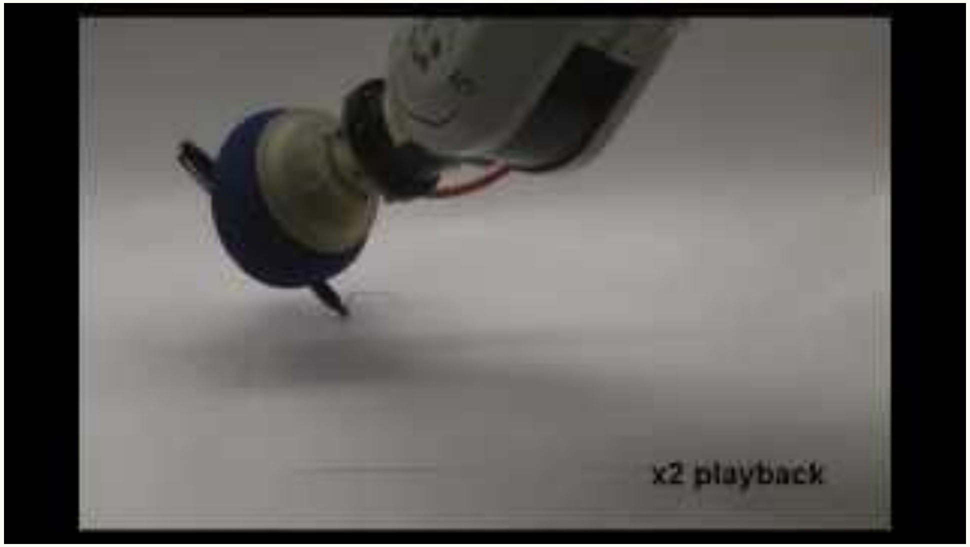


Fig. adapted from Blickhan et al. 2007

https://youtu.be/Zt7J0dly70M

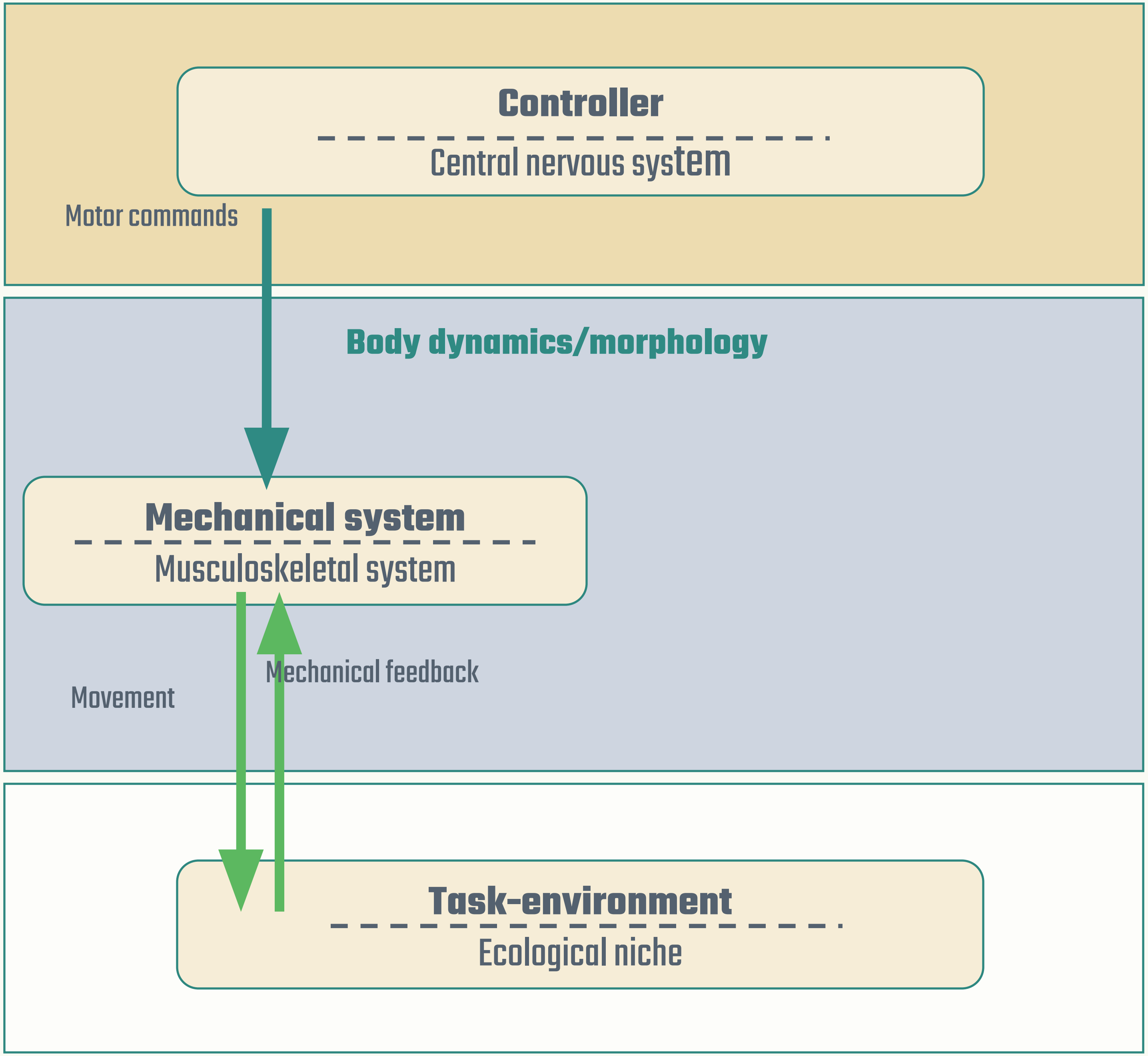
Grasping with coffee balloon grippers

Image: John Amend (jra224@cornell.edu)



https://youtu.be/ZK0I_lVDPpw

Brown et al. 2010



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

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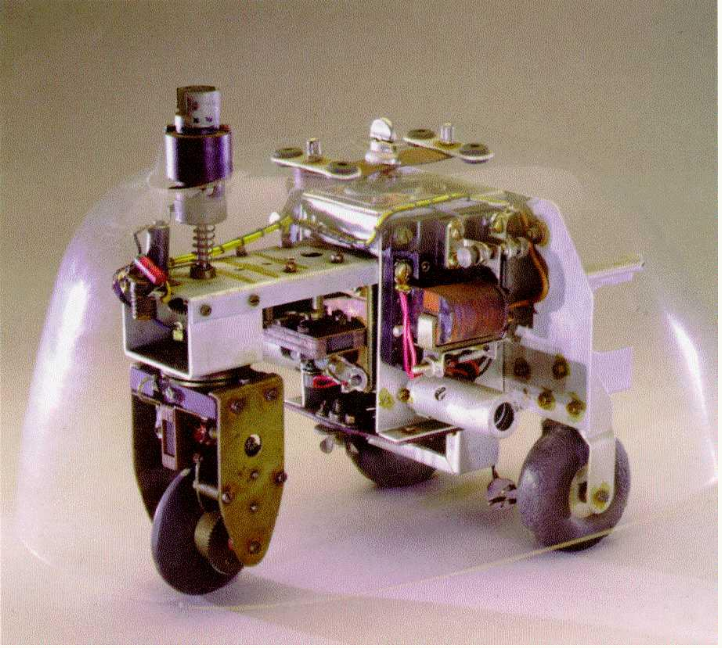
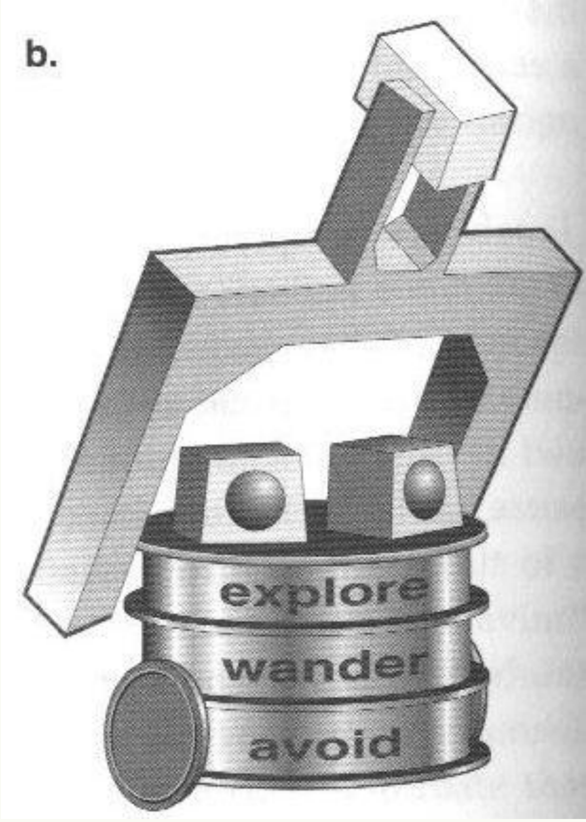
Our research examples and student projects



Grey Walter
Turtle, 1940s

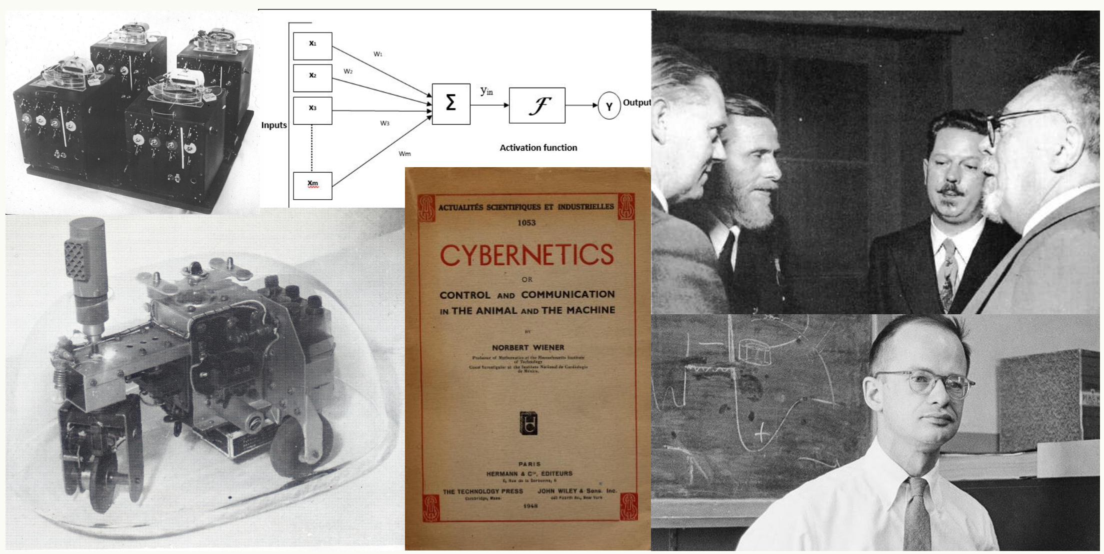
V. Breitenberg, 1980s



R. Brooks, 1980s
subsumption architecture

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

- 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



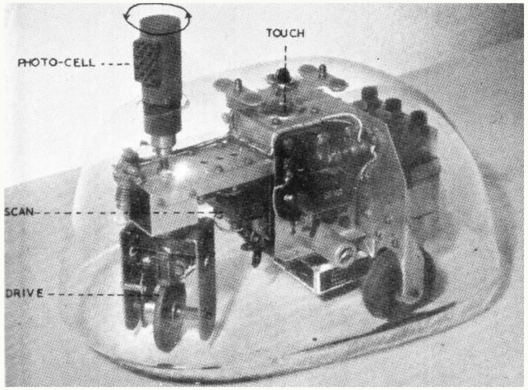
Slide source: Hagen Lehmann

William Grey Walter (1910-1977)

English neurophysiologist and roboticist

Work on EEG, conditioning, etc.

"Robotic tortoises" (1948-49)

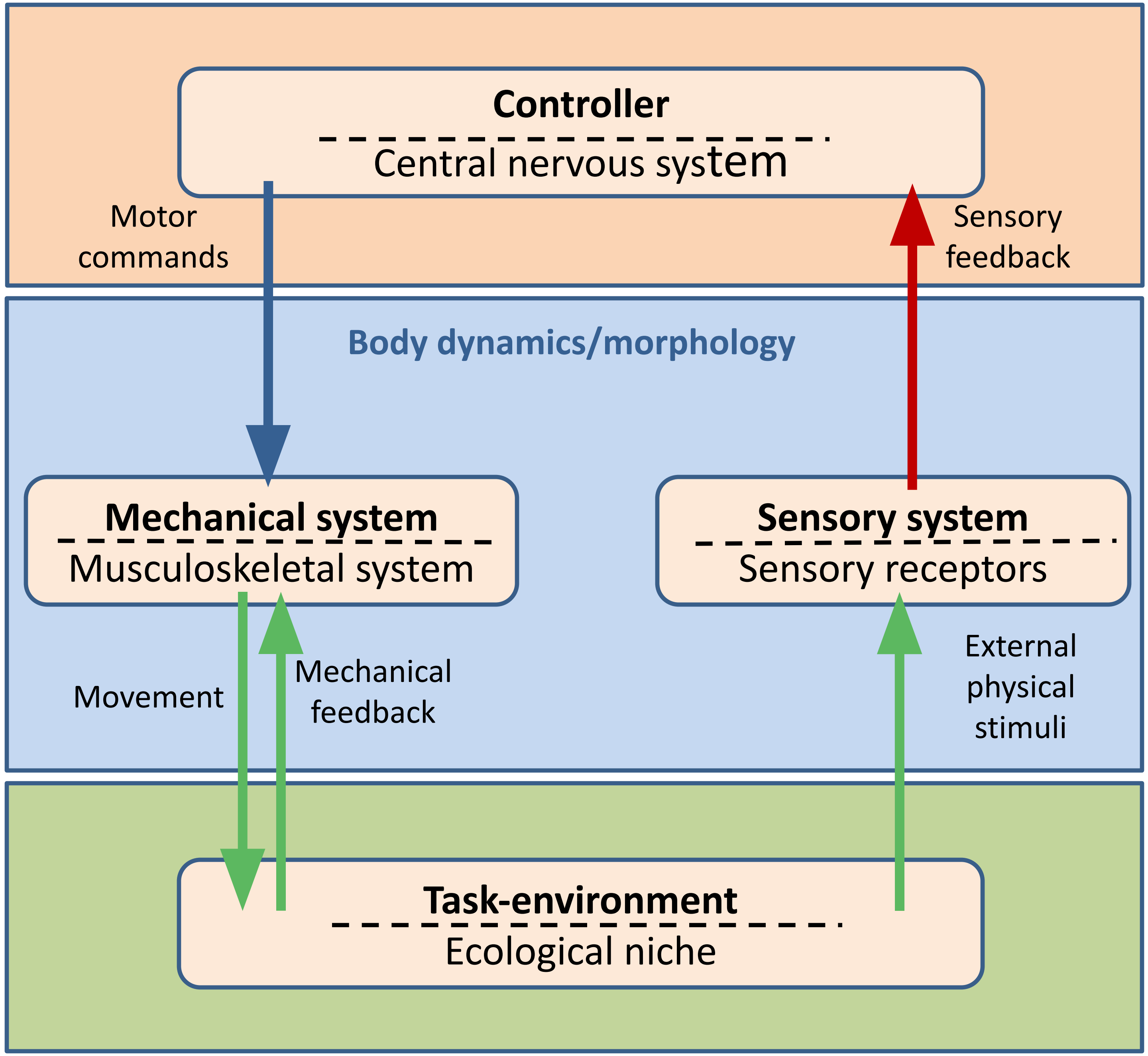


- Autonomous robots with touch and light sensors
- Simple "brain" (2 "neurons")
- "tortoises" influenced a number of roboticists (Hans Moravec, Rodney Brooks, etc.)
- "descendants": robotic vacuum cleaners

Slide source: Miloš Železný

Grey Walter's tortoises

https://youtu.be/lLULRlmXkKo


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

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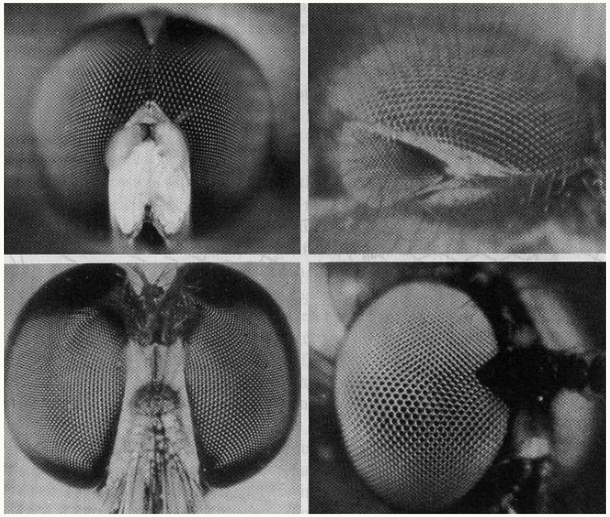
Insect eye morphology

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

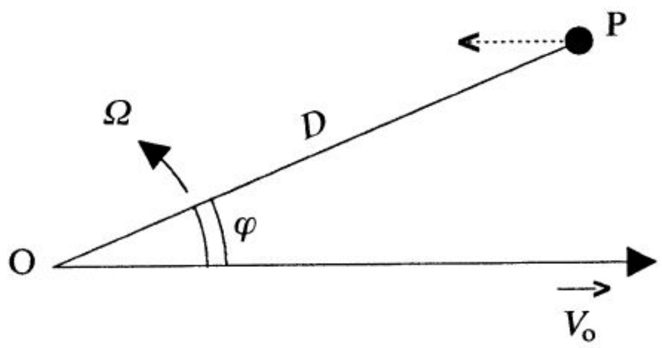


honeybee

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.

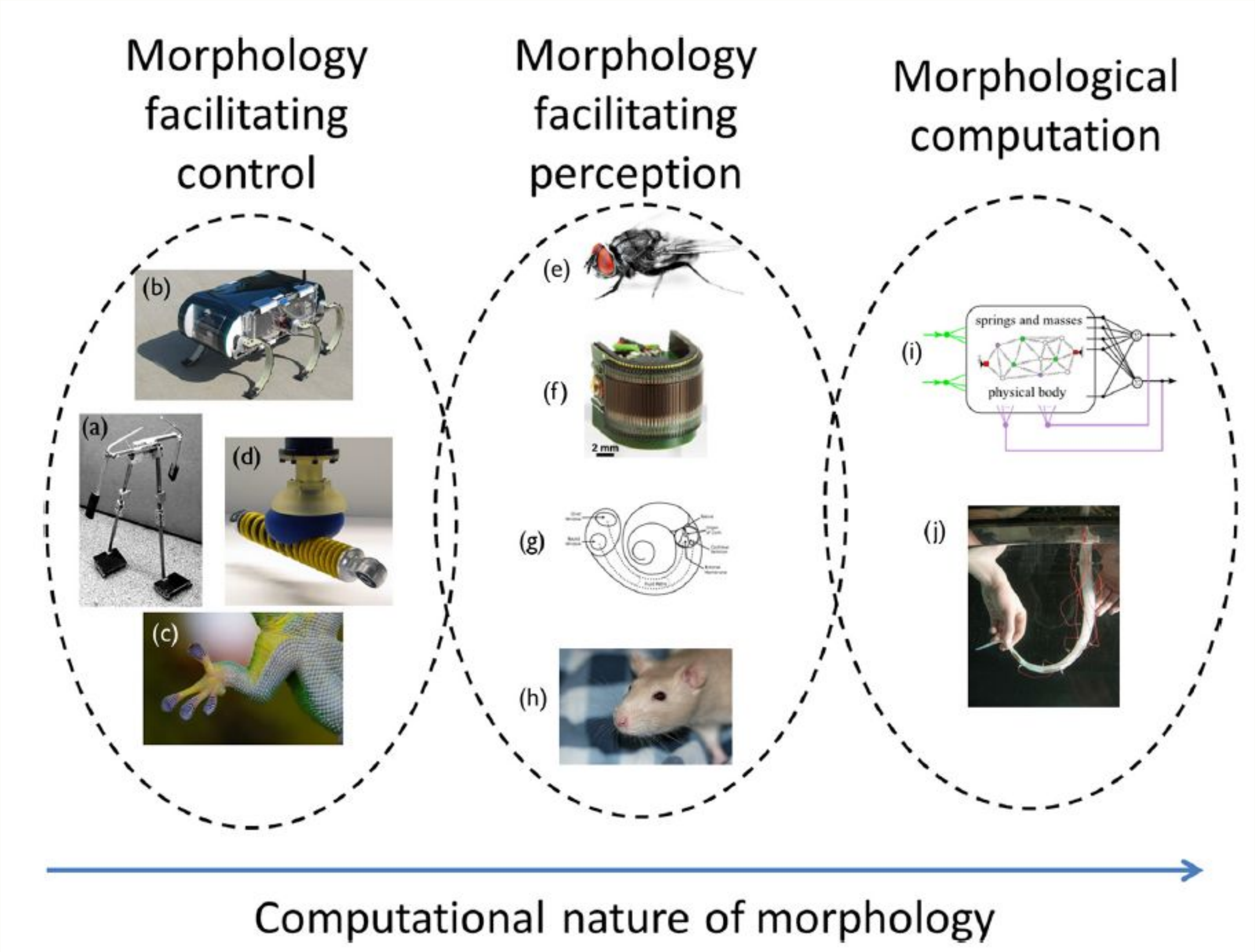
Nonuniform distribution & elementary motion detectors

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.

(a) (b)

CurvACE – artificial compound eye - image courtesy of Dario Floreano

Morphological "computation"

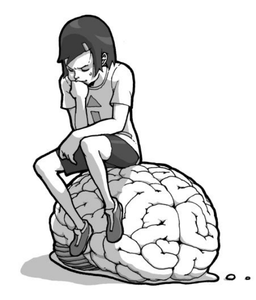


Müller, V.C. & Hoffmann, M. (2017), 'What is morphological computation? On how the body contributes to cognition and control', *Artificial Life* **23** (1), 1-24.

Embodiment

behavior is not in the brain

(or cell, molecule...)



"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)

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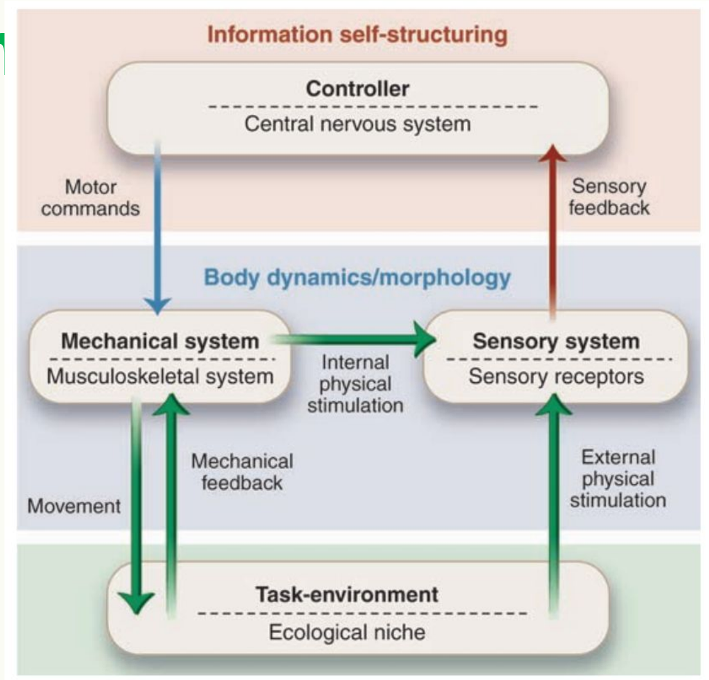
it is in the interaction



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

Pfeifer, R., Lungarella, M., & Iida, F. (2007). Self-organization, embodiment, and biologically inspired robotics. science, 318(5853), 1088-1093.

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"Embodied AI"- new trend in machine learning / deep learning

https://embodied-ai.org/

Deitke, M., Batra, D., Bisk, Y., Campari, T., Chang, A. X., Chaplot, D. S., ... & Wu, J. (2022). Retrospectives on the embodied AI workshop.

iROS KYOTO 2022 https://iros2022.org/

~Embodied AI for a Symbiotic Society~

2022-07-28: Sergey Levine, UC Berkeley, "From Reinforcement Learning to Embodied Learning".
at https://sites.google.com/view/developing-minds-series/home

What is this “Embodied AI”?

Retrospectives on the Embodied AI Workshop

Matt Deitke[1,17], Dhruv Batra[5,8], Yonatan Bisk[3], Tommaso Campari[4,16], Angel X. Chang[13], Devendra Singh Chaplot[8], Changan Chen[19], Claudia Pérez-D'Arpino[9], Kiana Ehsani[1], Ali Farhadi[2,17], Li Fei-Fei[14], Anthony Francis[6], Chuang Gan[11,15], Kristen Grauman[19,8], David Hall[20], Winson Han[1], Unnat Jain[8], Aniruddha Kembhavi[1,17], Jacob Krantz[12], Stefan Lee[12], Chengshu Li[14], Sagnik Majumder[19], Oleksandr Maksymets[8], Roberto Martín-Martín[19], Roozbeh Mottaghi[8,17], Sonia Raychaudhuri[13], Mike Roberts[7], Silvio Savarese[14], Manolis Savva[13], Mohit Shridhar[17], Niko Sünderhauf[20], Andrew Szot[5], Ben Talbot[20], Joshua B. Tenenbaum[10], Jesse Thomason[18], Alexander Toshev[2], Joanne Truong[5], Luca Weihs[1], Jiajun Wu[14]

[1]Allen Institute for AI, [2]Apple, [3]Carnegie Mellon University, [4]FBK, [5]Georgia Tech, [6]Google, [7]Intel Labs, [8]Meta AI, [9]NVIDIA, [10]MIT, [11]MIT-IBM Watson AI Lab, [12]Oregon State University, [13]Simon Fraser University, [14]Stanford University, [15]UMass Amherst, [16]University of Padova, [17]University of Washington, [18]University of Southern California, [19]UT Austin, [20]QUT Centre for Robotics

arXiv:2210.06849v3 [cs.CV] 5 Dec 2022

Abstract

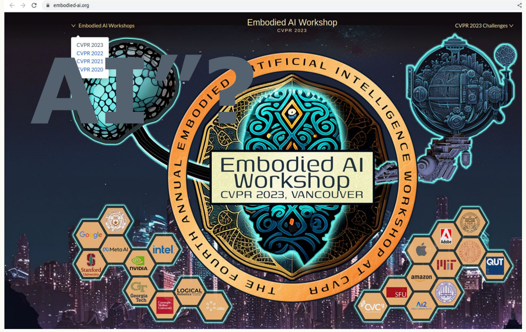
We present a retrospective on the state of Embodied AI research. Our analysis focuses on 13 challenges presented at the Embodied AI Workshop at CVPR. These challenges are grouped into three themes: (1) visual navigation, (2) rearrangement, and (3) embodied vision-and-language. We discuss the dominant datasets within each theme, evaluation metrics for the challenges, and the performance of state-of-the-art models. We highlight commonalities between top approaches to the challenges and identify potential future directions for Embodied AI research.

1. Introduction

Within the last decade, advances in deep learning, coupled with the creation of massive datasets and high-capacity models, have resulted in remarkable progress in computer vision, audio, NLP, and the broader field of AI. This progress has enabled models to obtain superhuman performance on a wide

of researchers and research challenges.

Consider asking a robot to *'Clean my room'* or *'Drive me to my favorite restaurant'*. To succeed at these tasks in the real world, the robots need skills like *visual perception* (to recognize scenes and objects), *audio perception* (to receive the speech spoken by the human), *language understanding* (to translate questions and instructions into actions), *memory* (to recall how items should be arranged or to recall previously encountered situations), *physical intuition* (to understand how to interact with other objects), *multi-agent reasoning* (to predict and interact with other agents), and *navigation* (to safely move through the environment). The study of embodied agents both provides a challenging testbed for building intelligent systems and tries to understand how intelligence emerges through interaction with an environment. As such, it involves many disciplines, such as computer vision, natural language processing, acoustic learning, reinforcement learning, developmental psychology, cognitive science, neuroscience, and robotics.



https://embodied-ai.org/

Deitke, M., Batra, D., Bisk, Y., Campari, T., Chang, A. X., Chaplot, D. S., ... & Wu, J. (2022). Retrospectives on the embodied AI workshop.

- rearrangement
- visual navigation
- vision-and-language
- audio-visual navigation
- sim-to-real transfer

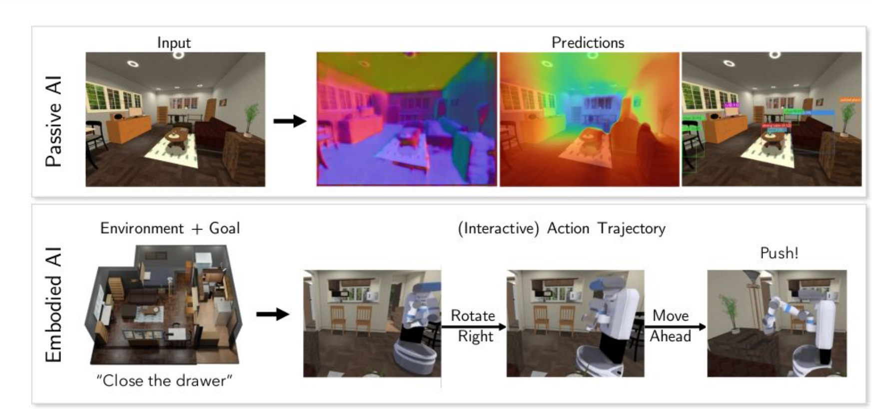
Challenges

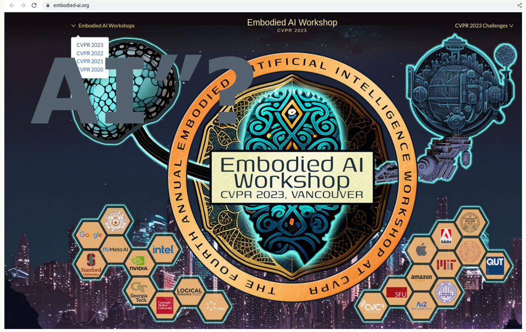
The Embodied AI 2023 workshop is hosting many exciting challenges covering a wide range of topics such as rearrangement, visual navigation, vision-and-language, and audio-visual navigation. More details regarding data, submission instructions, and timelines can be found on the individual challenge websites.

Challenge winners will be given the opportunity to present a talk at the workshop. Since many challenges can be grouped into similar tasks, we encourage participants to submit models to more than 1 challenge. The table below describes, compares, and links each challenge.

Challenge	Scene Dataset	Observations	Action Space	Interactive Actions?	Stochastic Acuation?
Habitat	HM3D Semantics	RGB-D, Localization	Continuous		
Habitat	HM3D Semantics	RGB-D, Localization	Continuous		
RxR-Habitat (Coming Soon)	Matterport3D	RGB-D	Discrete		
MultiON	HM3D Semantics	RGB-D, Localization	Discrete		
SoundSpaces	Matterport3D	RGB-D, Audio Waveform	Discrete		
SoundSpaces	Matterport3D	RGB-D, Audio Waveform	Discrete		
Robotic Vision Scene Understanding	Active Scene Understanding	RGB-D, Pose Data, Flatscan Laser	Discrete		Partially
Robotic Vision Scene Understanding	Active Scene Understanding	RGB-D, Pose Data, Flatscan Laser	Discrete		✓
TDW-Transport (Coming Soon)	TDW	RGB-D, Metadata	Discrete	✓	✓
AI2-THOR Rearrangement (Coming Soon)	iTHOR	RGB-D, Localization	Discrete	✓	
Language Interaction	iTHOR	RGB	Discrete	✓	
DialFRED	iTHOR	RGB	Discrete	✓	
ManiSkill	PartNet-Mobility, YCB, EGAD	RGB-D, Metadata	Continuous	✓	

What is this “Embodied AI”?





https://embodied-ai.org/

Deitke, M., Batra, D., Bisk, Y., Campari, T., Chang, A. X., Chaplot, D. S., ... & Wu, J. (2022). Retrospectives on the embodied AI workshop.

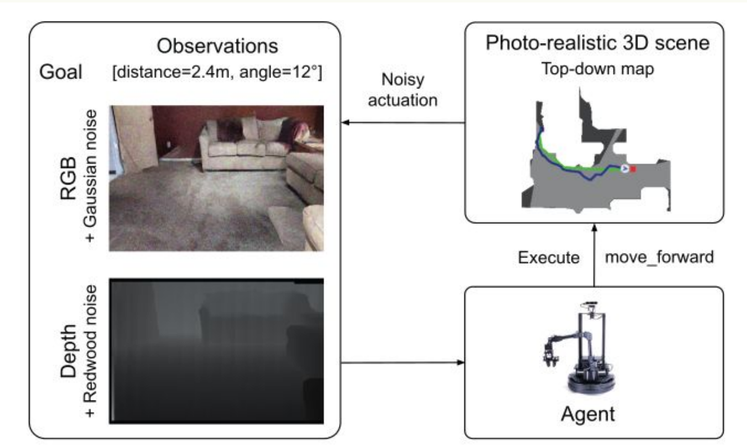
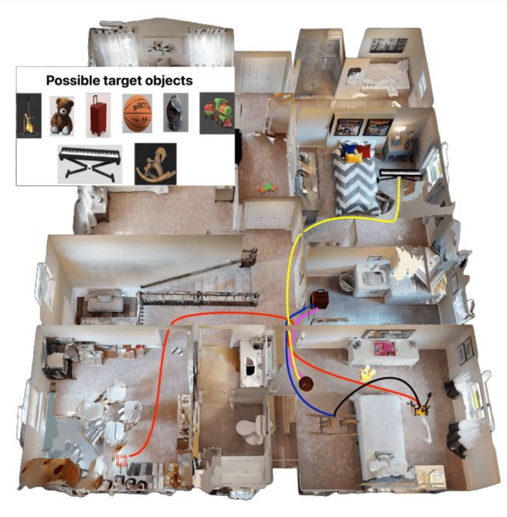


Figure 3. The *PointNav* task requires an agent to navigate to a goal coordinate in a novel environment (potentially with noisy sensory inputs), without access to a pre-built map of the environment.



(b)

Figure 6. *Multi-ObjectNav*: (a) Top-down visualization of a MultiON episode with 5 target cylinder objects in a particular sequence; (b) Top-down visualization of a MultiON episode with 5 target real objects in a particular sequence.

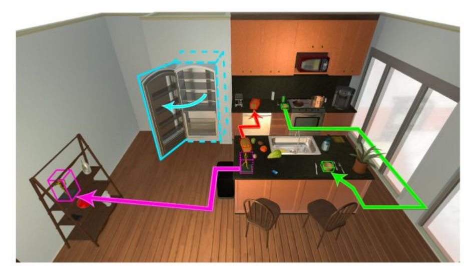
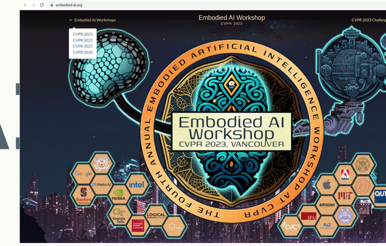


Figure 11. **AI2-THOR Visual Room Rearrangement Challenge.** An agent must change pose and attributes of objects in a household environment to restore the environment to an initial state.

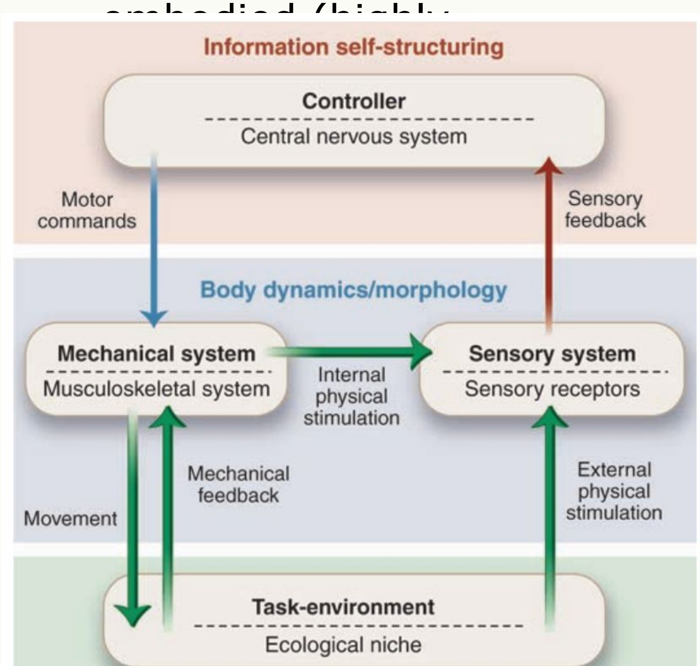
What is this “Embodied A



https://embodied-ai.org/

- embodied AI ~ sim-to-real transfer
- embodied AI ~ multimodal inputs

My interpretation:
- The tasks are weakly



Challenges

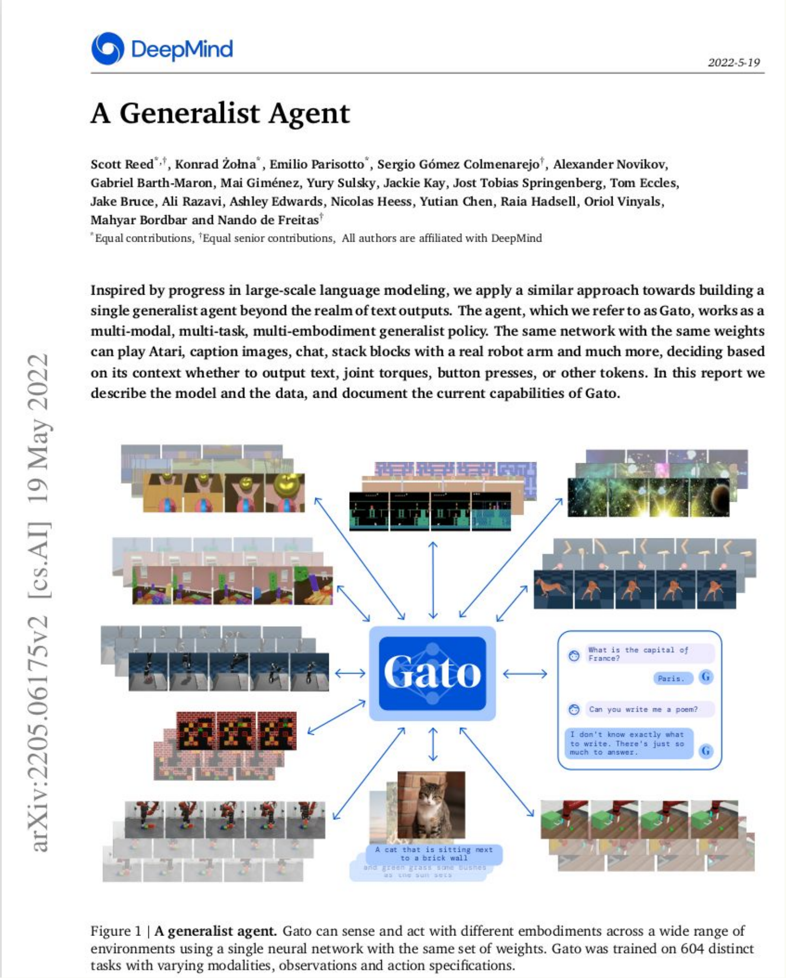
The Embodied AI 2023 workshop is hosting many exciting challenges covering a wide range of topics such as rearrangement, visual navigation, vision-and-language, and audio-visual navigation. More details regarding data, submission instructions, and timelines can be found on the individual challenge websites.

Challenge winners will be given the opportunity to present a talk at the workshop. Since many challenges can be grouped into similar tasks, we encourage participants to submit models to more than 1 challenge. The table below describes, compares, and links each challenge.

Challenge	Scene Dataset	Observations	Action Space	Interactive Actions?	Stochastic Acuation?
Habitat	HM3D Semantics	RGB-D, Localization	Continuous		
Habitat	HM3D Semantics	RGB-D, Localization	Continuous		
RxR-Habitat (Coming Soon)	Matterport3D	RGB-D	Discrete		
MultiON	HM3D Semantics	RGB-D, Localization	Discrete		
SoundSpaces	Matterport3D	RGB-D, Audio Waveform	Discrete		
SoundSpaces	Matterport3D	RGB-D, Audio Waveform	Discrete		
Robotic Vision Scene Understanding	Active Scene Understanding	RGB-D, Pose Data, Flatscan Laser	Discrete		Partially
Robotic Vision Scene Understanding	Active Scene Understanding	RGB-D, Pose Data, Flatscan Laser	Discrete		✓
TDW-Transport (Coming Soon)	TDW	RGB-D, Metadata	Discrete	✓	✓
AI2-THOR Rearrangement (Coming Soon)	iTHOR	RGB-D, Localization	Discrete	✓	
Language Interaction	iTHOR	RGB	Discrete	✓	
DialFRED	iTHOR	RGB	Discrete	✓	
ManiSkill	PartNet-Mobility, YCB, EGAD	RGB-D, Metadata	Continuous	✓	

What are the limits of generalization?

- across tasks, environments…
- across bodies?
- My take:
  - how much can a giraffe brain profit from a crocodile's brain?
  - only in very weakly embodied tasks….


DeepMind

2022-5-19

A Generalist Agent

Scott Reed*,†, Konrad Żołna*, Emilio Parisotto*, Sergio Gómez Colmenarejo†, Alexander Novikov, Gabriel Barth-Maron, Mai Giménez, Yury Sulsky, Jackie Kay, Jost Tobias Springenberg, Tom Eccles, Jake Bruce, Ali Razavi, Ashley Edwards, Nicolas Heess, Yutian Chen, Raia Hadsell, Oriol Vinyals, Mahyar Bordbar and Nando de Freitas†

*Equal contributions, †Equal senior contributions, All authors are affiliated with DeepMind

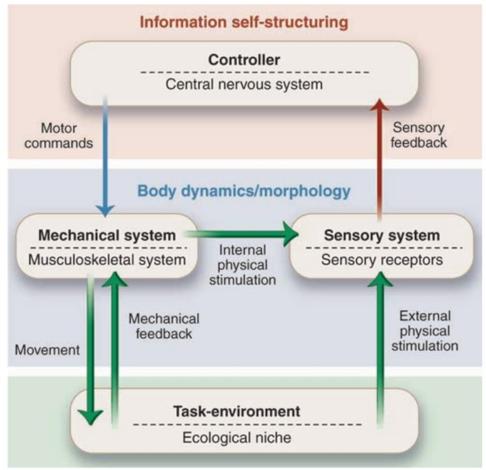
Inspired by progress in large-scale language modeling, we apply a similar approach towards building a single generalist agent beyond the realm of text outputs. The agent, which we refer to as Gato, works as a multi-modal, multi-task, multi-embodiment generalist policy. The same network with the same weights can play Atari, caption images, chat, stack blocks with a real robot arm and much more, deciding based on its context whether to output text, joint torques, button presses, or other tokens. In this report we describe the model and the data, and document the current capabilities of Gato.

arXiv:2205.06175v2 [cs.AI] 19 May 2022

Figure 1 | **A generalist agent.** Gato can sense and act with different embodiments across a wide range of environments using a single neural network with the same set of weights. Gato was trained on 604 distinct tasks with varying modalities, observations and action specifications.

Summary

- Embodied AI within deep learning
  - giving deep learning architectures the body and closing the loop (with reservations)
  - weak embodiment
  - What is not exploited:
    - morphology for control
    - morphology for perception
    - information self-structuring



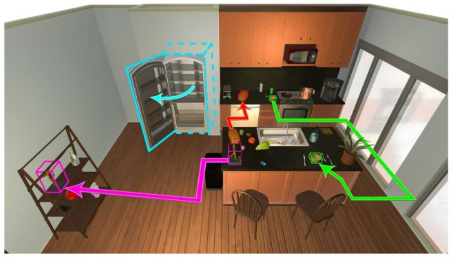
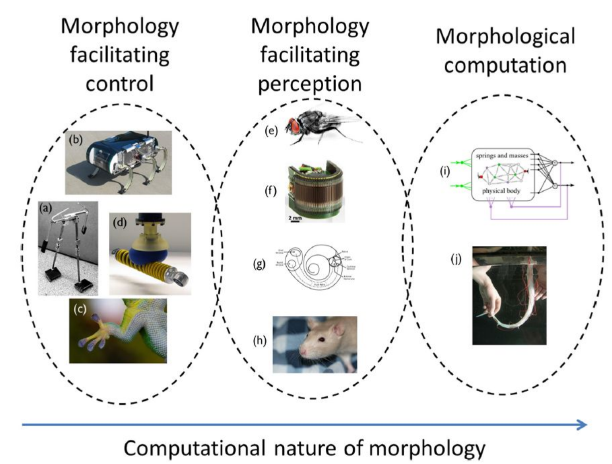
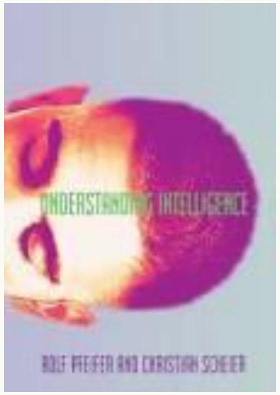


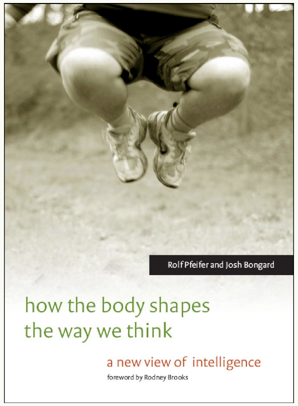
Figure 11. **AI2-THOR Visual Room Rearrangement Challenge.** An agent must change pose and attributes of objects in a household environment to restore the environment to an initial state.

versus



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

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.

Deitke, M., Batra, D., Bisk, Y., Campari, T., Chang, A. X., Chaplot, D. S., ... & Wu, J. (2022). Retrospectives on the embodied AI workshop.

Reed, S., Zolna, K., Parisotto, E., Colmenarejo, S. G., Novikov, A., Barth-Maron, G., ... & de Freitas, N. (2022). A generalist agent. arXiv preprint arXiv:2205.06175.

Outline

Synthetic methodology ~ “understanding by building”

Classical AI – intelligence as computation

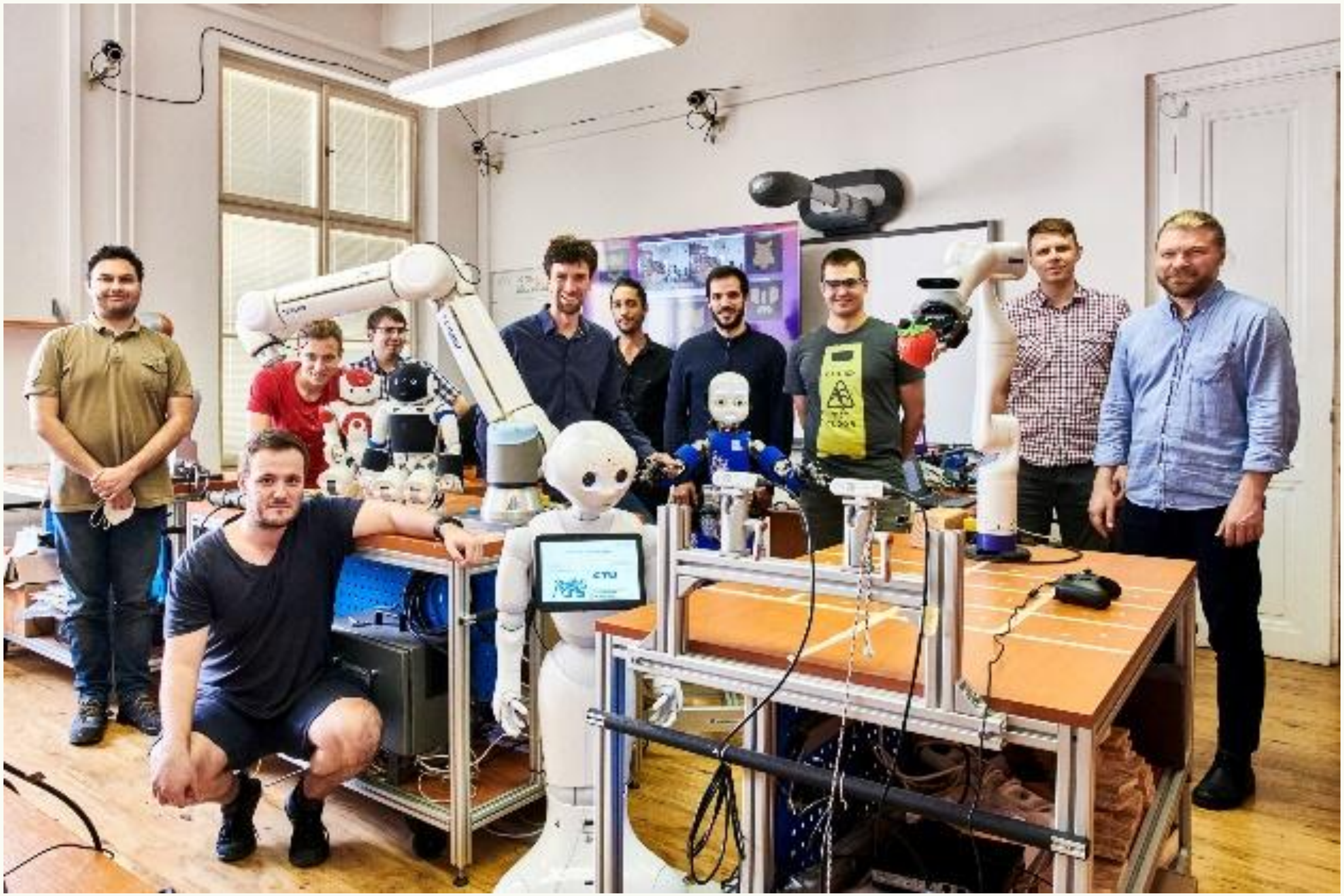
Embodied intelligence

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

Embodied AI

Our research examples and student projects

Humanoid and cognitive robotics



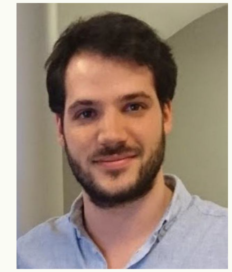
Humanoid and cognitive robotics

Coordinator

Matej Hoffmann
origin: Czechia
PhD: Zurich, Switzerland (Rolf Pfeifer)
postdoc: IIT, Genoa, Italy

Postdocs

Sergiu Tcaci Popescu
origin: Moldova, France
PhD: Cognitive Science, Paris, France
postdoc: sensorimotor contingencies (Kevin O'Regan)
sensorimotor contingencies, tactile localization, body schema development, self-touch



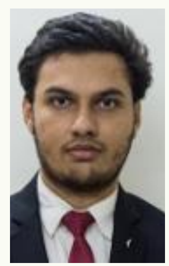
Valentin Marcel
origin: France
PhD: Robotics, Paris, France
formal approaches to sensorimotor development, machine learning, embodied comp. models

PhD students

Zdeněk Straka
origin: Czechia
BSc: Cybernetics and Robotics @ FEE, CTU
MSc: AI @ FEE, CTU
machine learning, neural networks, peripersonal space representations

Petr Švarný
origin: Czechia
MSc: logic, business informatics
PhD: logic, Prague
physical human-robot

Filipe Gama
origin: France, Portugal
MSc.: AI & robotics @ Cergy-Pontoise
active exploration,



Shubhan Patni
origin: India
MSc.: Robotics @ Bristol, UK
haptic exploration, grasping

Jason Khoury
origin: France
MSc: psychology, game design @ Lyon, Montpellier
tactile localization, body schema development,

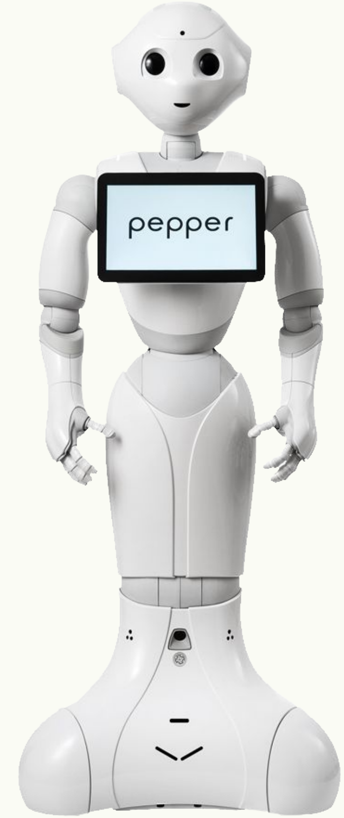
Jakub Rozlivek
origin: Czechia
MSc.: Cybernetics and Robotics @ FEE, CTU
physical HRI, reactive motion control,

Lukáš Rustler
origin: Czechia
MSc.: Cybernetics and Robotics @ FEE, CTU
visuo-haptic exploration, physical HRI,

Humanoids

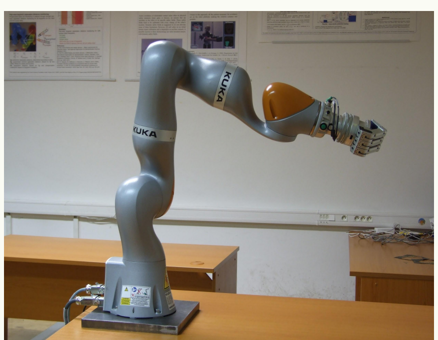
iCub

Naos (1 with “iCub skin”)



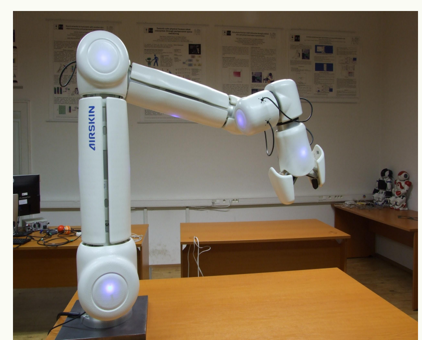
Pepper

Collaborative robots



KUKA LBR iiwa

Kinova Gen3

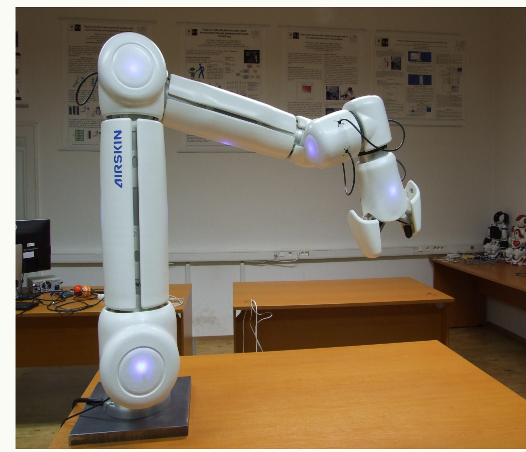


UR10 + Airskin

Large-scale robot skin

iCub humanoid ~ 4000 taxels

Nao humanoid retrofitted with “iCub skin” – 970 taxels

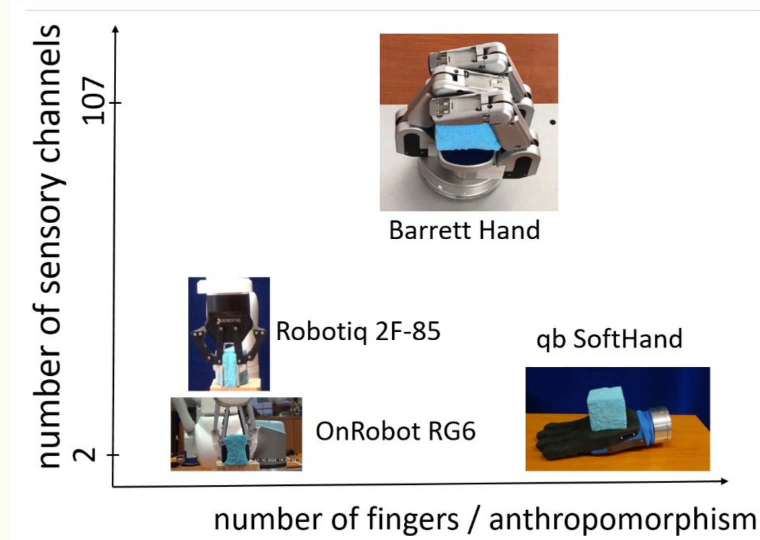


UR 10 manipulator with Airskin

Robot hands and grippers

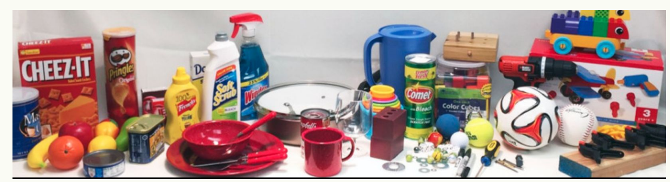
Anthropomorphic hands

Barrett Hand
(96 tactile + 3 fingertip joint torque + 8 joint pos. sensors)

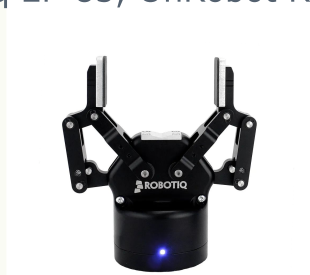


Qb SoftHand (1 motor with position and current sensor)

YCB object and model set

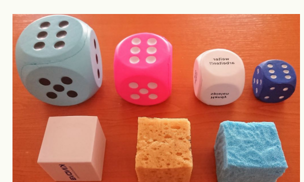


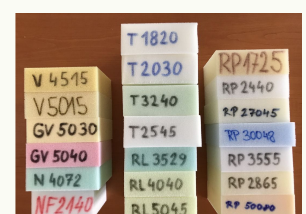
Industrial parallel jaw 2-finger grippers
Robotiq 2F-85, OnRobot RG6



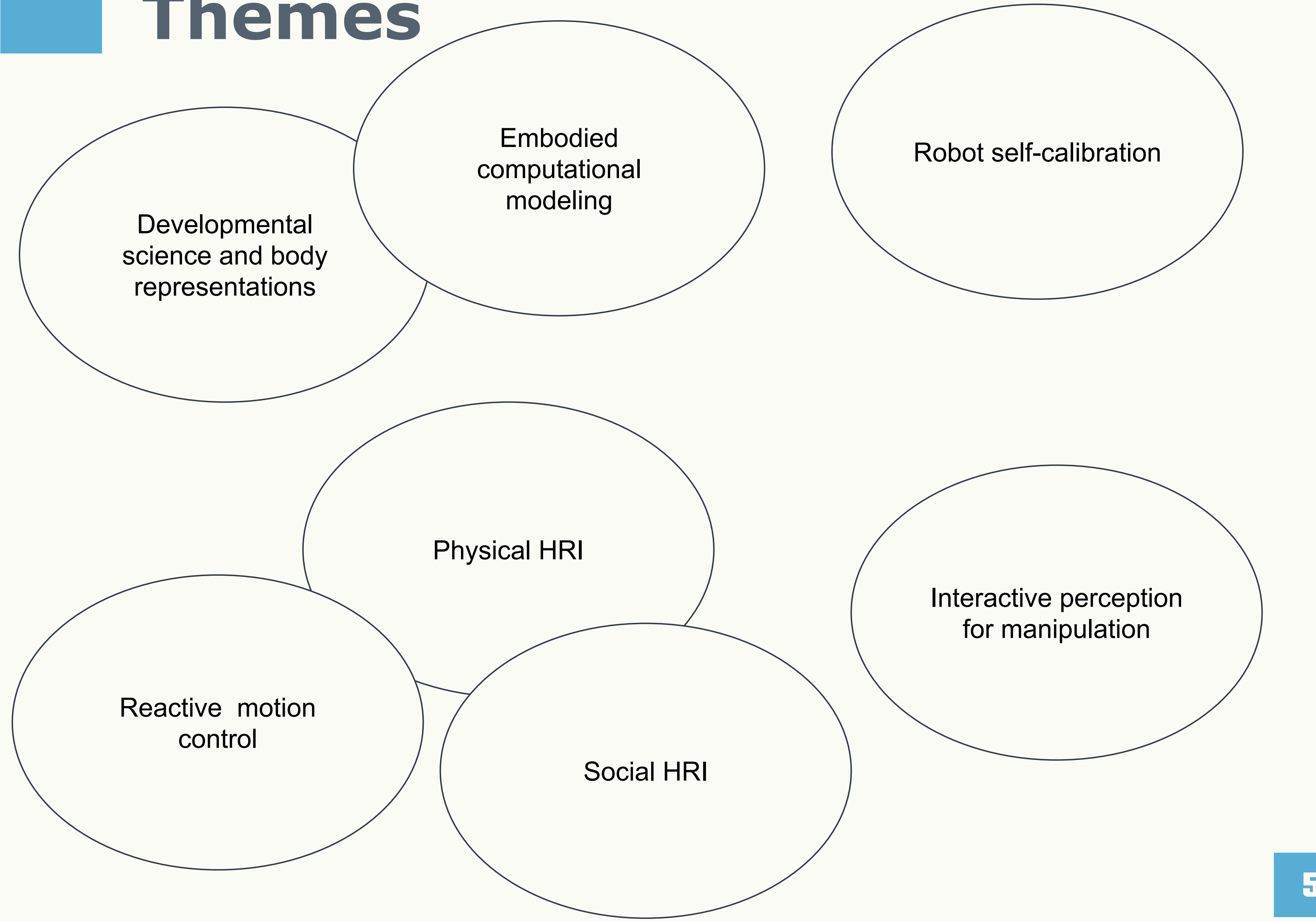
iCub hand

deformable objects set

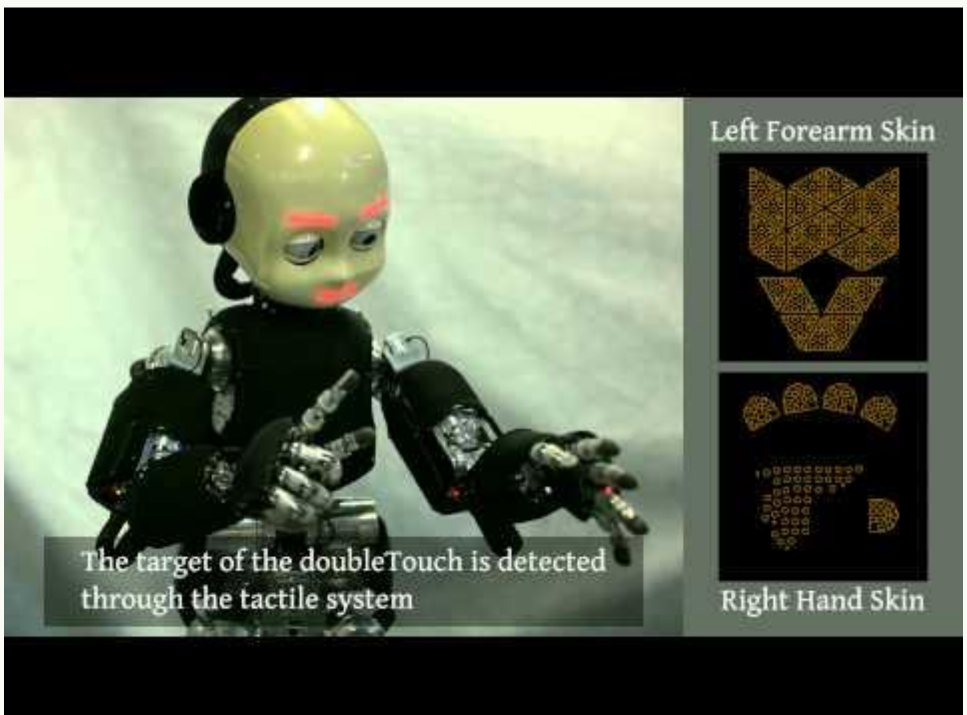




Themes


Developmental science and body representations
Embodied computational modeling
Robot self-calibration
Physical HRI
Interactive perception for manipulation
Reactive motion control
Social HRI

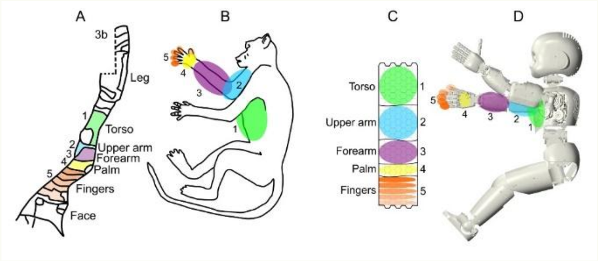
robots as embodied computational models of child and brain development

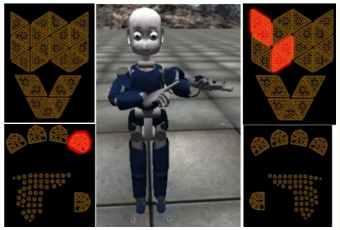


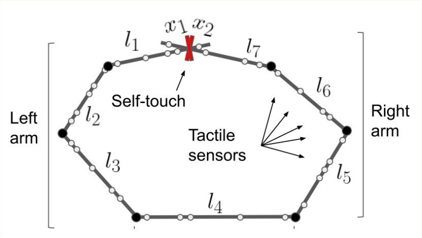
autonomous, adaptive, resilient, and self-calibrating robots

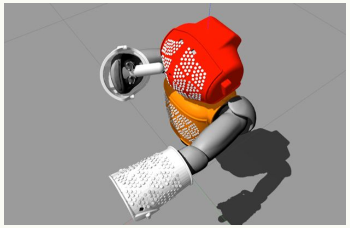
Robot case studies and neural network models

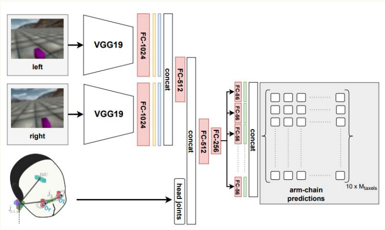
1. iCub tactile homunculus (SOM)
2. Learning to predict touch from proprioception (UBAL)
3. From self-touch to reaching to the body (VAE)
4. Active exploration of skin space
5. Learning to reach (deep NN)
6. Models of peripersonal space

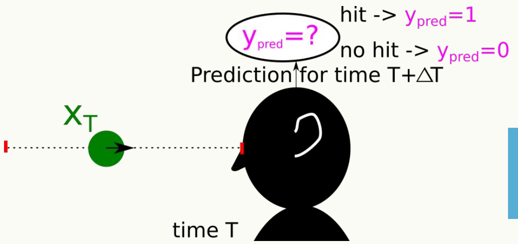




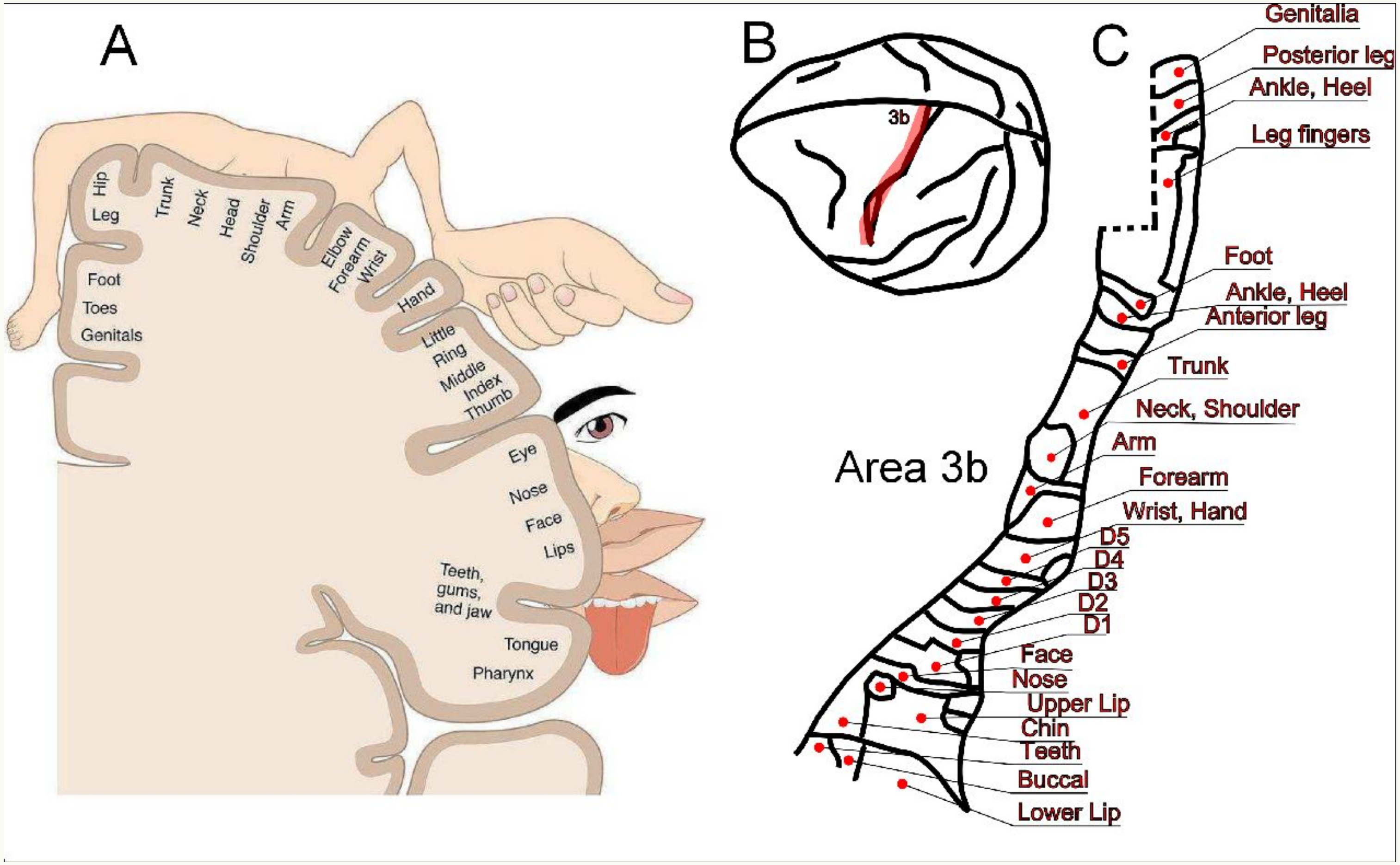






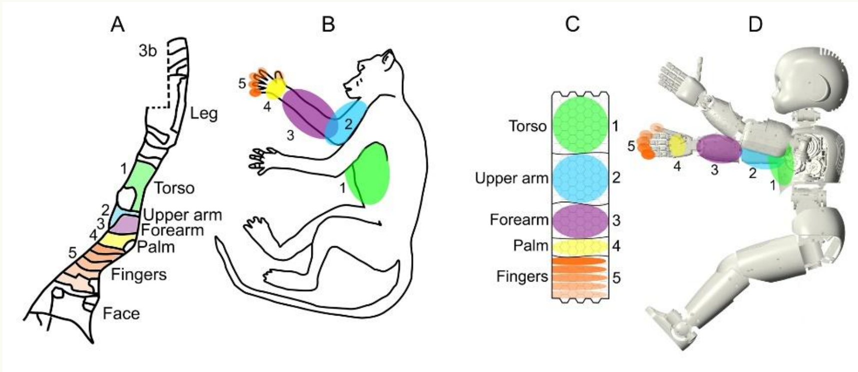


“Somatosensory homunculus”



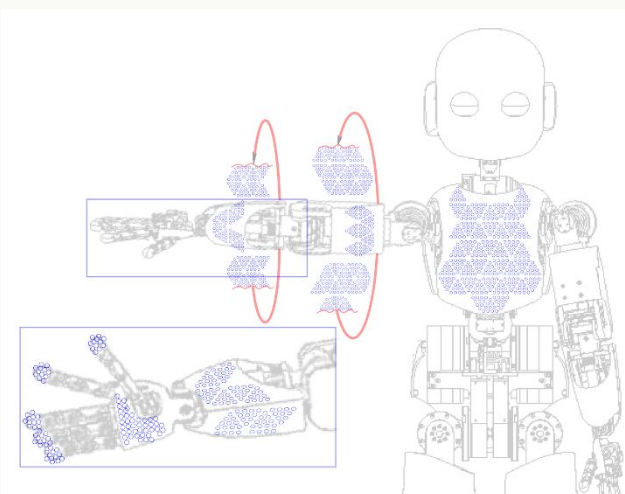
(A) Penfield W., Rasmussen T.: The cerebral cortex of man; a clinical study of localization of function, 1950. (pic from OpenStax College)
(B,C) Organization of the representations of body surface in area 3b of the cynomolgus macaque. (after Nelson 1980)

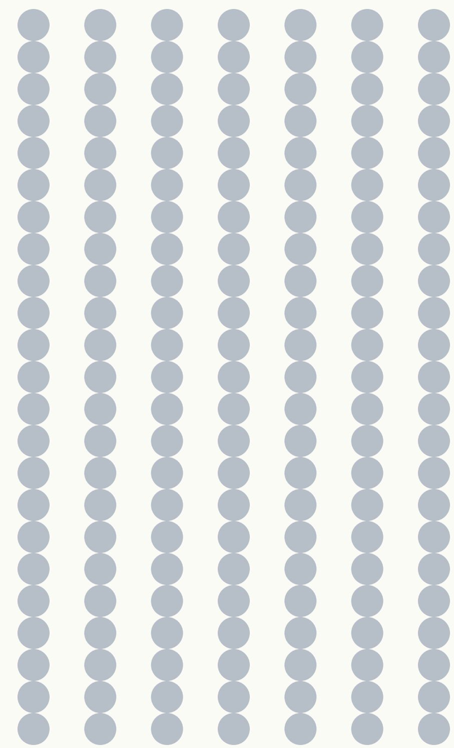
Learning using Self-Organizing (Kohonen) map (SOM)

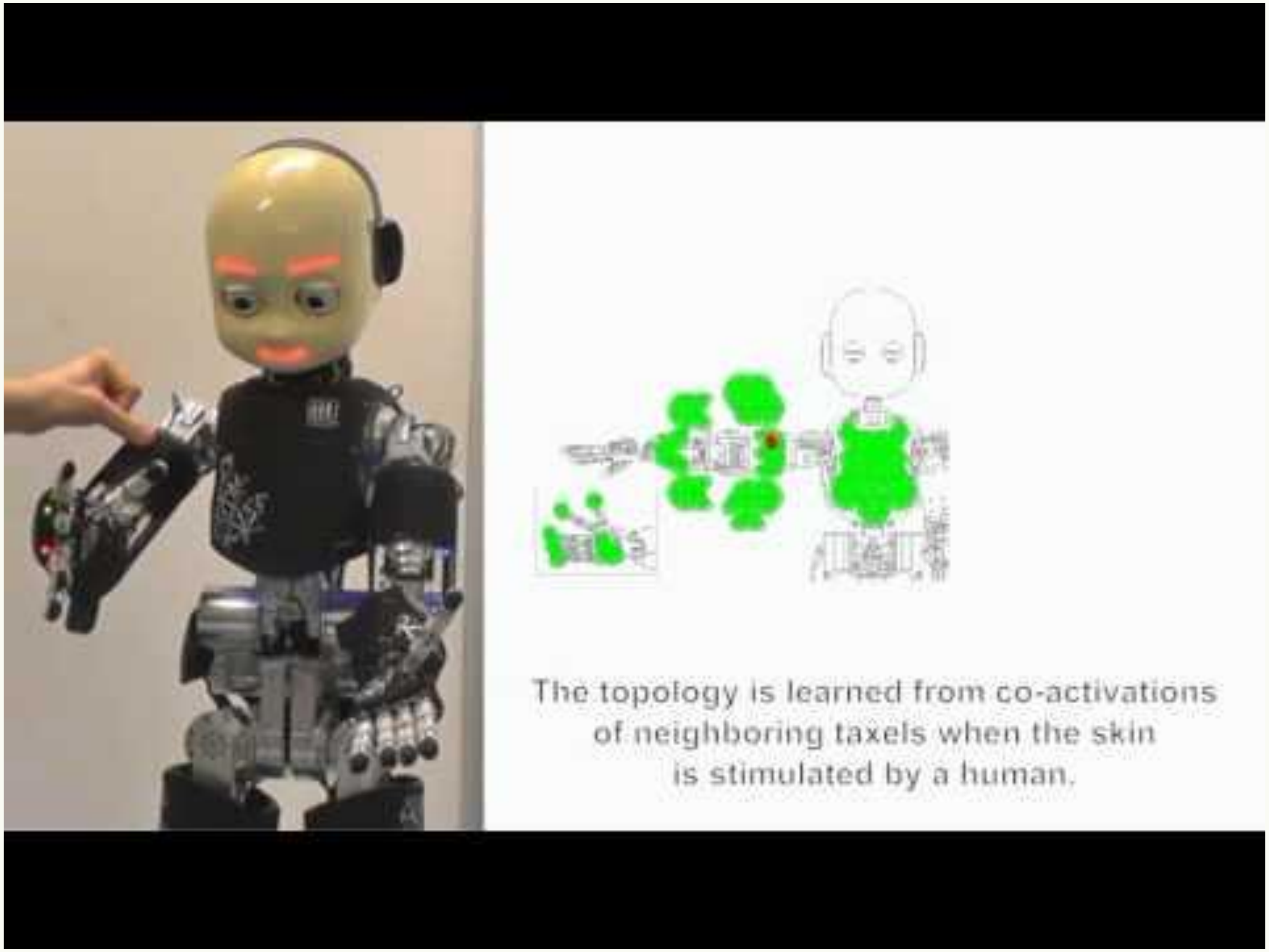


Output layer: 7 x 24 neurons

input layer: 1154 taxels



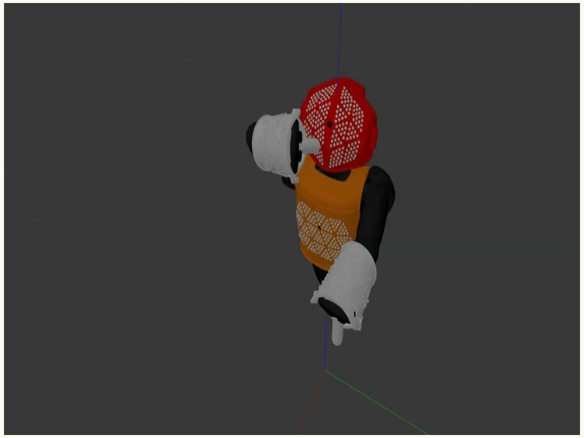




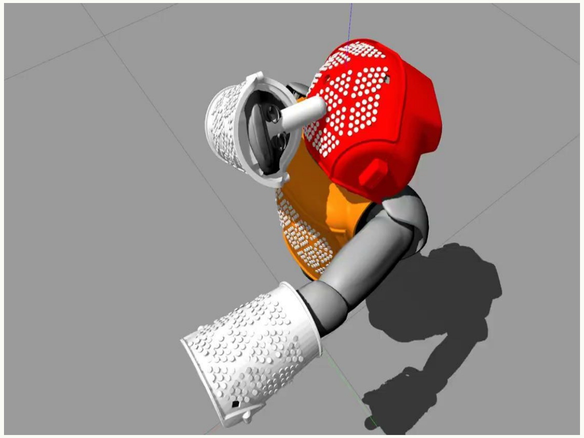
Hoffmann, M.; Straka, Z.; Farkas, I.; Vavrecka, M. & Metta, G. (2018), 'Robotic homunculus: Learning of artificial skin representation in a humanoid robot motivated by primary somatosensory cortex', *IEEE Transactions on Cognitive and Developmental Systems* **10**(2), 163-176.

Active exploration of "skin space"

Random Motor Babbling



Discretized Goal Babbling



Path-Based Continuous Goal Babbling

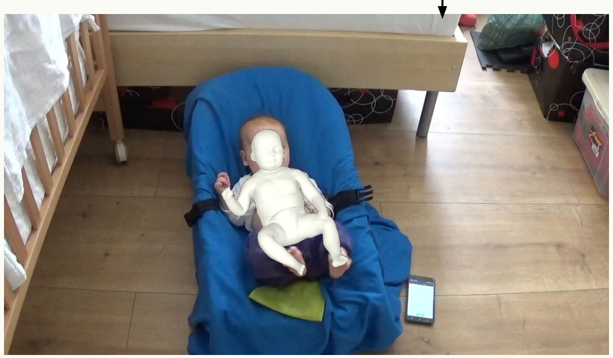
Gama, F.; Shcherban, M.; Rolf, M. & Hoffmann, M. (2021), 'Goal-directed tactile exploration for body model learning through self-touch on a humanoid robot', *IEEE Transactions on Cognitive and Developmental Systems*.

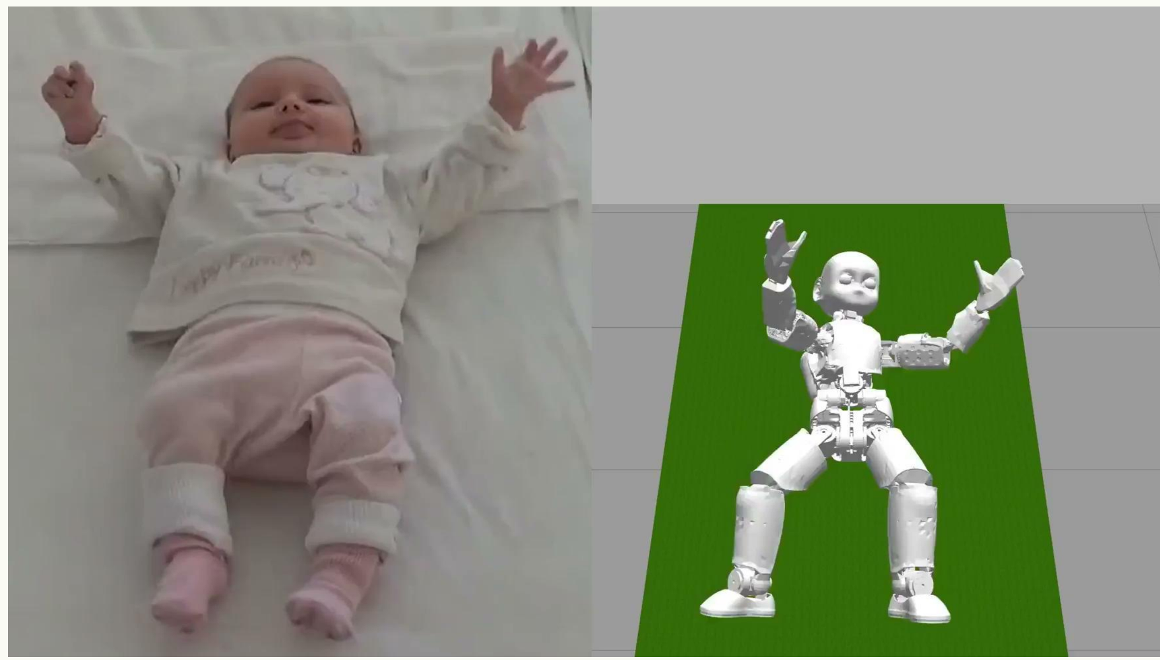
Motion retargeting – babies to humanoids

Input RGB Image

MMpose (HRNet) / Alphapose / Detectron2 / OpenPose / Deep(er)Cut

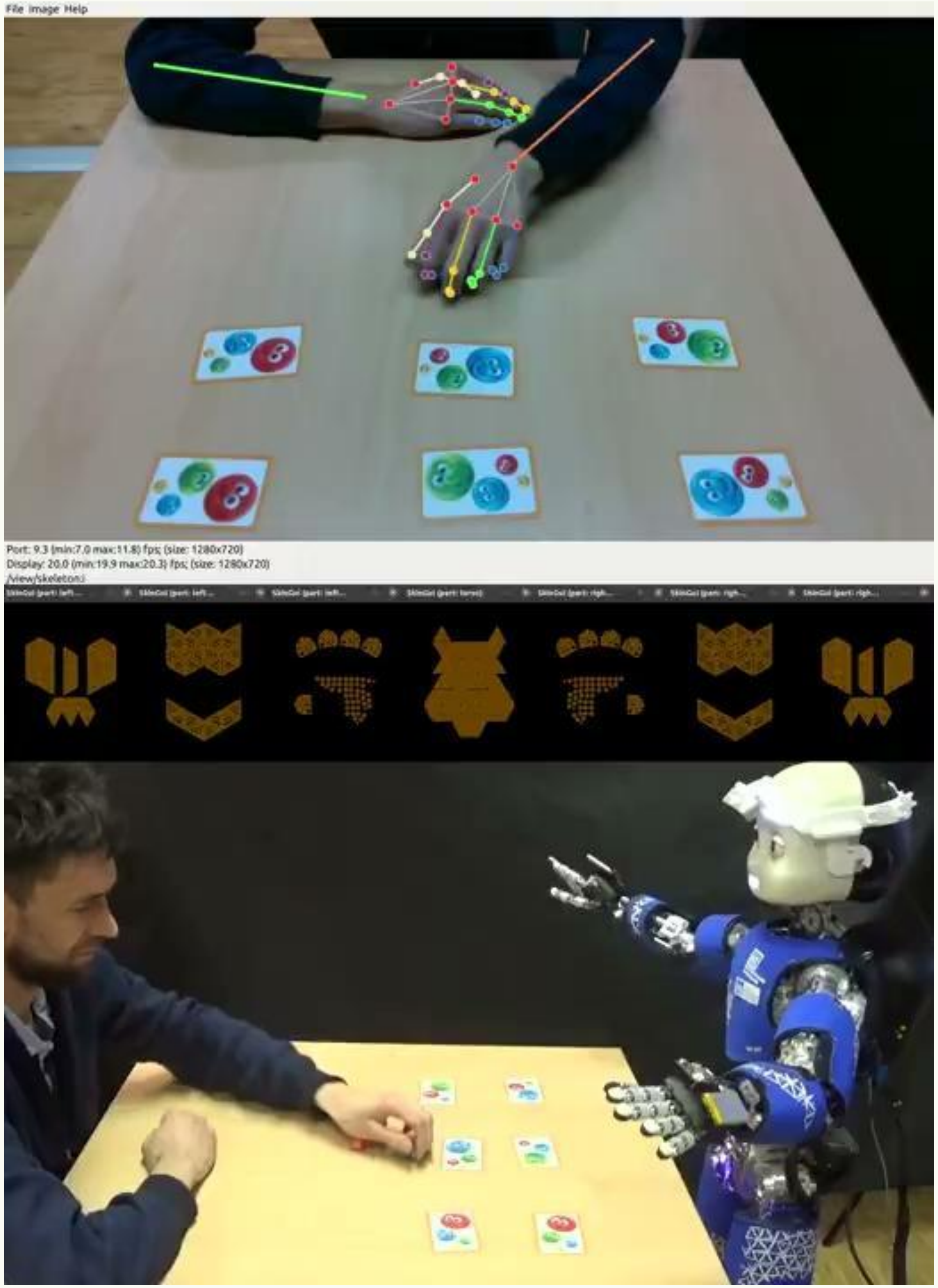
SMIL ⟶ Smplify-x



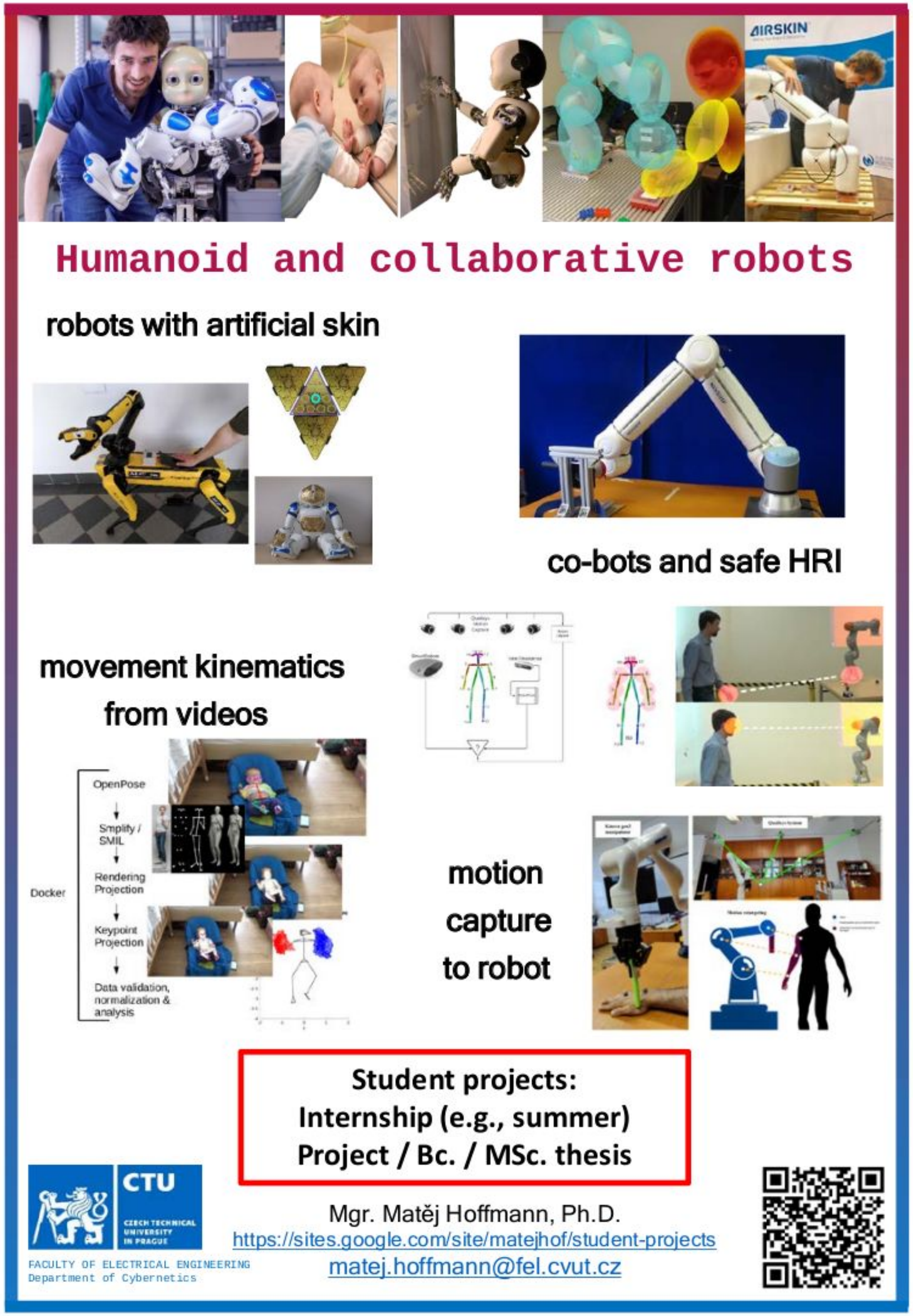


Bc. thesis Ondřej Fiala

iCub playing "Bubbles"



Rozlivek, Roncone, Pattacini & Hoffmann (2023) - in preparation



https://sites.google.com/site/matejhof/student-projects/open-and-ongoing

check also

https://sites.google.com/site/matejhof/student-projects/past-projects

Témata semestrálních projektů

Přihlásit se

Vyhledat

Vyhledat

Oblíbené projekty

Můj projekt

Typ studia

Bakalářské Magisterské

Studijní program

Nevybráno

Katedra vedoucího

(13133) Katedra kybernetiky

Vedoucí

doc. Mgr. Matěj Hoffmann, Ph.D.

Kategorie témat

Nevybráno

Počet nalezených témat: 6

Název tématu	Vedoucí	Určeno pro	Obsazenost	Katedra vedoucího
Řízení hlavy a očí humanoidního robota pro interakci s člověkem	doc. Mgr. Matěj Hoffmann, Ph.D.	BS & MS	0 / 2	(13133) Katedra kybernetiky
Měření a modelování sil při kolizi s robotem	doc. Mgr. Matěj Hoffmann, Ph.D.	BS & MS	0 / 1	(13133) Katedra kybernetiky
Získání kinematiky pohybu z videí dětí	doc. Mgr. Matěj Hoffmann, Ph.D.	BS & MS	0 / 2	(13133) Katedra kybernetiky
Real-time mapování dat z motion capture systému do pohybů robota	doc. Mgr. Matěj Hoffmann, Ph.D.	BS & MS	0 / 1	(13133) Katedra kybernetiky
Transformace pohybových dat dítěte na humanoidního robota	doc. Mgr. Matěj Hoffmann, Ph.D.	BS & MS	0 / 1	(13133) Katedra kybernetiky
Doplnění vnímání průchodnosti LIDARu dotykem	doc. Mgr. Matěj Hoffmann, Ph.D.	BS & MS	0 / 1	(13133) Katedra kybernetiky

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