The ShanghAI Lectures

人工智能

上海授课

The Shanghai Lectures 2022

Natural and Artificial Intelligence in Embodied Physical Agents

December 8^{st}, 2022

From Zagreb, Croatia

Today's program (CET)

08:30 sites begin connecting
08:55 all sites are ready
09:00 (Fabio) Welcome
09:05 Embodied Intelligence: principles and open issues.
10:00 Break
10:10 Guest lecture by Sven Behnke, Computer Science Department VI - Intelligent Systems and Robotics, Autonomous Intelligent Systems Group, University of Bonn, Bonn, Germany: Perception, Planning, and Learning for Cognitive Robots
11:00 Wrap-up

Today’s Guest Lecture

10:10 Sven Behnke

Computer Science Department VI - Intelligent Systems and Robotics, Autonomous Intelligent Systems Group, University of Bonn, Bonn, Germany

«Perception, Planning, and Learning for Cognitive Robots»

Stay tuned!

Lecture 6

Embodied Intelligence: principles and open issues.

Fabio Bonsignorio
Professor, ERA CHAIR in AI for Robotics

University of Zagreb
Faculty of Electrical Engineering and Computing
Laboratory for Autonomous Systems and Mobile Robotics

lamor

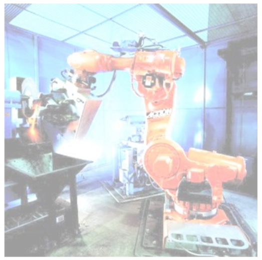
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No. 952275

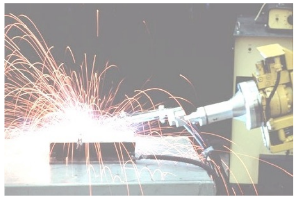
www.heronrobots.com

The need for an embodied perspective

- "failures" of classical AI (and limits of Deep Learning, don't miss today's guest lecture)
- fundamental problems of classical approach
- Wolpert's quote: Why do plants not have a brain? (but check Barbara Mazzolai's lecture at the ShanghAI Lectures 2014)
- Interaction with environment: always mediated by body
- F-O-R also affects Deep Learning and ML in general

Industrial robots vs. natural systems





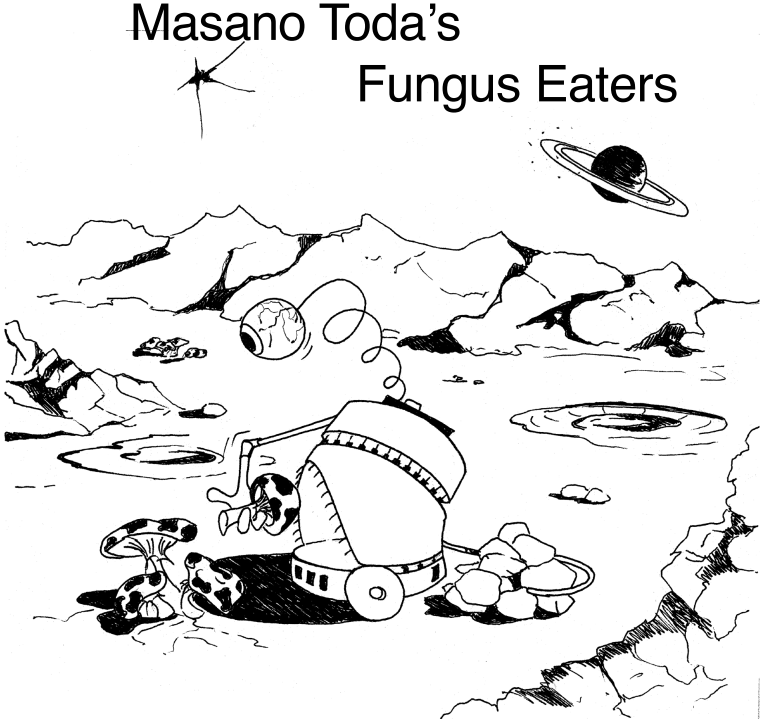
principles:
- **low precision**
- **compliant**
- **reactive**
- **coping with uncertainty**

humans

(GOF) robots

→ **no direct transfer of methods**

Complete agents



Properties of embodied agents

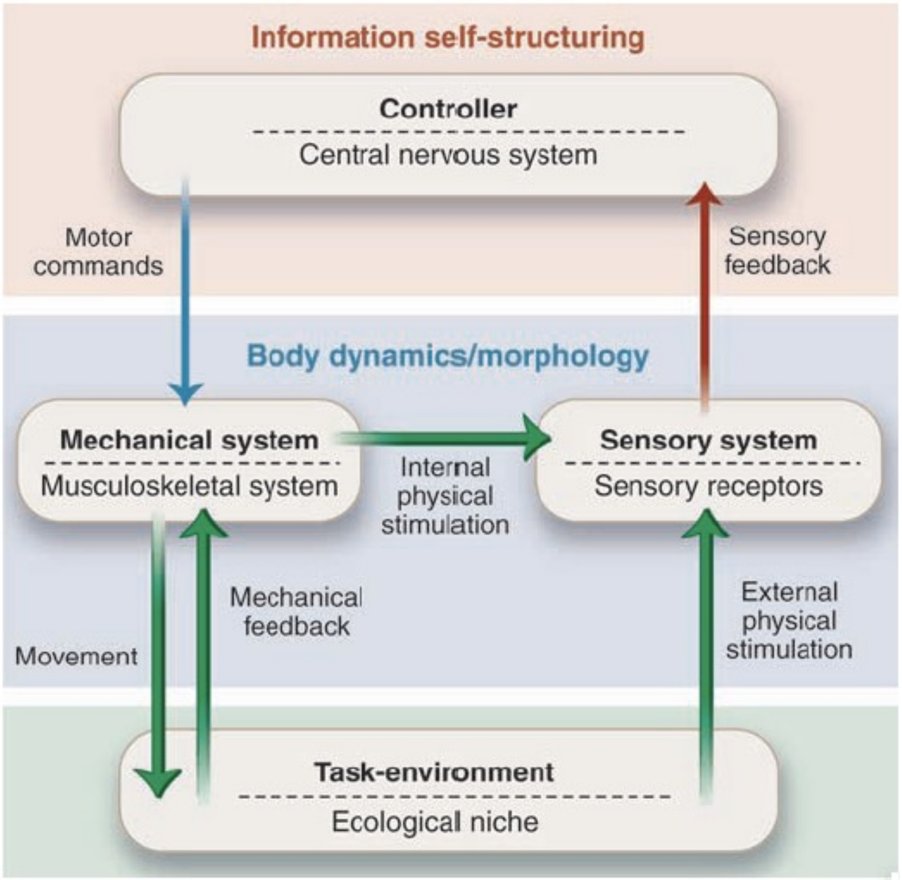
- subject to the laws of physics
- generation of sensory stimulation through interaction with real world
- affect environment through behavior
- complex dynamical systems
- perform morphological computation

Parallel, loosely coupled processes

Intelligent behavior:

- **emergent from system-environment interaction**
- **based on large number of parallel, loosely coupled processes**
- **asynchronous**
- **coupled through agent's sensory-motor system and environment**

Implications of embodiment
Self-stabilization



Pfeifer et al.,Science,
16 Nov. 2007

How to quantify?

Some hints Today!

Approaches to evolutionary robotics

- given robot $\longrightarrow$ evolve control (neural network)
- embodied approach $\longrightarrow$ co-evolution of morphology and control

The “symbol grounding” problem

real world:
doesn’t come
with labels …

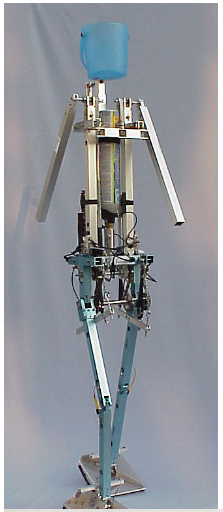
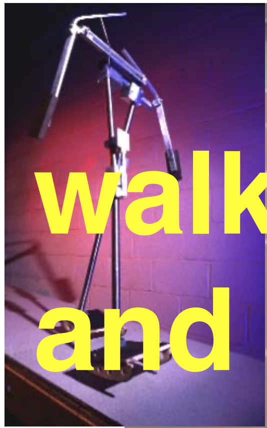
How to put the

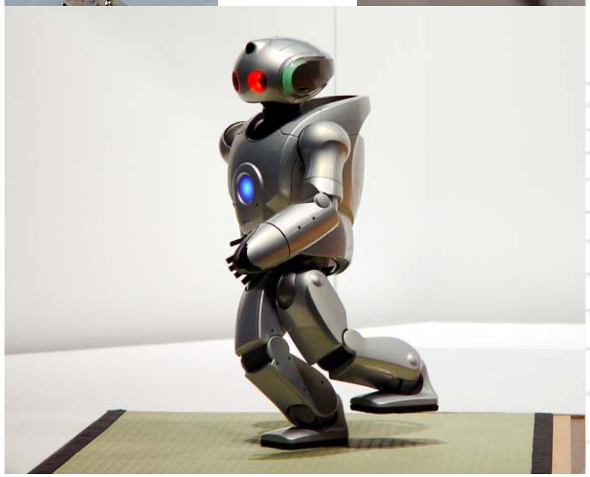
labels??

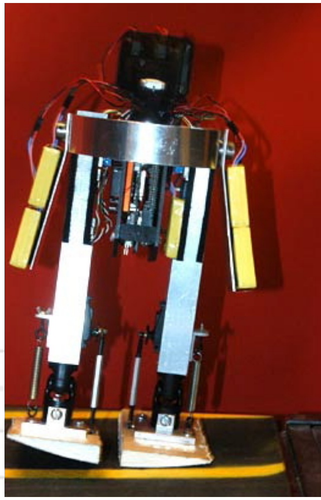
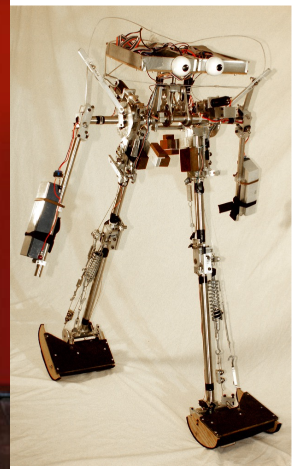
Gary Larson

“Now! … *That* should clear up a few things around here!”

walking: GOF :-)
and new designs

Design principles for intelligent systems

Principle 1: Three-constituents principle (ecological niche, desired behaviors/tasks, agent's organization)

Principle 2: Complete-agent principle

Principle 3: Parallel, loosely coupled processes

Principle 4: Sensory-motor coordination/ information self-structuring

Principle 5: Cheap design

Principle 6: Redundancy

Principle 7: Ecological balance

Principle 8: Value

The principle of sensory-motor coordination

induction of structured sensory stimulation through sensory-motor coordinated action

principle of information self-structuring: effect

(leads into development)

Principle of “cheap design”

The principle of “cheap design” states that if agents are built to exploit the properties of their *ecological niche* and the characteristics of *the interaction with the environment*, their design and construction will be much easier, or *“cheaper”.*

Principle of “ecological balance”

balance in complexity

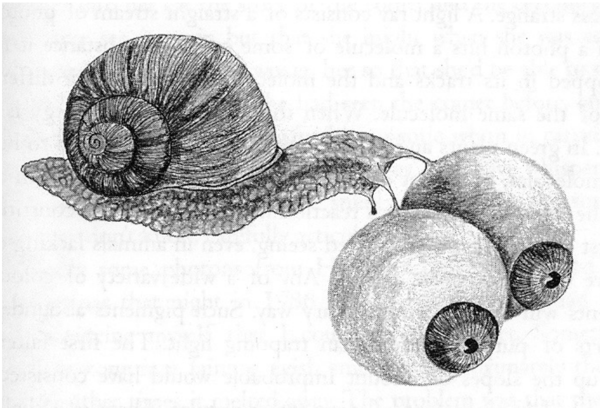
given task environment: match in complexity of sensory, motor, and neural system

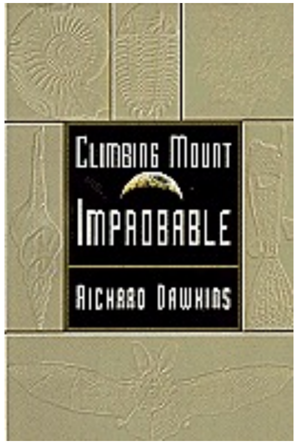
balance / task distribution

brain (control), morphology, materials, and interaction with environment

Richard Dawkins's snail with giant eyes

ecologically _unbalanced_ system





Author of:
"The selfish gene" and
"The blind watchmaker"

Task distribution

between brain, morphology, materials, and environment

extreme case: Passive Dynamic Walker

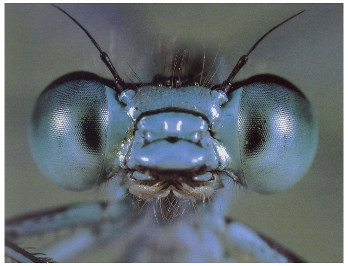
Puppy, Stumpy

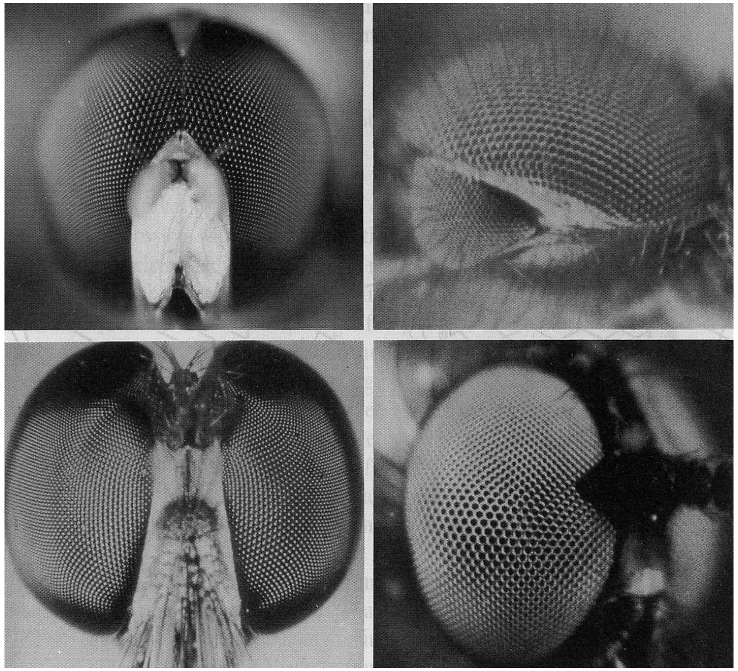
Animals, humans: dynamic change of muscle stiffness

Loosely swinging arm (later today)

Different morphologies of insect eyes


housefly

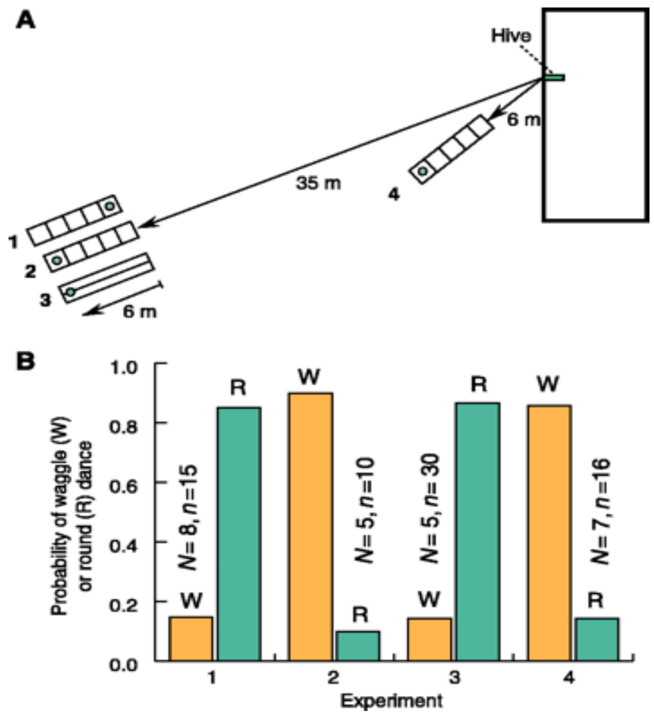



honey bee

large variation of shapes!

Optic flow-based odometry in bees

Srinivasan's fascinating experiments (2000)



(A) Layout for experiments using tunnels. Each tunnel represents a separate experiment (1, 2, 3, or 4). The dot in the tunnel shows the position of the feeder in each case. (B) Probability of waggle (W) round (R) dance for experiments 1 to 4. N and n represent the numbers of bees and dances analyzed, respectively in each experiment. Science, 287, p. 852, 2000.

The value principle

The value principle states that intelligent agents are equipped with a ***'value system'*** which constitutes a basic set of assumptions about ***what is good for the agent***.

Grasping an object

- many ways
- winding spring (effort)
- release
- exploitation by brain
  - “cheap design”, exploitation of material properties, “free”
  - “ecological balance”: outsourcing of functionality to morph. and material characteristics

Grasping an object

- **induction of sensory stimulation**
- **dependence on**
  - **morphology: high density of touch, temperature, vibration sensors in hand**
  - **actuation: sensory-motor coordination**
  - **induction of correlations**

→ “raw material” for information processing of brain"

Loosely swinging arm

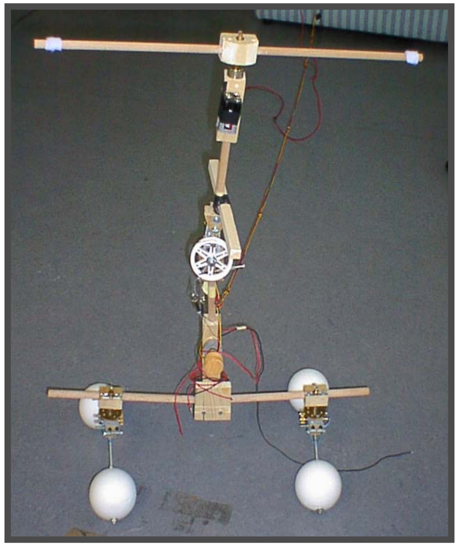
- **complex trajectory of hand**
- **simple control (“cheap design” “ecological balance”)**
- **exploitation of morphology/ materials (biomechanical contraints)**

→ control “decentralized”
“free”

Robot Frog ”Mowgli” driven by pneumatic actuators

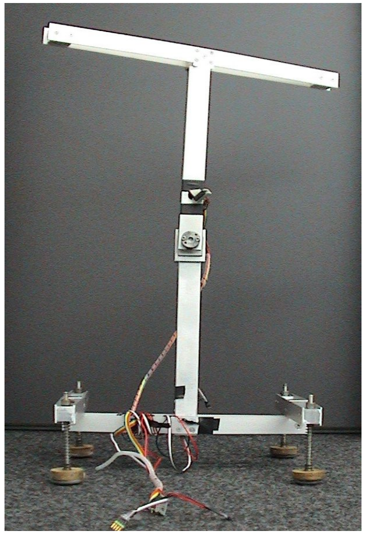
Design and construction:
Ryuma Niiyama, Yasuo Kuniyoshi
The University of Tokyo

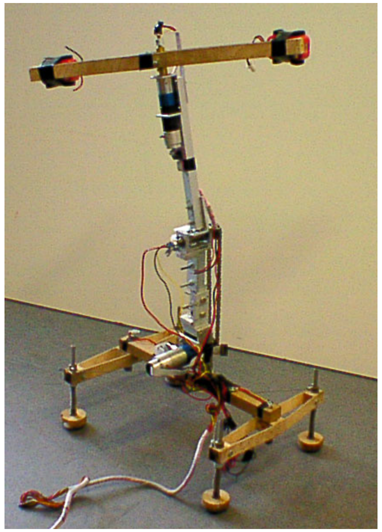
“Stumpy”: task distribution



almost brainless: 2 actuated joints
springy materials
surface properties of feet

Design and construction: Raja Dravid, Chandana Paul, Fumiya Iida





self-stabilization

Cognition: Memory: Are ‘symbols’ always needed?

which part of diagram relevant?
–>

memory for walking?

Water fountain

Where is the memory for shape?

Water fountain
Where is the memory for shape?

clear structure visible

underlying mechanism?

Where is the “structure” stored?
What can we learn for human memory?

Ashby’s concept of “memory as a theoretical construct”

W. Ross Ashby (1956). An introduction to cybernetics.

a. b.

copyright: Isabelle Follath, Zurich

Where does ‘symbols’ come from?: physical dynamics and information processing

- morphology and materials
- orchestration control
- exploration
- preferred trajectories from biomechanical constraints
- induction of patterns of sensory stimulation in different sensory channels
- sensory-motor coordination —> induction of information structure

The “story”: physical dynamics and information processing

- good “raw material” for brain
- cross-modal association, learning, concept formation
- extraction of mutual information —> prediction (expectations: crucial for motor control)
- categorization (fundamental for cognition)

Sensory-motor coordination (“active perception”)

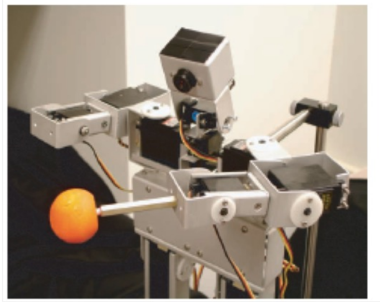
“We begin not with a sensory stimulus, but with a sensory-motor coordination […] In a certain sense it is the movement which is primary, and the sensation which is secondary, the movement of the body, head, and eye muscles determining the quality of what is experienced. In other words, the real beginning is with the act of seeing; it is looking, and not a sensation of light.” (“The reflex arc concept in psychology,” John Dewey, 1896)

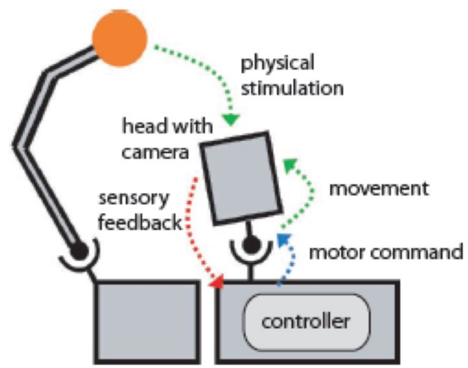
“Since all the stimulations which the organism receives have in turn been possible only by its preceding movements which have culminated in exposing the receptor organ to external influences, one could also say that behavior is the first cause of all the stimulations.” (“The structure of Behavior,” Maurice Merleau-Ponty, 1963)

Information self-structuring

Experiments:

Lungarella and Sporns**, 2006**
Mapping information flow
in sensorimotor networks
PLoS Computational Biology





Quantitative measures

entropy: disorder, information

$$H(X) = -\sum_i p(x_i) \log p(x_i)$$

mutual information: statistical dependency

$$MI(X,Y) = H(X) + H(Y) - H(XY) = -\sum_i \sum_j p(x_i, y_j) \log \frac{p(x_i)\, p(y_j)}{p(x_i, y_j)}$$

integration: global statistical dependence

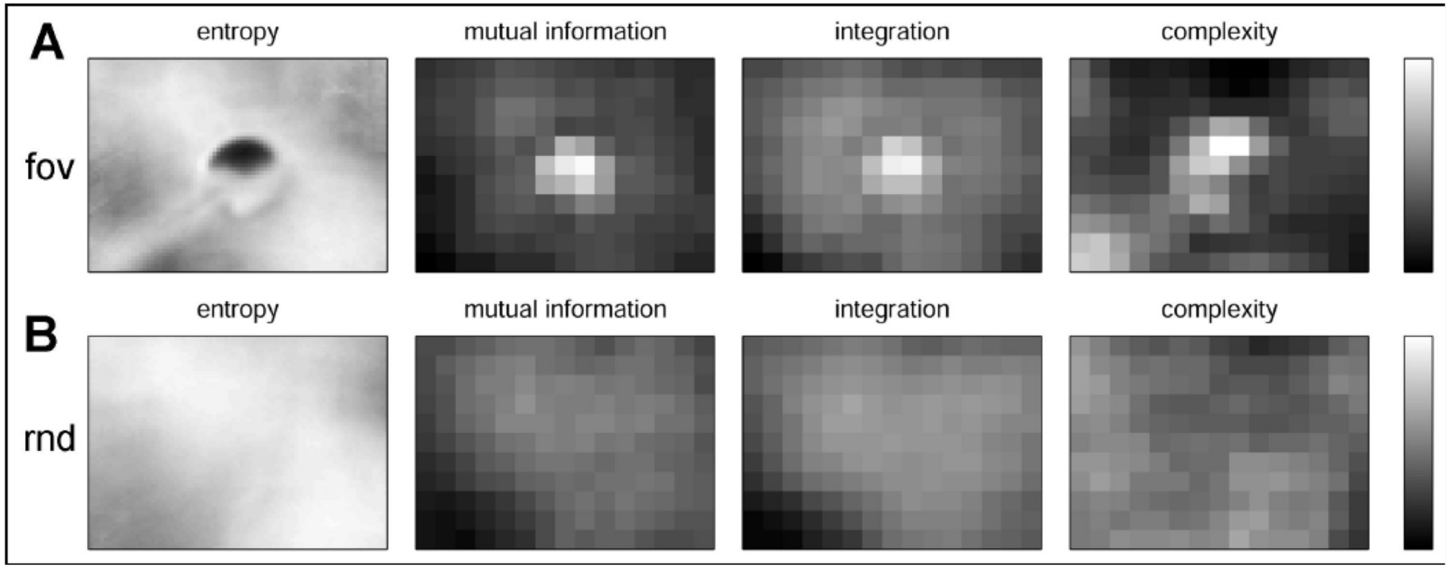
$$I(\boldsymbol{X}) = \sum_i H(x_i) - H(\boldsymbol{X})$$

complexity: co-existence of local and global structure

$$C(\boldsymbol{X}) = H(\boldsymbol{X}) - \sum_i H(x_i | \boldsymbol{X} - x_i).$$

from: **Tononi, Sporns, and Edelman, PNAS, 1994, 1996**

Results: foveation vs. random



entropy **mutual information** **integration (over patch)** **complexity (over patch)**

Information Driven Self Organization

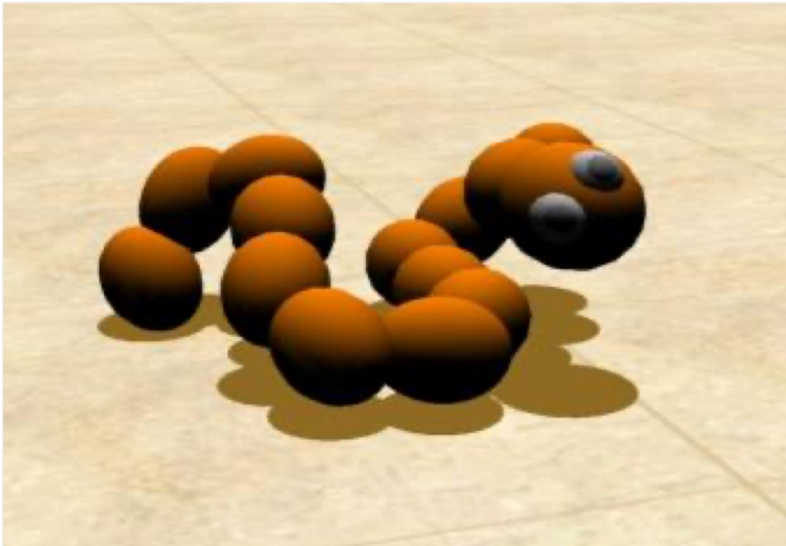
Why not using information metrics to implement an emergent control?

Several researchers have shown the importance of Information Driven Self Organization (IDSO).

In particular Prokopenko, Ralf Der and others have shown simple demonstrators, mainly in simulation, with snake-bots, humanoids and grasping systems.

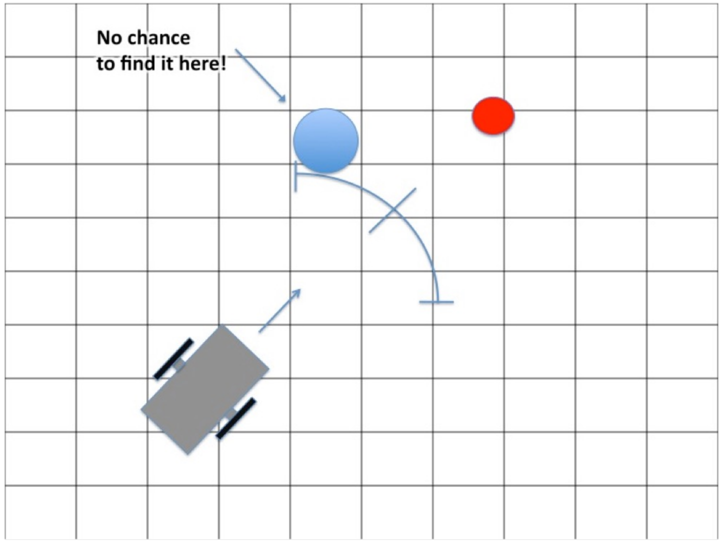
These approaches seem very promising.

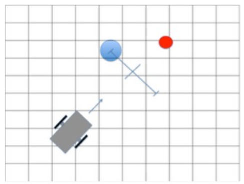
Snakebot



see: **Tanev et. al, IEEE TRO, 2005**

Maybe not GOF Euclidean space? :-)



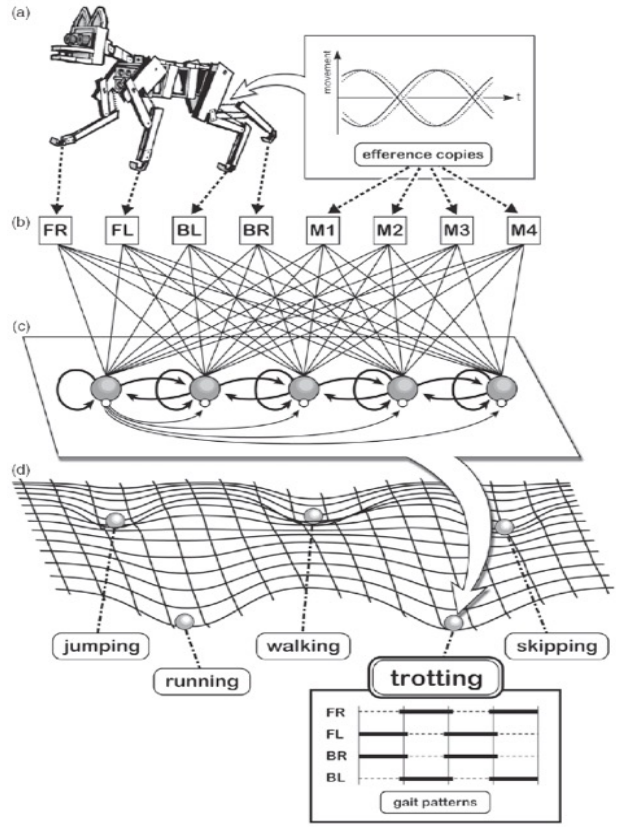


see: **Bonsignorio, Artificial Life, 2013**

Building grounded symbols (labeling!)

Human: **grasping object — patterns of sensory stimulation “match” morphology of agent**

Puppy: **patterns from pressure sensors or joint angle trajectories: match morphology of agent**

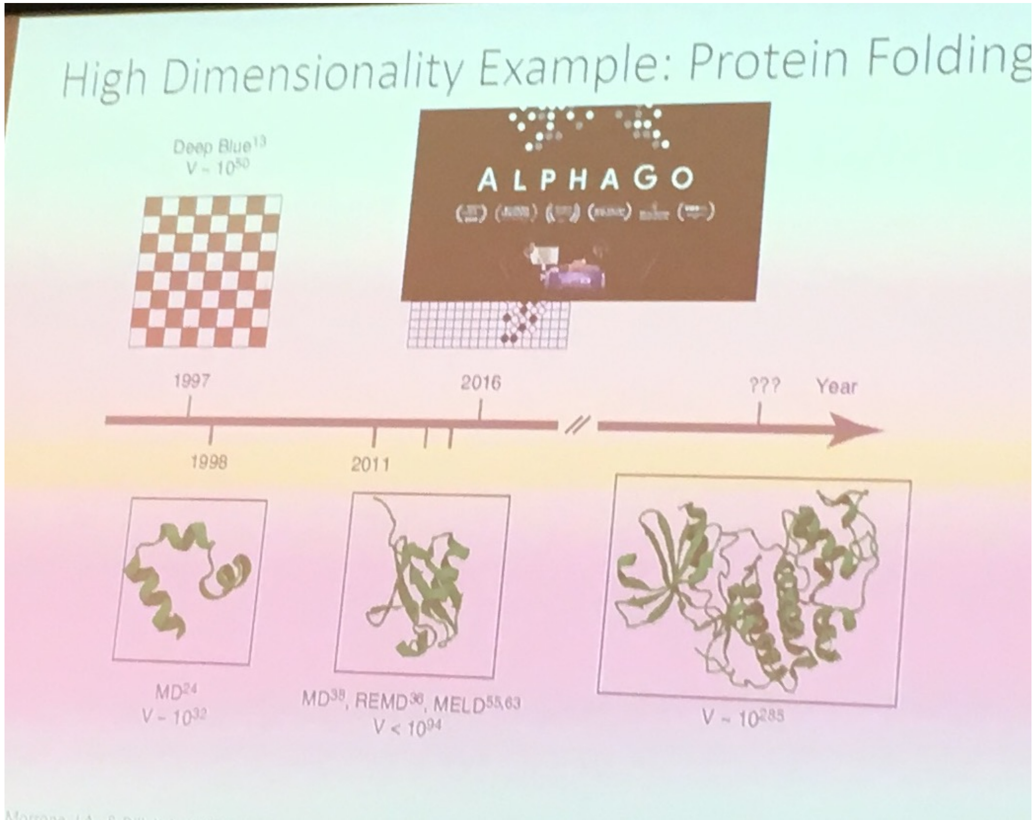


→ **grounding for “high-level” cognition**

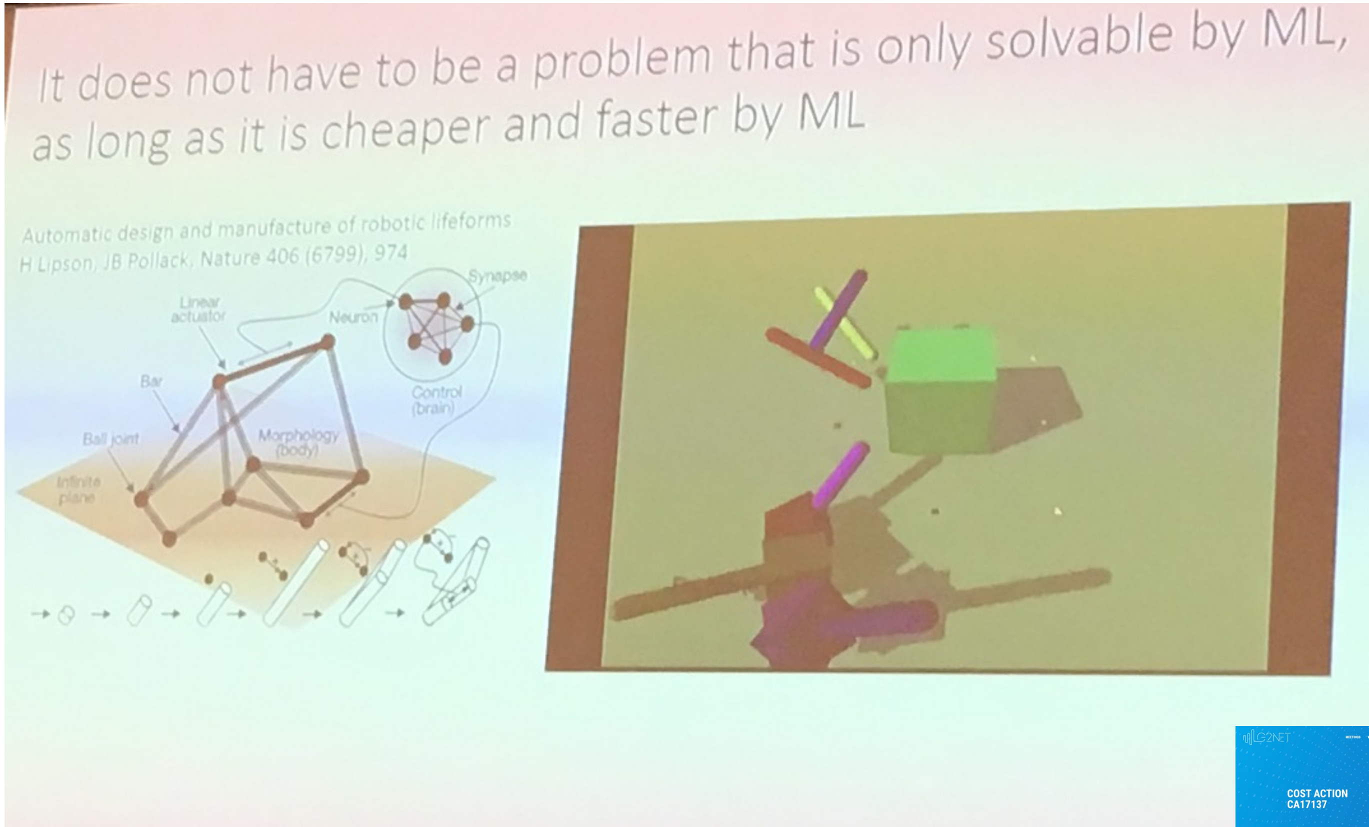
Bottom Line: Physics Matters!

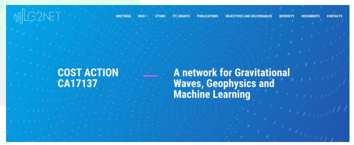
Coping with the common underlying theoretical issues implied by the application of ML and DL to physical systems might have deep and wide scientific and technological impact

Bottom Line: Physics Matters!



Bottom Line: Physics Matters!





How to quantify?

Appendix: Information Metrics Relation Proofs

We will derive in the following the relations given in section 3.
In a network model like those adopted in this discussion, [53,54], the probability βi that a new node will connect to a node i already present in the network is a function of the connectivity k_i and on the fitness ηi of that node, such that

$$\prod_i = \frac{\eta_i k_i}{\sum_j \eta_j k_j} \tag{A.1}$$

A node *i* will increase its connectivity *ki* at a rate that is proportional to the probability that a new node will attach to it, giving

$$\frac{\partial k_i}{\partial t} = m \frac{\eta_i k_i}{\sum_j k_j \eta_j} \tag{A.2}$$

The factor m accounts for the fact that each new node adds m links to the system.
In [26] it is shown that the connectivity distribution, i.e. the probability that a node has k links, is given by the integral

$$P(k) = \int_0^{\eta_{\max}} d\eta \frac{\partial P\left(k_\eta(t) > k\right)}{\partial t} \propto \int d\eta \rho(\eta) \left(\frac{m}{k}\right)^{\frac{C}{\eta}+1} \tag{A.3}$$

where $\rho(\eta)$ is the fitness distribution and C is given by:

$$C = d\eta \rho(\eta) \frac{\eta}{1-\beta(\eta)} \tag{A.4}$$

We define a proper ηi function which may basically be a performance index of the effectiveness of sensory motor coordination and which control the growth of the network.

The physical agents constituting the system are connected physically, but also from an information standpoint.

Equation (A.5) gives the expression for the Shannon entropy of the network of elements:

$$HN = -\sum_{k=1}^{\infty} P(k)\log P(k) \tag{A.5}$$

where $P(k)$ represents the distribution of node connections and the 'infinite' in the summation is actually the big finite number of physical elements, considered, as a simplification, coinciding with the finite elements.

It is important to notice that this is only a part of the information 'stored' into the system: the information in a single neuron or body element is given by equation (2).

The aim of this short discussion is to show that a network of physical elements can actually manage information into the structure of its internal relations, as it can be shown starting from equation (A.5). The concept model described here actually represent a large class of similar models.

In this section the discussion is related to the one in section 3, as the networks of agents we are considering here are actually embodied and situated dynamical systems, which do have a phase space representation. This allows to derive a few further relations.

We can state, for a network of n physical elements, that:

$$\Delta H_{controller} = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{A.6}$$

where $\Delta H_{controller}$ represents the information variation due to the controller, ΔHN is the information variation in the network itself, ΔH_i is the information variation for a single embodied agent, ΔI the multi information between the n agents of the network and the network itself, this last term account for redundancies in information measures between the individual 'intelligent elements' of the structure and the structure itself.

From equation (1), we have:

$$\Delta H_{closed} - \Delta H_{open}^{\max} = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{A.7}$$

And:

$$\Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \le I(X;C) \tag{A.8}$$

This is relation (II)

Furthermore:

$$K(X) = \Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I \tag{A.9}$$

This is relation (III)

And from (2) and (A.6):

$$\Delta HN + \sum_{i}^{n} \Delta H_i - \Delta I = \log \frac{W_{closed}}{W_{open}^{\max}} \tag{A.10}$$

Applying again equation (2):

$$\Delta HN + \sum_{i}^{n} \log \frac{W_{closed(i)}}{W_{open(i)}^{\max}} - \Delta I = \log \frac{W_{closed}}{W_{open}^{\max}} \tag{A.11}$$

We derive:

$$\Delta HN - \Delta I = \log \frac{W_{closed}}{W_{open}^{\max}} - \log \prod_{i}^{n} \frac{W_{closed(i)}}{W_{open(i)}^{\max}} \tag{A.12}$$

If we define the quantities in (A.13), (A.14):

$$\Omega_{closed} = \frac{W_{closed}}{\prod_{i}^{n} W_{closed(i)}} \tag{A.13}$$

$$\Omega_{open}^{\max} = \frac{W_{open}^{\max}}{\prod_{i}^{n} W_{open}^{\max}} \tag{A.14}$$

We obtain equation (A.15):

$$\Delta HN = \log \frac{\Omega_{closed}}{\Omega_{open}^{\max}} + \Delta I \tag{A.15}$$

This is relation (IV)

see: **Bonsignorio, 2008**

Some references (Feedback is welcome!)

F. Bonsignorio, Preliminary considerations for a quantitative theory of networked embodied intelligence,
In: 50 years of artificial intelligence, 112-123, Springer, 2007

F. Bonsignorio, Steps to a cyber-physical model of networked embodied anticipatory behavior, In: Anticipatory Behavior in Adaptive Learning Systems, LNAI, 549, 77-94, Springer, 2008

F. Bonsignorio, On the Stochastic Stability and Observability of Controlled Serial Kinematic Chains, ESDA2010-25131, 379-386, ASME, 2010

F. Bonsignorio, Quantifying the evolutionary self-structuring of embodied cognitive networks, Artificial life 19 (2), 267-289, MIT Press, 2013

F Bonsignorio, E Messina, AP Del Pobil, J Hallam, Metrics of Sensory Motor Coordination and Integration in Robots and Animals: How to Measure the Success of Bioinspired Solutions with Respect to their Natural Models, Cognitive Systems Monographs, Springer, 2020

Assignments for next week

- Check “How the body…” for self-study
- Think about how …’cheap design’…how to apply to specific ‘robots’….STUDENTS’ PREZ ALWAYS WELCOME.

End of lecture 7

Thank you for your attention!

stay tuned for lecture 7 and this year's last

"Grab Bag, Summary and topics to discuss: Video is killing the radio stars»

Today's Guest Lecture

10:10 Sven Behnke

Computer Science Department VI - Intelligent Systems and Robotics, Autonomous Intelligent Systems Group,
University of Bonn, Bonn, Germany

«Perception, Planning, and Learning for Cognitive Robots»

Stay tuned!

Short Bio

The ShanghAI Lectures 2013-

Prof. Fabio Bonsignorio is **ERA Chair in AI for Robotics** at FER, University of Zagreb, Croatia. He is **Founder and CEO of Heron Robots (advanced robotics solutions),** see **www.heronrobots.com**. He has been visiting professor at the **Biorobotic Institute of the Scuola Superiore Sant'Anna in Pisa from 2014 to 2019**. He has been a professor in the Department of System Enginering and Automation at the **University Carlos III of Madrid until 2014**. In 2009 he got the **Santander Chair of Excellence in Robotics** at the same university. He has been working for some 20 years in the high tech industry before joining the research community.

He is a **pioneer and has introduced the topic of Reproducibility of results in Robotics and AI**. He is a **pioneer in the application of the blockchain to robotics and AI (smart cities, smart land, smart logistics, circular economy). He coordinates the Topic Group of euRobotics about Experiment Replication, Benchmarking, Challenges and Competitions. He is co-chair of the IEEE Robotics & Automation Society (RAS) Technical Committee, TC-PEBRAS (PErformance and Benchmarking of Robotics and Autonomous Systems)**.

He is a **Distinguished Lecturer** for **IEEE Robotics and Automation Society,** Senior Member of IEEE and member of the Order of the Engineers of Genoa, Italy.

He coordinates the task force robotics, in the G2net,an EU network studying the application of **Machine Learning and Deep Learning (Apprendimento Profondo) to Gravitational wave research, la Geophysics and Robotics**.

Has given invited seminars and talks in many places: MIT Media Lab, Max Planck Institute, Imperial College, Politecnico di Milano in Shenzhen, London, Madrid, Warsaw, San Petersburg, Seoul, Rio Grande do Sul.…

Thank you!

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