Collective Robotics

Part 1: Introduction

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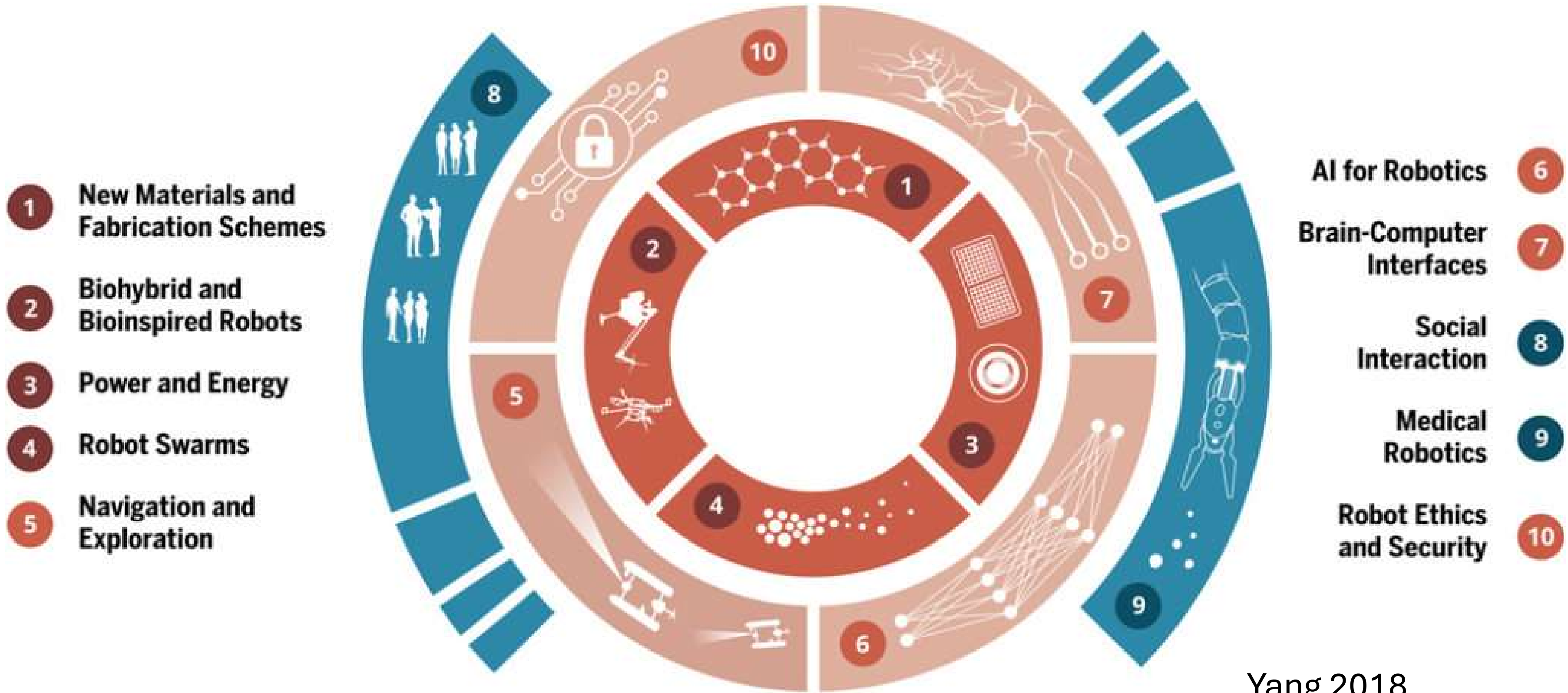
Lecture & tutorial

Collective Robotics

(Autonomous systems, computer science, etc. / master studies)

- Lectures: Tuesday 13:30 – 15:00
- room: C120
- Tutorials: every 2 weeks, after the lecture
- first tutorial/lab on April 22
- room: C120
- slides, announcements: https://lea.hochschule-bonn-rhein-sieg.de/
- oral exam
- (exam days will be announced)

10 Biggest Challenges in Robotics



Yang 2018

The 10 biggest challenges in robotics that may have breakthroughs in 5-10 years. (Credit: Science Robotics)

Outline

1. Introduction to collective robotics
2. Short journey through nearly everything
3. Scenarios of collective robotics
4. Modeling collective systems
5. Local sampling
6. Collective decision-making
7. Case study – adaptive aggregation
8. Bio-hybrid systems

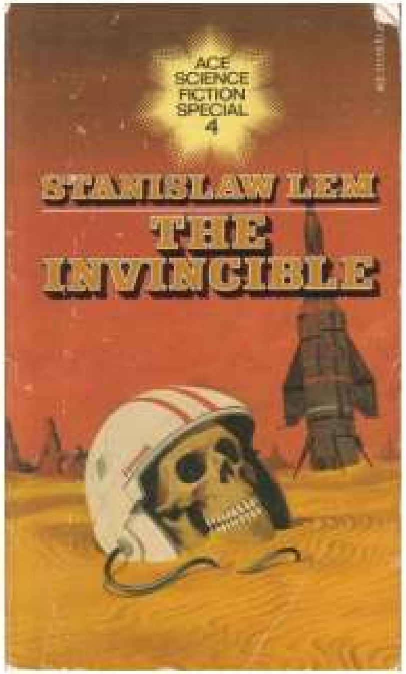
optional: recap robotics & behavior-based robotics

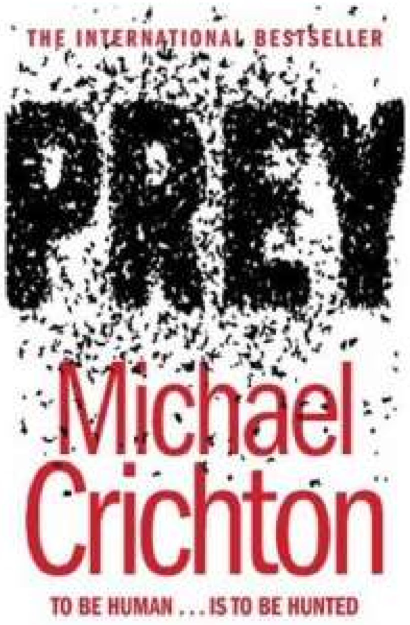
Bibliography

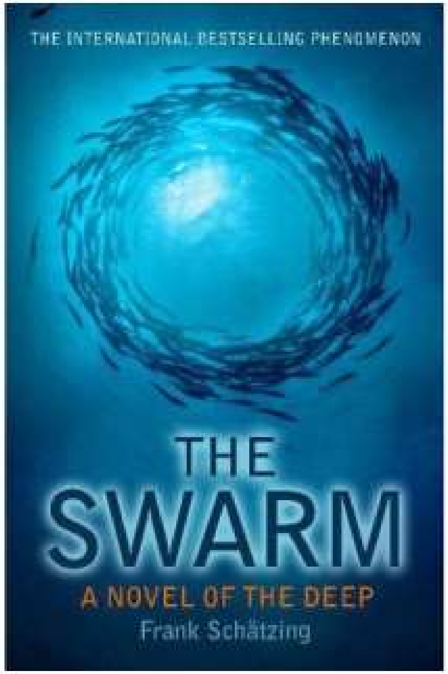
- Floreano, Dario, and Claudio Mattiussi. *Bio-inspired artificial intelligence: theories, methods, and technologies*. MIT press, 2008.

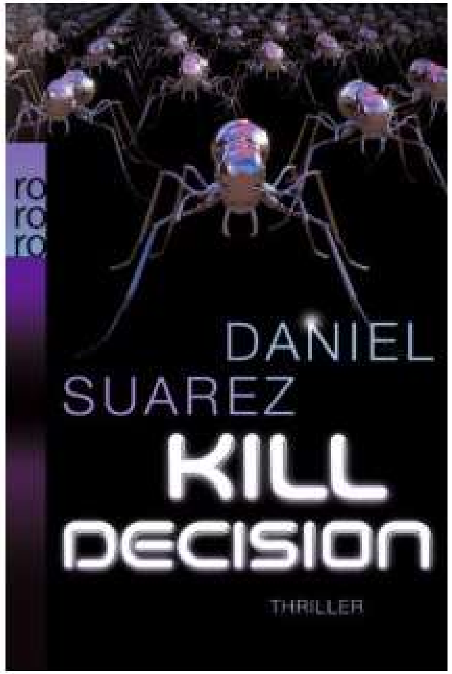
- Hamann, Heiko. *Swarm robotics: A formal approach*. Vol. 221. Cham: Springer, 2018.

(inofficial bibliography)









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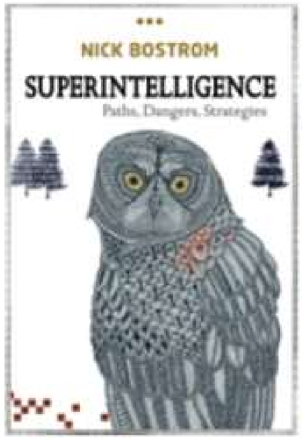


Superintelligence: Paths, Dangers, Strategies NEW
This is the new book.

[Oxford University Press, 2014]

Stephen Hawking warns of the dangers of 'intelligent' robots

Rob Waugh for Metro.co.uk Tuesday 13 Jan 2015 11:35 am

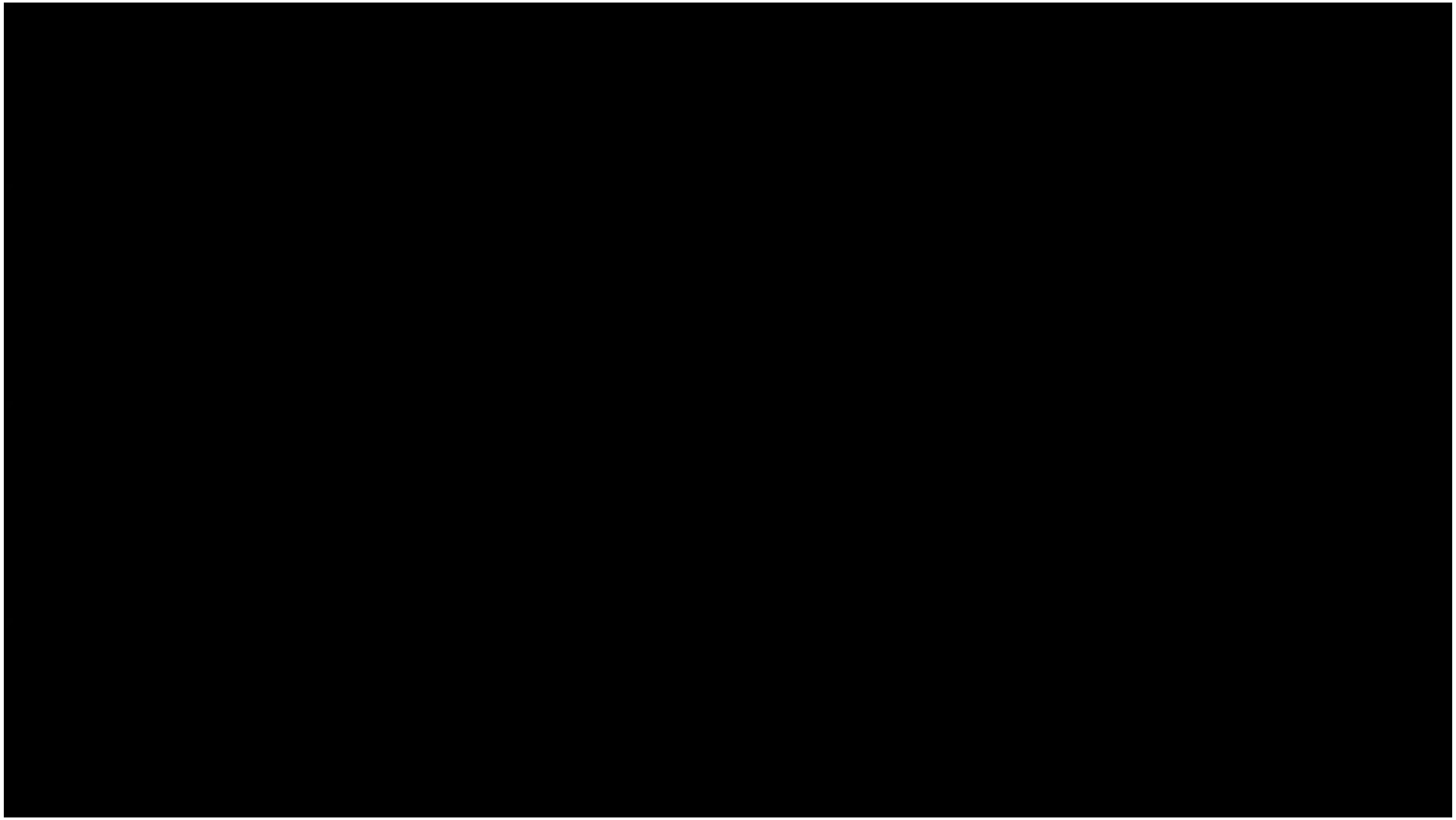
Stephen Hawking is among 150 scientists who have written an open letter warning of the dangers of artificial intelligence – and calling for limits in its use, especially in hi-tech robotic weapons systems.

Hawking has previously warned that the development of 'true' artificial intelligence could be the beginning of a process that ends with the annihilation of all life on Earth.

"Nick Bostrom makes a persuasive case that the future impact of AI is perhaps the most important issue the human race has ever faced. Instead of passively drifting, we need to steer a course. Superintelligence charts the submerged rocks of the future with unprecedented detail. It marks the beginning of a new era."

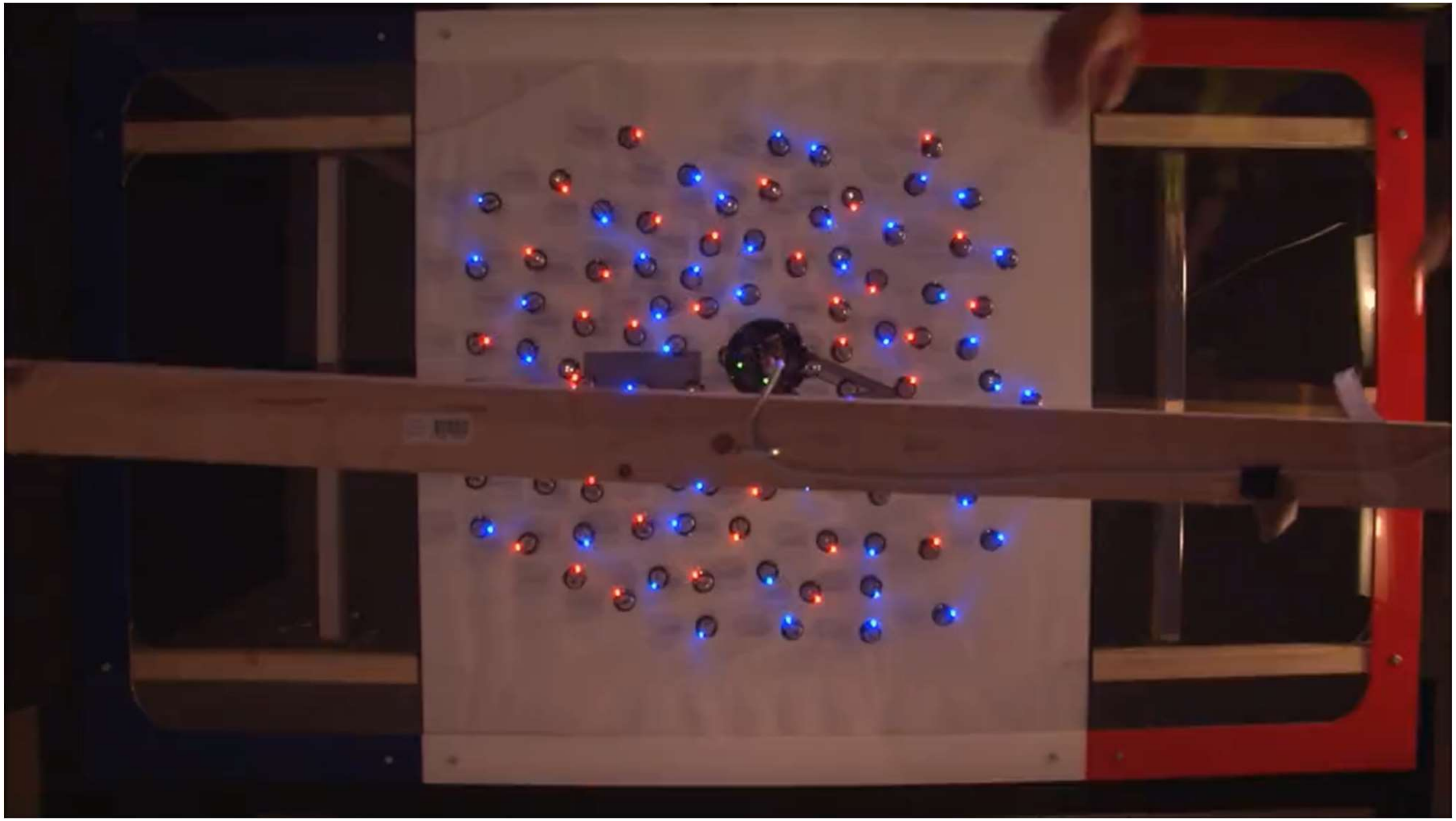
(Stuart Russell, Professor of Computer Science, University of California, Berkley)

Swarm Intelligence



1000 swarm robots

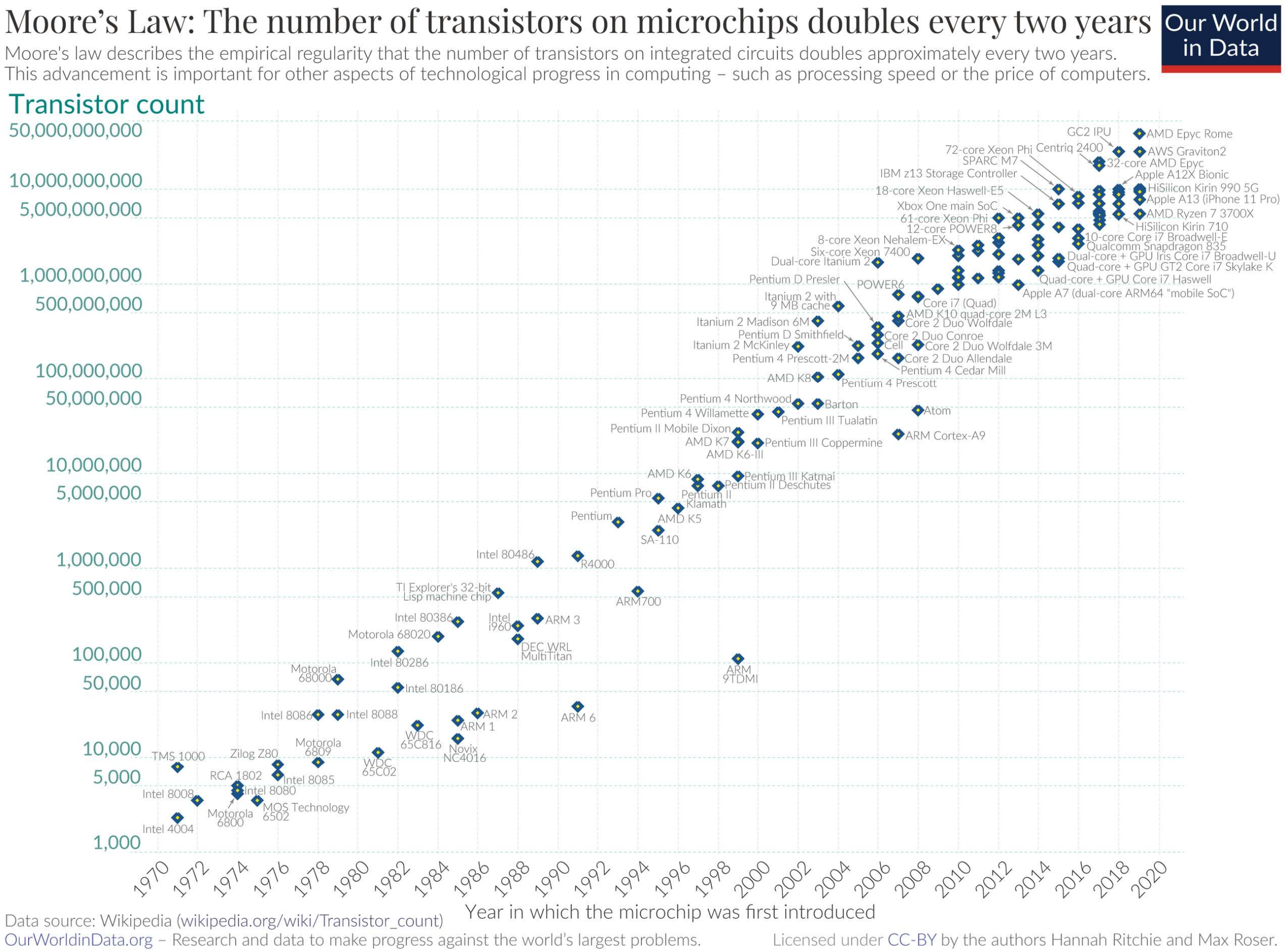
100 swarm robots



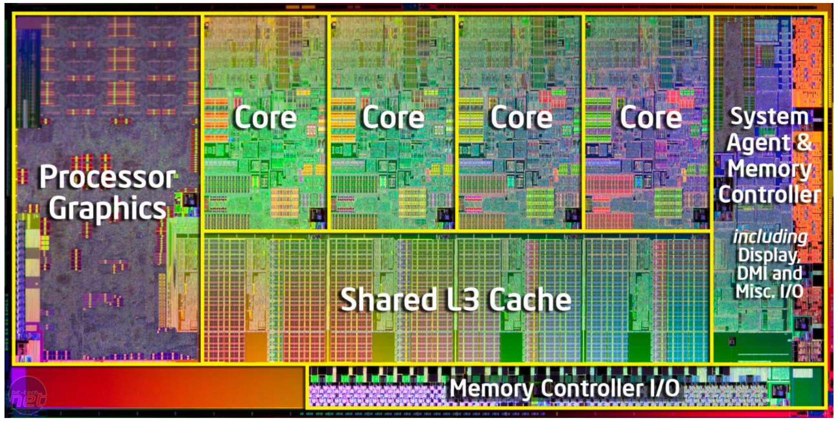
What do you think? (3X5 minutes discussions)

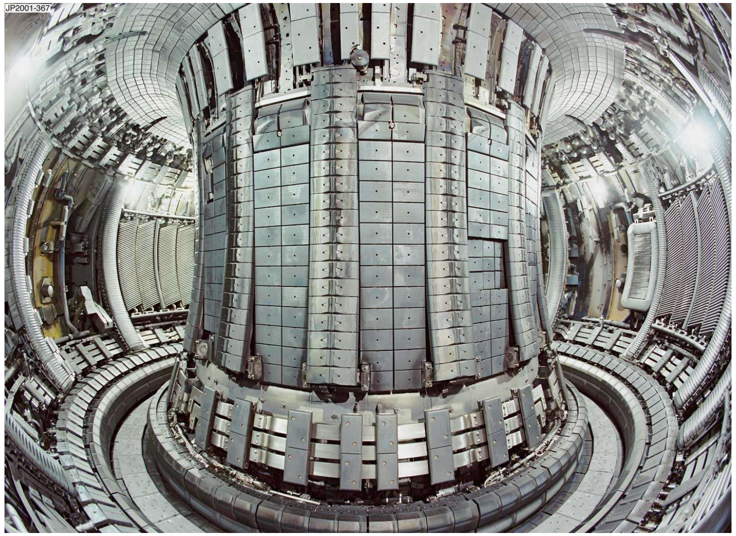
1. Why do we need to investigate collective robotics?
2. How would you define collective robotics?
   What are its key features?
3. What advantages can you envision in using collective robotics?
   How does it differ from other fields of robotics?

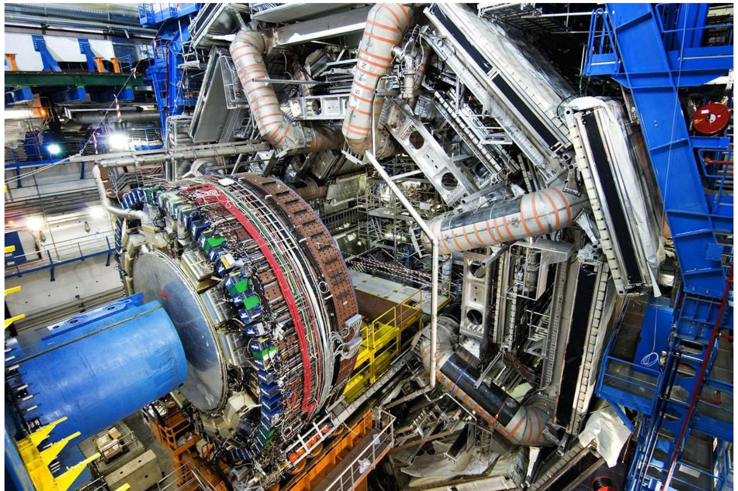
Ever increasing complexity



Ever increasing complexity







Agent complexity & complexity of behavior

~ 2.5 × 105 neurons

(not simple, but simpler!)

~ 8.6 × 1010 neurons

(beware of fallacy*: transistor , neuron)

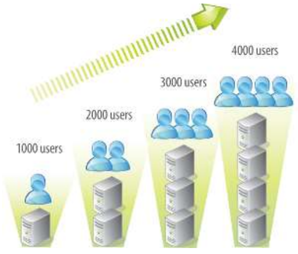
*(cf. senseless extrapolations, Manfred Eigen vs Ray Kurzweil)

Social insects as architects

Complexity and the art of simplicity

How to create complex & reliable systems based on simple & unreliable components?

Main ideas of swarm robotics



➢scalability

maximal scalability requirement

⇒ unlimited swarm size

➢keep it simple!

simple individual behaviors of robots

but complex swarm behavior

➢key technology

self-organization

⇒ exploiting feedback processes and fluctuations

Collective behaviors across species

LOCUSTS

Behavior: Cannibalism When enough locusts squeeze together, bites from behind send individuals fleeing to safety. Eventually they organize into conga-line-like clusters to avoid being eaten. They also emit pheromones to attract even more locusts, resulting in a swarm.

STARLINGS

Behavior: Do what the neighbors do These birds coordinate their speed and direction with just a half dozen of their closest murmuration-mates, regardless of how packed the flock gets. Those interactions are enough to steer the entire group in the same direction.

HONEYBEES

Behavior: Head-butting When honeybees return from searching for a new nest, they waggle in a dance that identifies the location. But if multiple sites exist, a bee can advocate for its choice by ramming its head into other waggling bees. A bee that gets butted enough times stops dancing, ultimately leaving the hive with one option.

GOLDEN SHINERS

Behavior: Seek darkness Presumably for protection, shiners search out dark waters. But they can't actually perceive changes in light levels that might guide their way. Instead, they follow one simple directive: When light disappears, slow down. As a result, the fish in a school pile up in dark pools and stay put.

ANTS

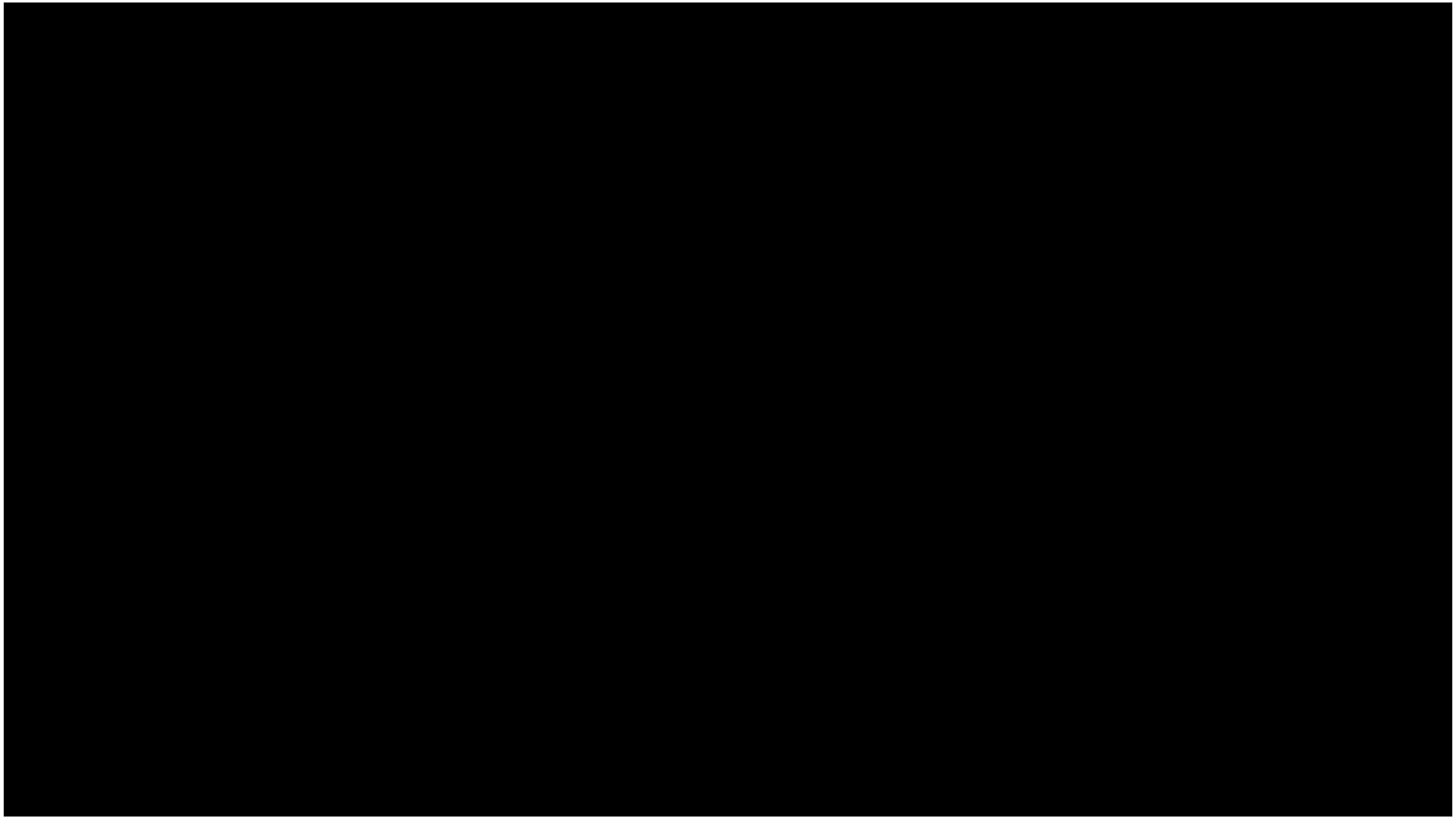
Behavior: Work in rhythm When ants of a certain species get crowded enough to bump into each other, coordinated waves of activity pulse through every 20 minutes.

HUMANS

Behavior: Be a follower Absent normal communication, humans can be as impressionable as a flock of sheep. If one member of a walking group is instructed to move toward a target, though other members may not know the target—or even that there is a target—the whole group will eventually be shepherded in its direction.

Starlings

Fish



Locusts

Sheep

What is a swarm?

Biology defines a swarm via swarming behavior

swarm behavior is aggregation,
often combined with collective motion

examples which have their own word for the behavior:

- ➢birds (e.g., starlings) – flocking
- ➢fish (e.g., herring) – shoaling/schooling
- ➢quadrupeds (e.g., buffaloes) – herding

other examples:
social insects: ants, termites, honeybees, wasps, cockroaches, locusts

How big is a swarm?

1, 2, many?

swarm size (number of units) (Beni, 2005)
not as large as to be dealt with statistical averages
not as small as to be dealt with as a few-body problem
⇒ order of 10^2 to $\ll 10^{23}$ (i.e., not in “Avogadro-large” numbers)

footnote:
Avogadro constant, 6.02×10^{23} 1/mol
Mole: amount of substance containing as many elementary entities as in 12 grams of pure carbon-12

Question: why not more than Avogadro number?

Avogadro's number is huge — it's the number of atoms or molecules in a mole of a substance. Having that many *physical* robots is simply not feasible.

If you want to control 10^{23} agents, you're essentially entering the realm of molecular robotics or synthetic biology, not traditional swarm robotics.

Swarm robotics typically involves 10s to 1000s of robots (maybe up to millions in theory), but Avogadro-scale swarms are purely theoretical, and beyond the bounds of physics, engineering, and current computation.

What is swarm robotics?

- swarm robotics (Dorigo and Şahin, 2004)

  Swarm robotics is the study of how a large number of relatively simple physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment.

- properties of a robot swarm (Beni, 2005)

  1. decentralized control
  2. lack of synchronicity,
  3. simple (quasi) identical members / quasi-homogeneous
  4. mass produced

What is swarm robotics?

Minimalist approach (primarily concerning the hardware) seems not to be a consensus in the community anymore:

- scalable swarm robotics: not minimalist and not directly nature-inspired
- practical minimalist swarm robotics: not directly nature-inspired
- nature-inspired minimalist swarm robotics

Synonyms and related fields:

- minimalist robotics
- robot colonies
- distributed robotics
- large-scale minimalist multi-robot systems
- collective robotics

(Sharkey, 2007)

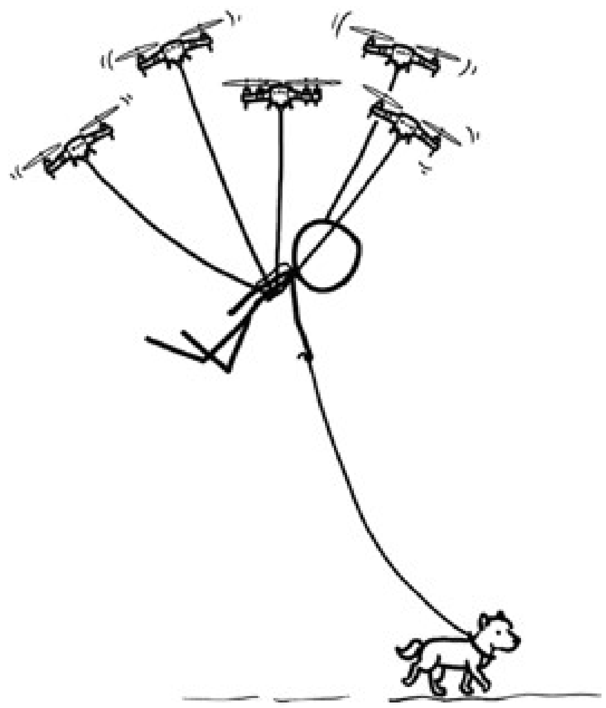
Why swarm robotics?

3 main advantages:

Robustness: redundant system, no single-point-of-failure, loss of certain percentages of the swarm possible without big effects on effectivity

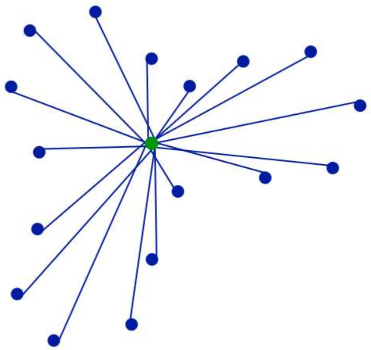
Flexibility: identical members, no specialization in hardware

Scalability: same algorithm is applied for different swarm sizes, efficiency per robot does not decrease considerably with increasing swarm size

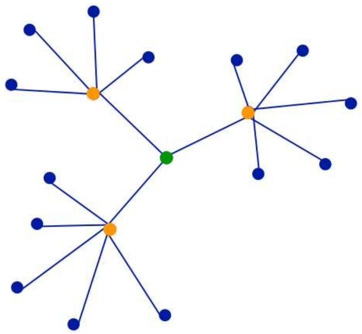


Coordination schemes

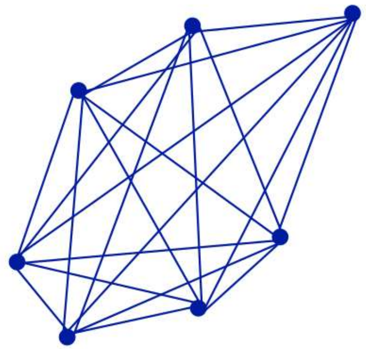
centralized



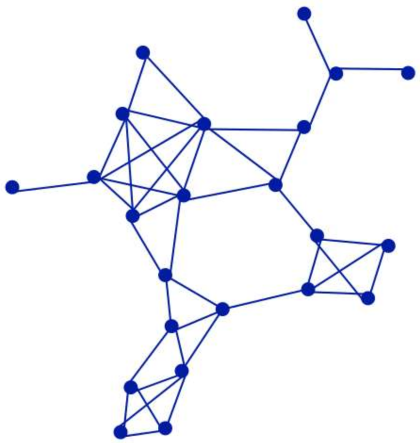
hierarchical



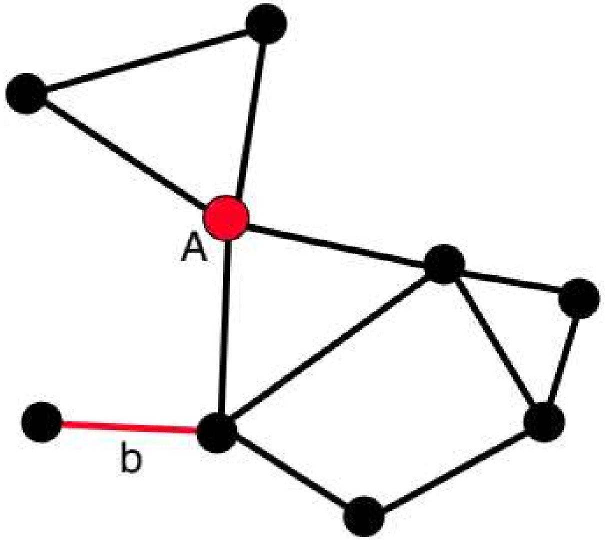
coordination



emergent / distributed



Robustness

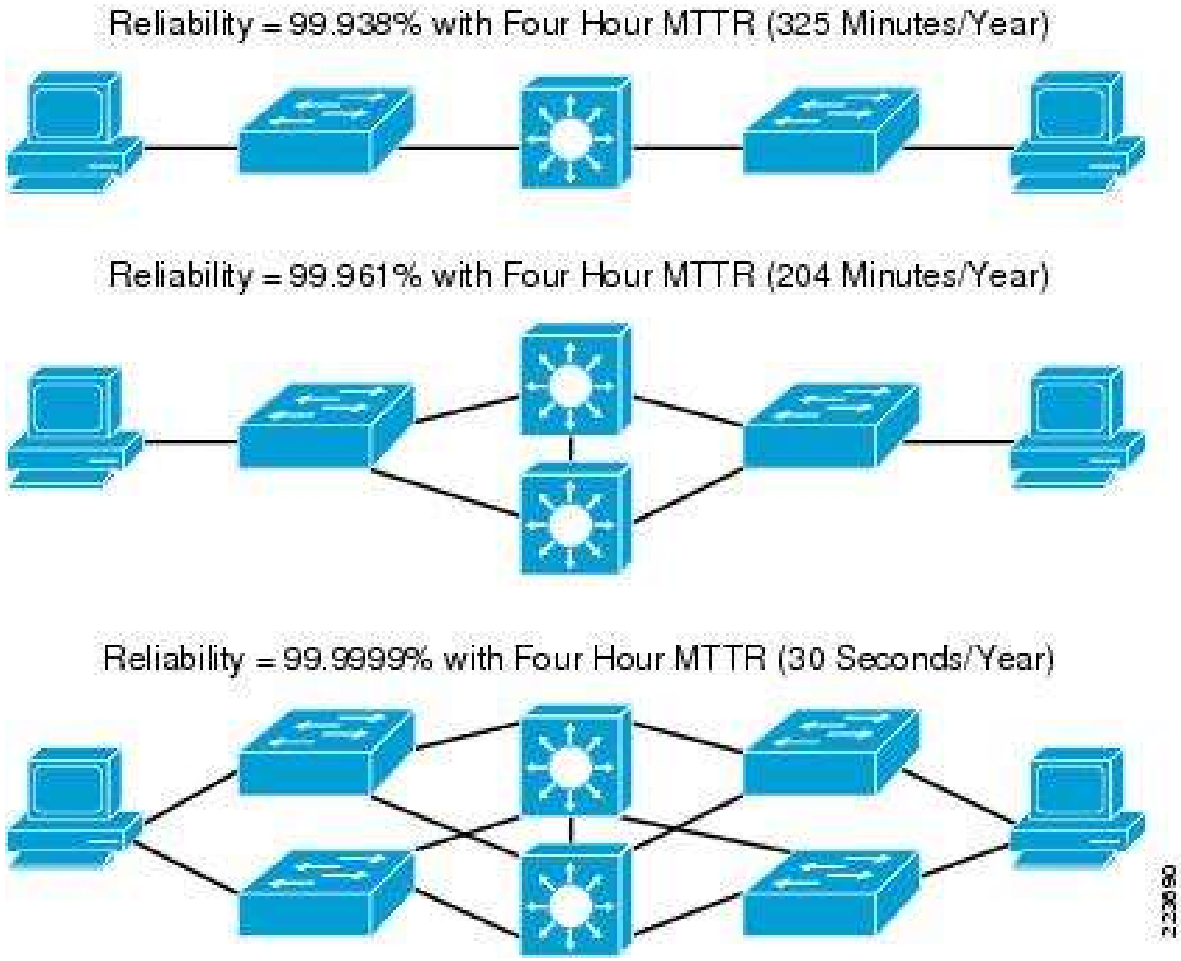


avoid single-point-of-failure:
If node A or edge b is lost
the graph is separated into
two connected components

in robot groups: avoid concentration of responsibilities or information within a single robot, every robot needs to be substitutable any time without too much overhead

⇒ no central control, no central data storage, no specialization

Robustness: Design guide line

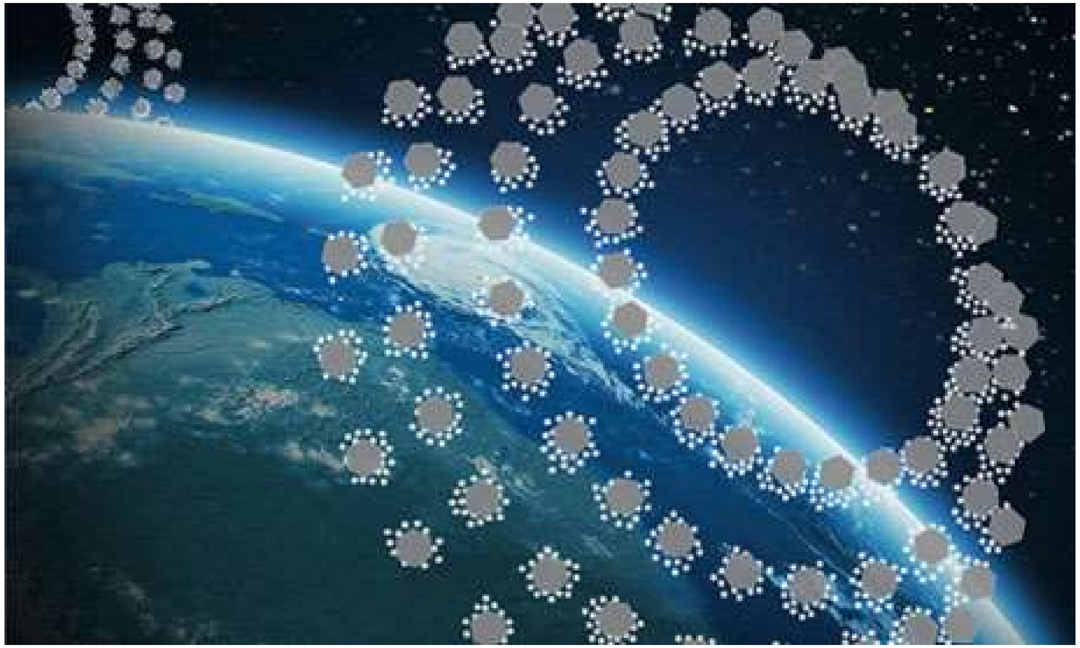


avoid single-point-of-failure:

by redundancy

and/or by **flexibility**
(each robot is able to switch to any other task)

Robustness: Example

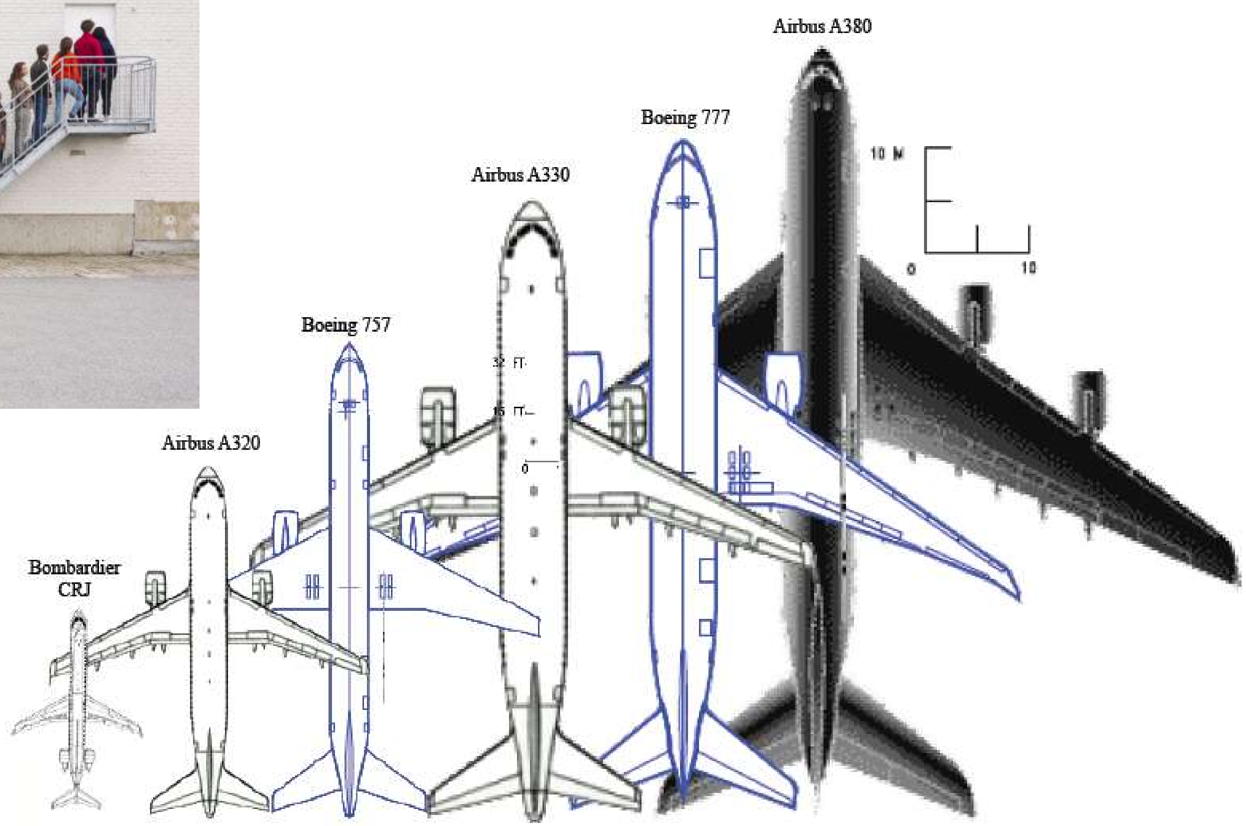


Instead of sending up 1 space probe for 3 billion Euros

send up 100 small space probes for 30 million each

Scalability

How does system performance scale with increasing work load?

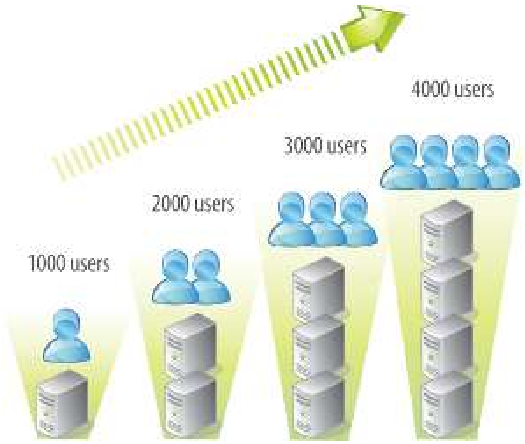


How does a design concept scale with increasing size?

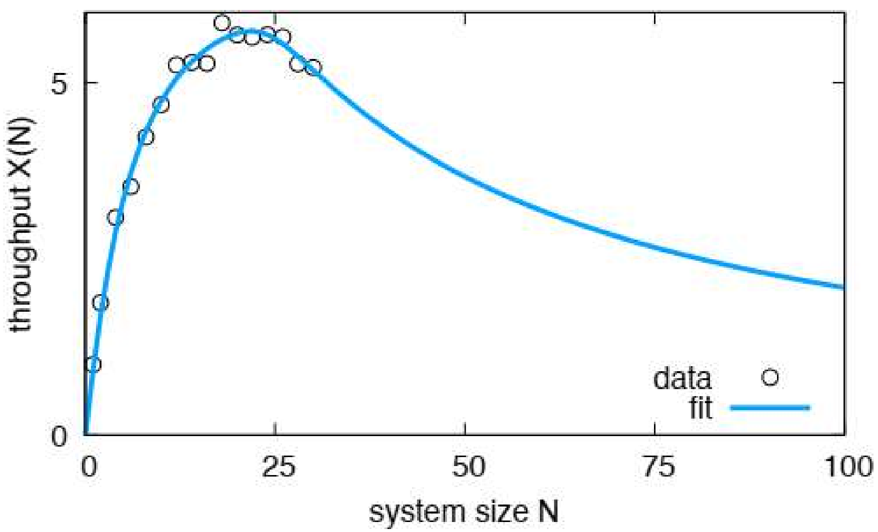
Scalability in computer systems

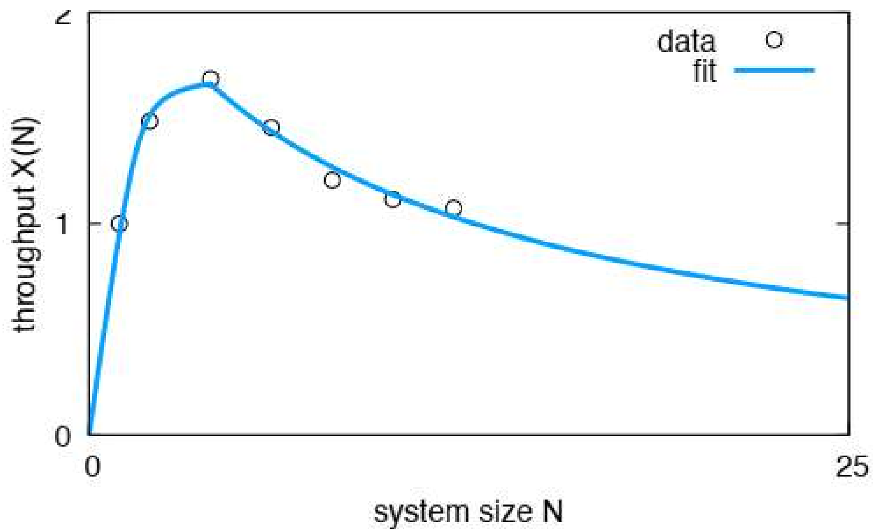
Increasing number of users is answered with increasing number of servers.

Does it scale (1 server for 1000 users, for any number of users)?



Scalability in computer systems



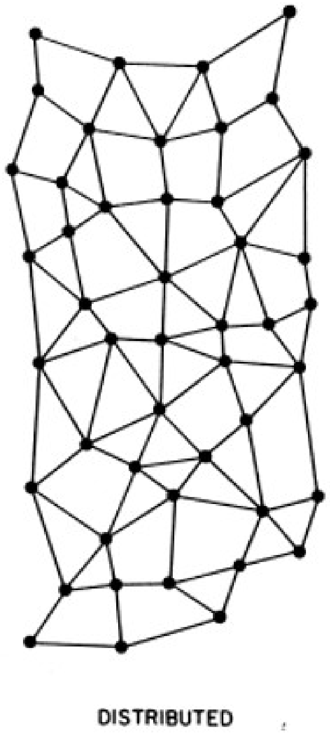


left: SQL server benchmark (Gunther, 2007), transactions per second over number of virtual users

right: NAS Parallel Benchmark (Jin et al., 1999), computational fluid dynamics (Navier-Stokes eq.), numerical solver for scalar pentadiagonal bands of linear equations, speedup over number of cores

→ arbitrary scalability not feasible (bottlenecks, overheads etc.)

Scalability: Design guide line



- only local interactions,
- only storage of local data,
- no broadcasting,
- no traveling on swarm-scale
- (circling swarm, crossing swarm)
- swarm size might increase
- but swarm density should be limited

What is not swarm robotics?

multi-agent systems / multi-robot system (e.g., RoboCup)

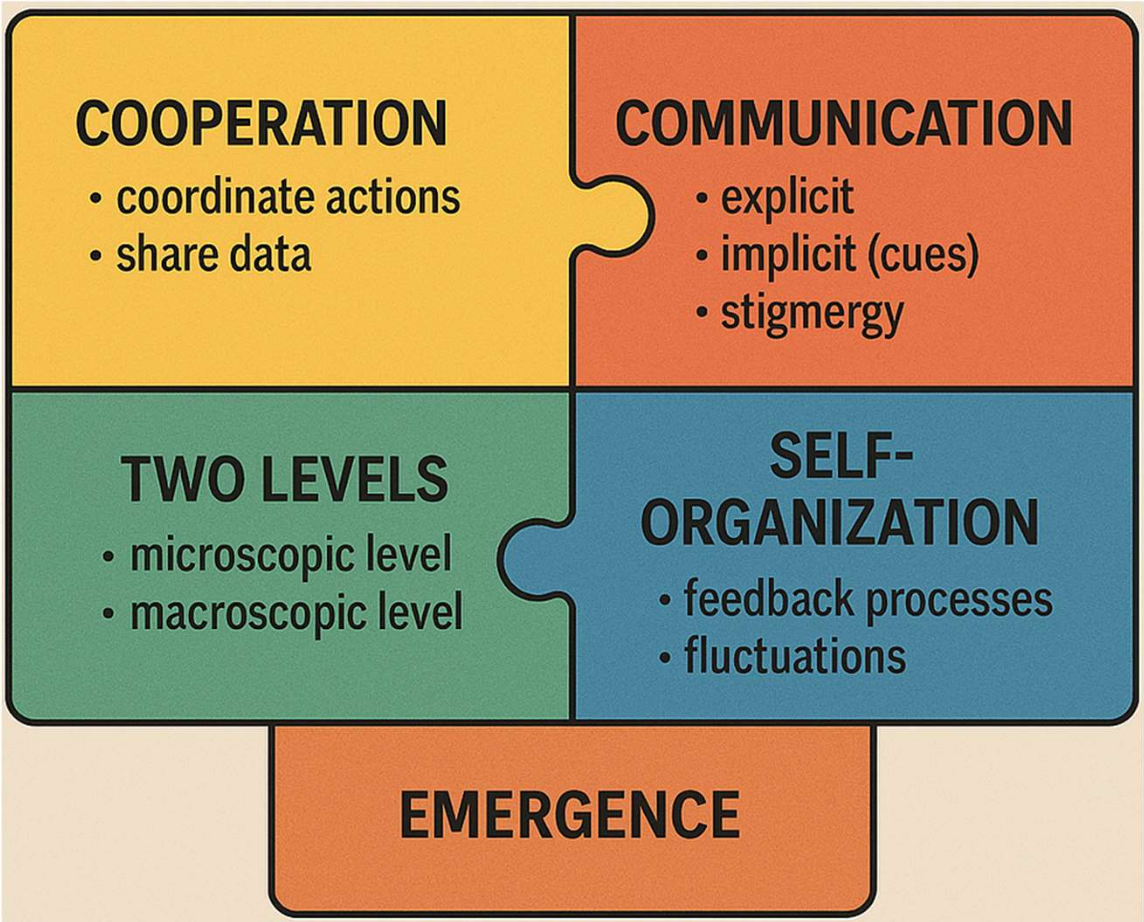
- distribution of / access to global information
- all2all communication (broadcasts)
- sophisticated communication protocols
- explicit assignment of roles
- negotiations between agents
- generally not scalable

Recap

1. Why do we need to investigate collective robotics?
2. How would you define collective robotics?
   What are its key features?
3. What advantages can you envision in using collective robotics?
   How does it differ from other fields of robotics?

Q: Size of the swarm?

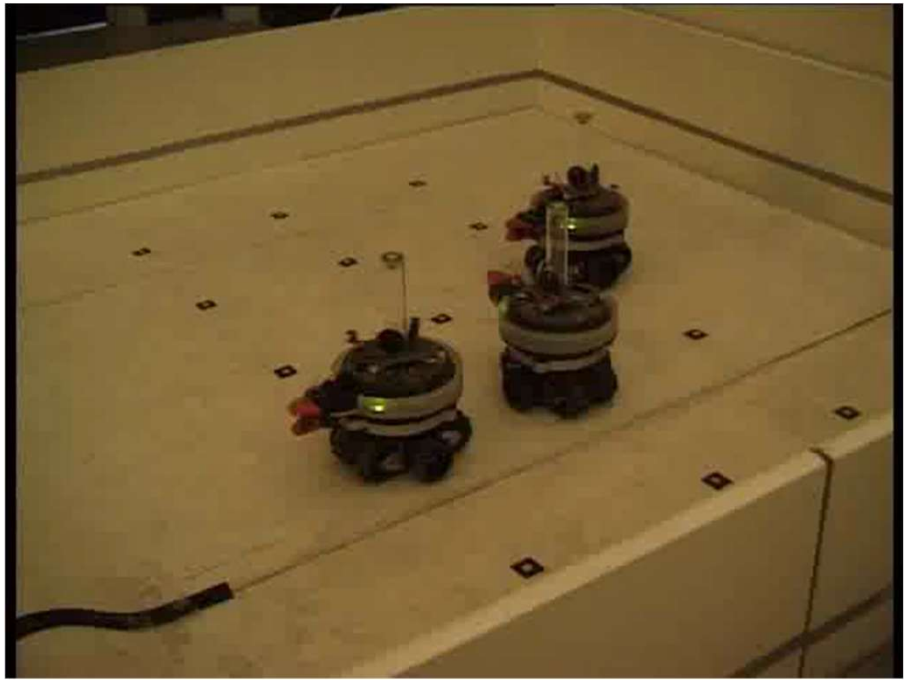
Building blocks of swarm robotics



Cooperation

Natural System

artificial system

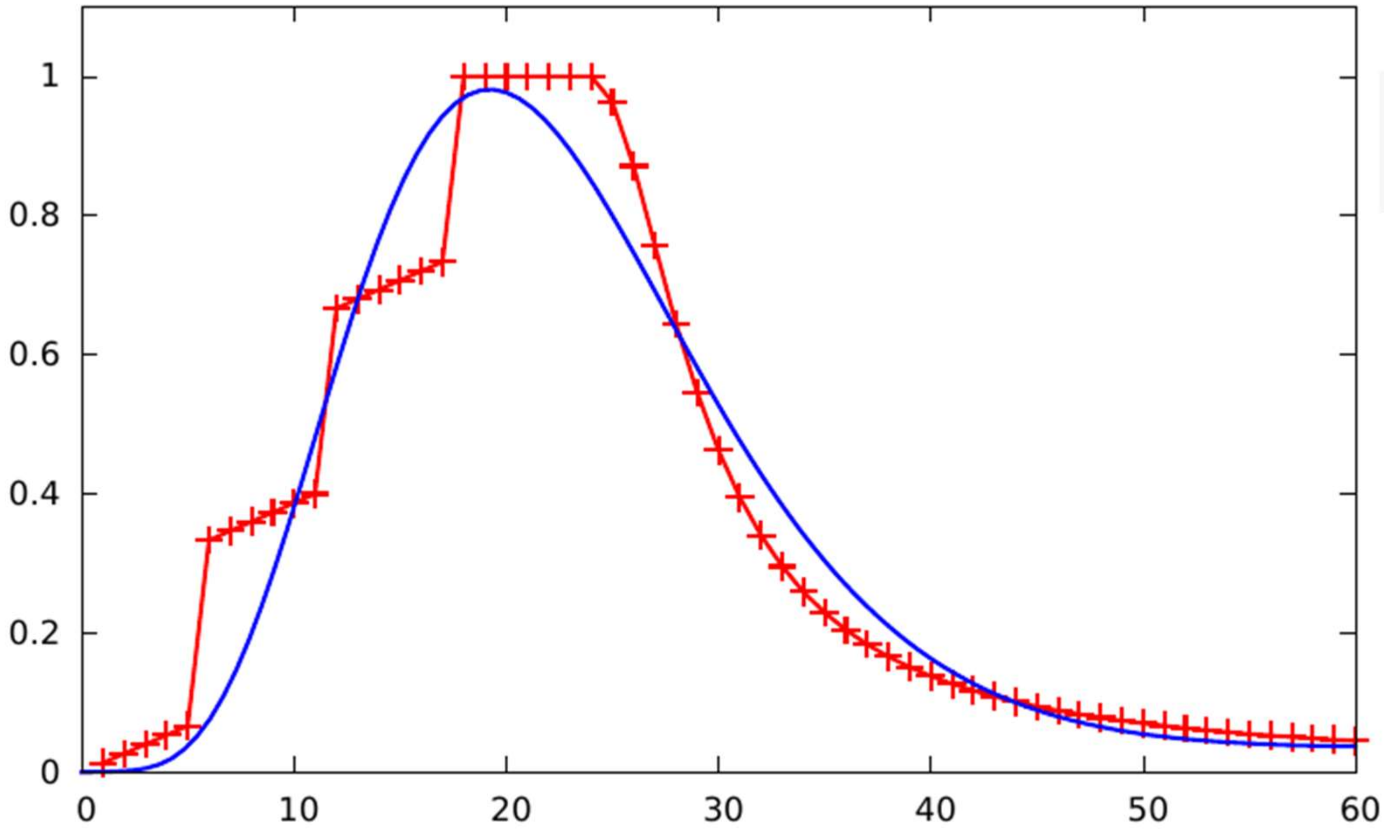


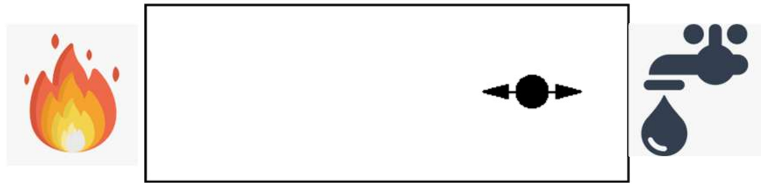
Effect of cooperation on swarm performance

- adding agents to the system creates more opportunities to cooperate

- is adding agents (increase of swarm size N) complemented with adding space?
  - if not, then we actually increase the swarm density $\rho = N/A$ (for a fixed area A)
  - $\Rightarrow$ problems of interference
- there is an optimal swarm density $\rho*$
  - well-balanced between potential for cooperation and interference

Swarm performance: Bucket brigade





Universal Scalability Law (USL) (1/4)

parallel processing performance in distributed systems:

Universal Scalability Law (USL)

relative capacity C(N) (i.e., performance)

$$C(N) = \frac{N}{1 + \alpha(N-1) + \beta N(N-1)} \tag{1}$$

coefficient α: the degree of contention (interference) in the system

coefficient β: the lack of coherency in the distributed data

4 qualitatively different situations:

A. "equal bang for the buck" ($\alpha = 0, \beta = 0$)

B. cost of sharing resources ($\alpha > 0, \beta = 0$)

C. diminishing returns from contention ($\alpha \gg 0, \beta = 0$)

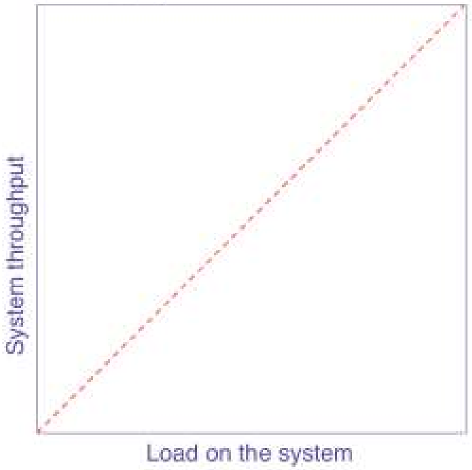
[Each additional unit of input contributes less and less to the output]

D. negative returns from incoherency ($\alpha \gg 0, \beta > 0$) [making things worse by adding more of something]

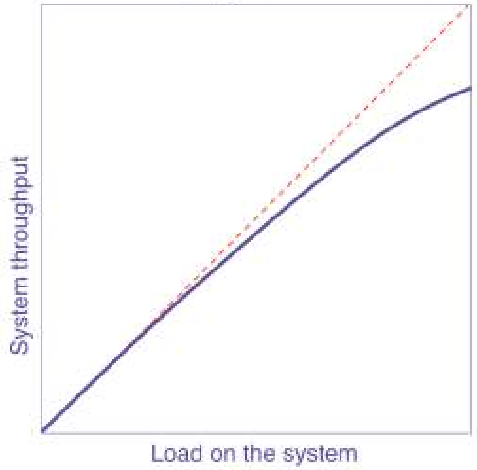
N. J. Gunther, A Simple Capacity Model of Massively Parallel Transaction Systems, CMG National Conf., 1993
http://www.perfdynamics.com/Papers/njgCMG93.pdf

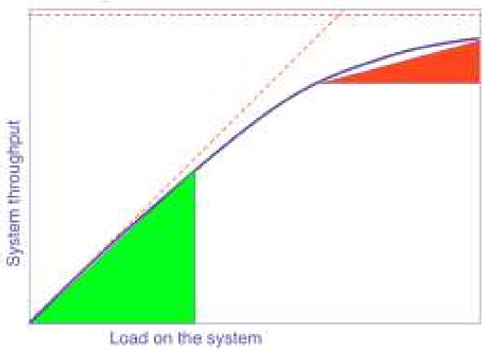
Universal Scalability Law (USL) (2/4)

$\alpha = 0, \beta = 0$

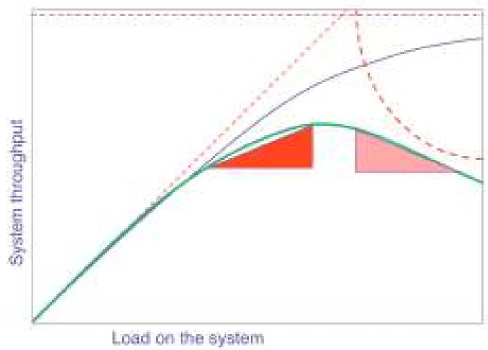


$\alpha > 0, \beta = 0$





$\alpha \gg 0, \beta = 0$

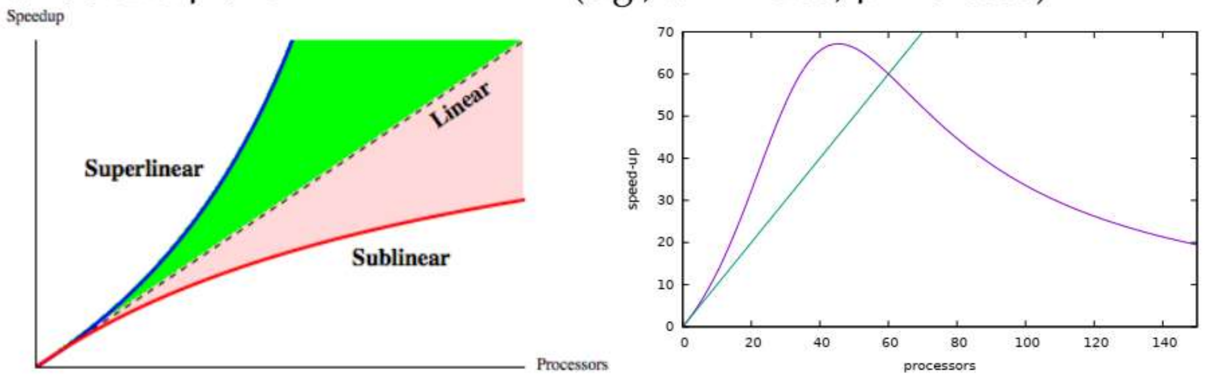


$\alpha \gg 0, \beta > 0$

Universal Scalability Law (USL) (3/4)

super-linear scaling effects as modeled by USL

$\alpha < 0$ and $\beta > 0$ (e.g., $\alpha = -0.03$, $\beta = 0.0005$)



inversion of contention? ⇒ capacity boost

for example due to cache effects in memory hierarchies

or branch-and-bound algorithms in optimization

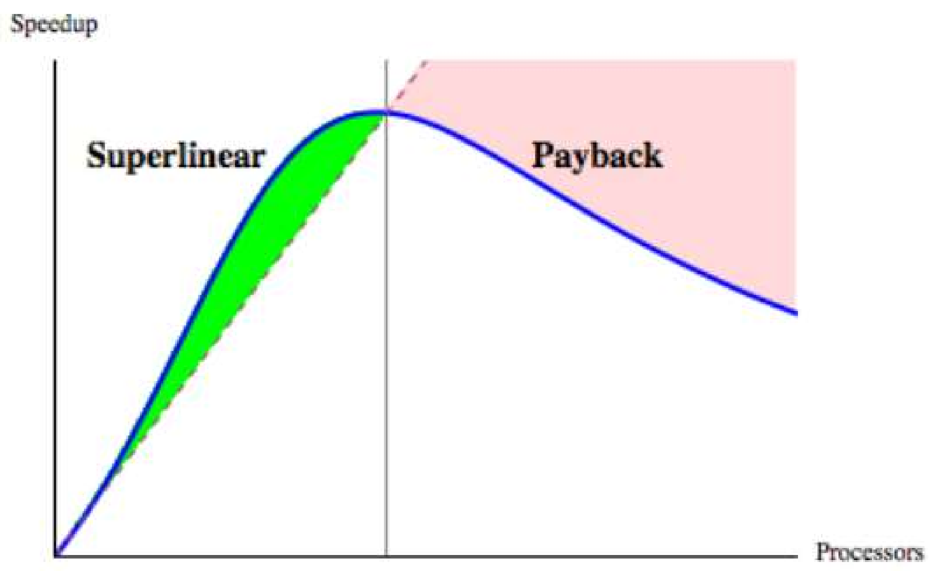
N. J. Gunther, P. Puglia and K. Tomasette, "Hadoop Super-linear Scalability: The perpetual motion of parallel performance," ACM Queue, Volume 13, issue 5, June 4, 2015. Unabridged version of Communications of the ACM, Vol. 58 No. 4, Pages 46-55, 2015.
http://queue.acm.org/detail.cfm?id=2789974

Universal Scalability Law (USL) (4/4)

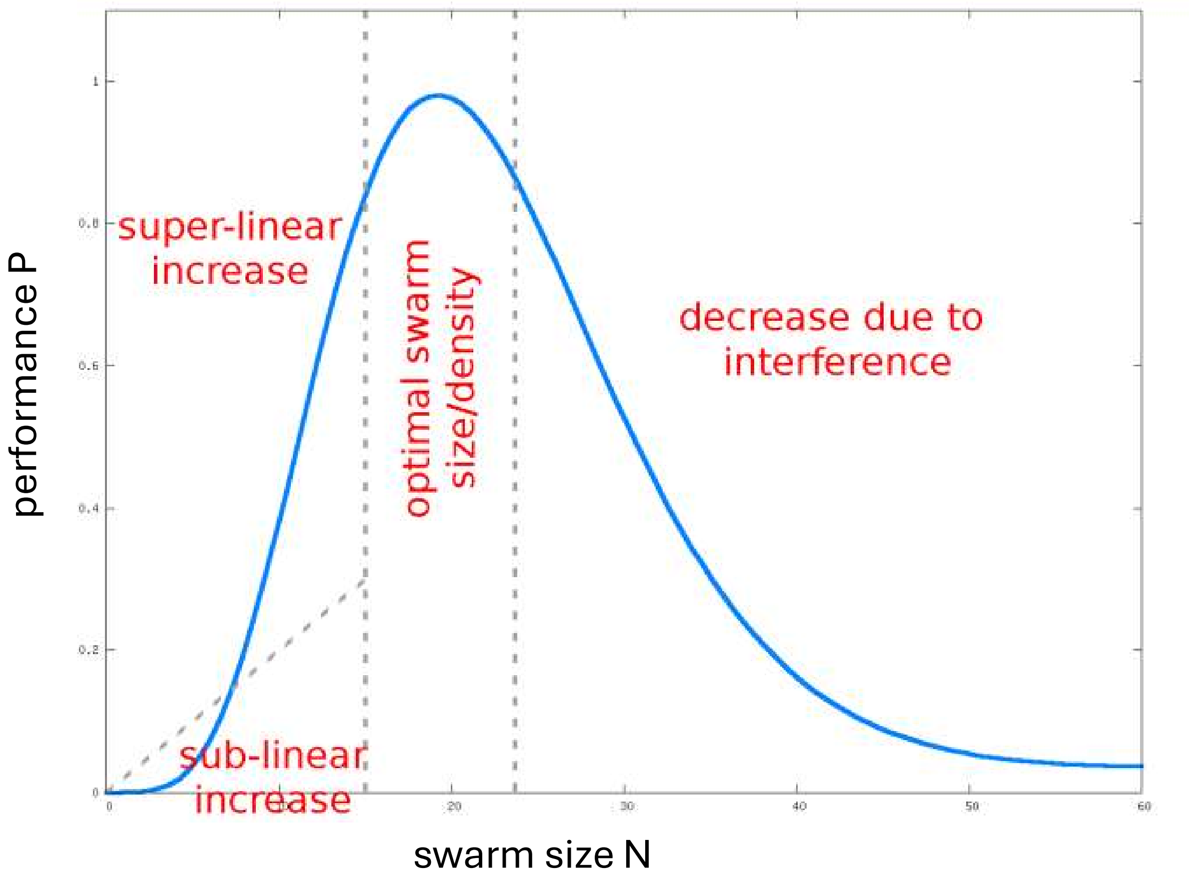
payback region

- ➢"That's where you pay the piper for
- ➢(apparently) getting a super-linear ride
- ➢for free."

initial super-linear scaling followed by sub-linear scaling

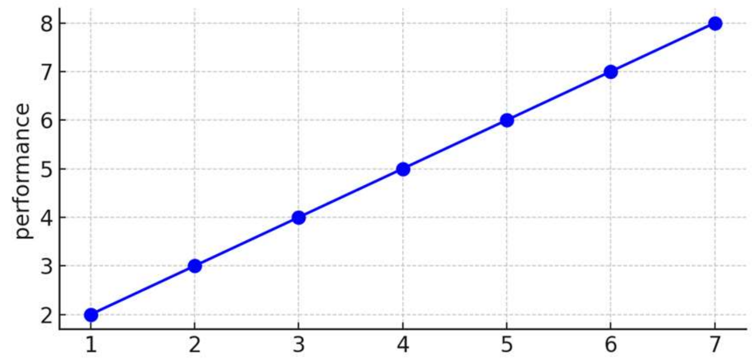


Swarm performance: 3 phases

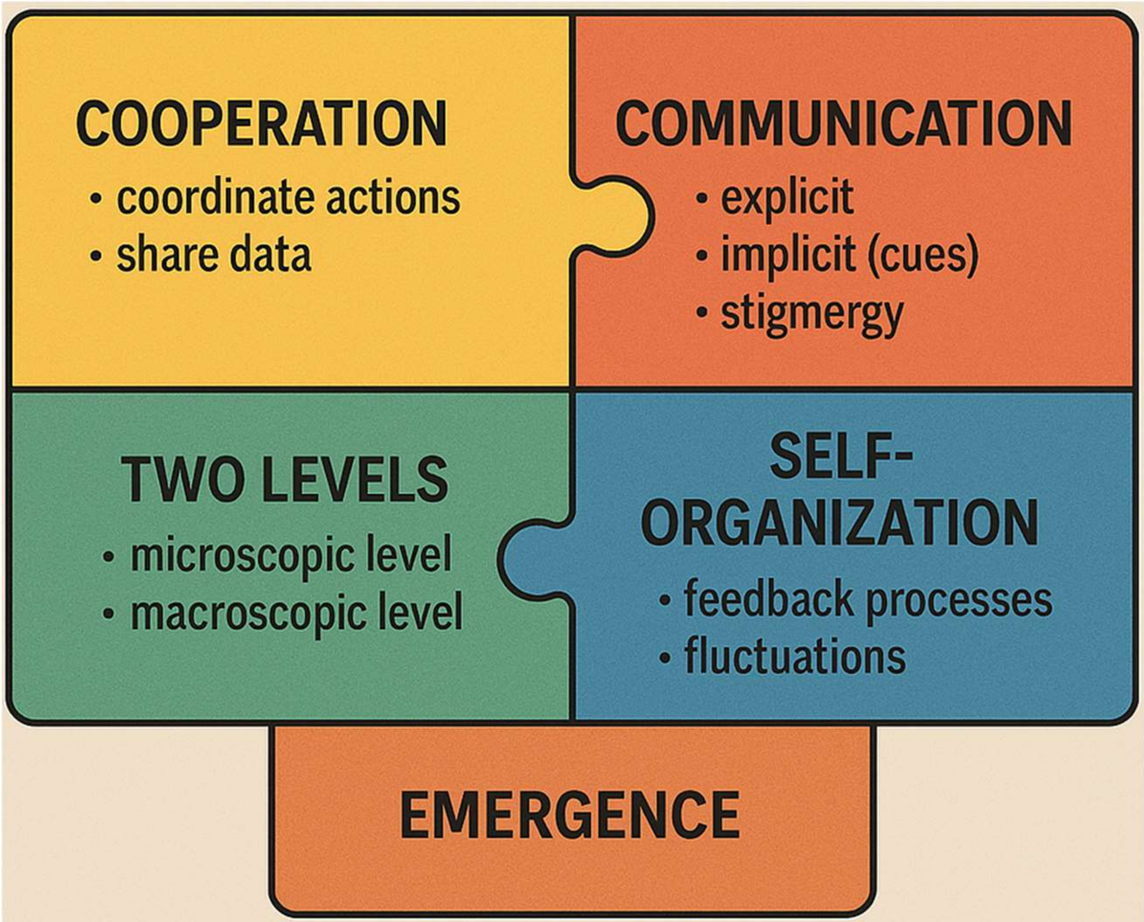


Performance increase: linear, sub-/super-linear

Several workers achieve more than 1 worker
– but how much more?
Example 1:
Performance of 1 worker is 1,
performance of N workers is N ⇒ linear
Example 2:
Performance of 1 worker is 1,
performance of N workers is log(N) + 1 ⇒ sub-linear
Example 3:
Performance of 1 worker is 1,
performance of N workers is N + log(N) ⇒ super-linear



Communication



Communication

explicit
standard message-based communication

implicit
Alice thinks: “Hm, Bob is here – that surely means something.” cue-based communication (synonyms for cue: hint, idea, indication) Paul Watzlawick: “One cannot not communicate

Cues and signals

interaction at a distance between animals

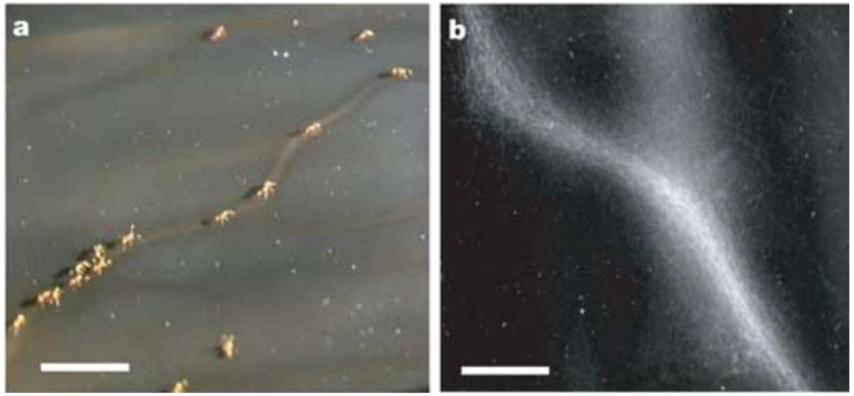
cue

- ➢unintentional index,
- ➢example: trail in snow
- ➢the perceiving animal can decide:
- ➢to follow ⇒ positive feedback
- ➢or avoid ⇒ negative feedback

signal

- ➢intentional index,
- ➢example: alarm cry of a bird
- ➢intention to affect the behavior of other receiving
- ➢animals

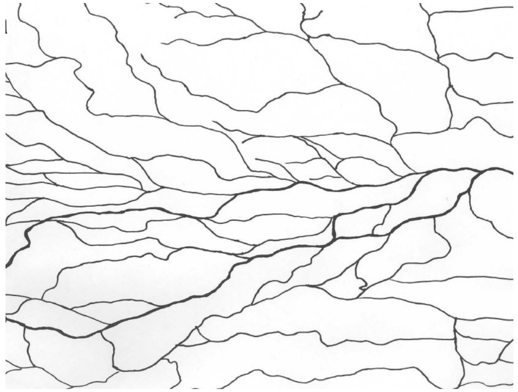
Stigmergy



Communication by way of the environment,

for example, by adding something to the environment (pheromone, etc.),

or by changing the environment (moving objects, etc.)



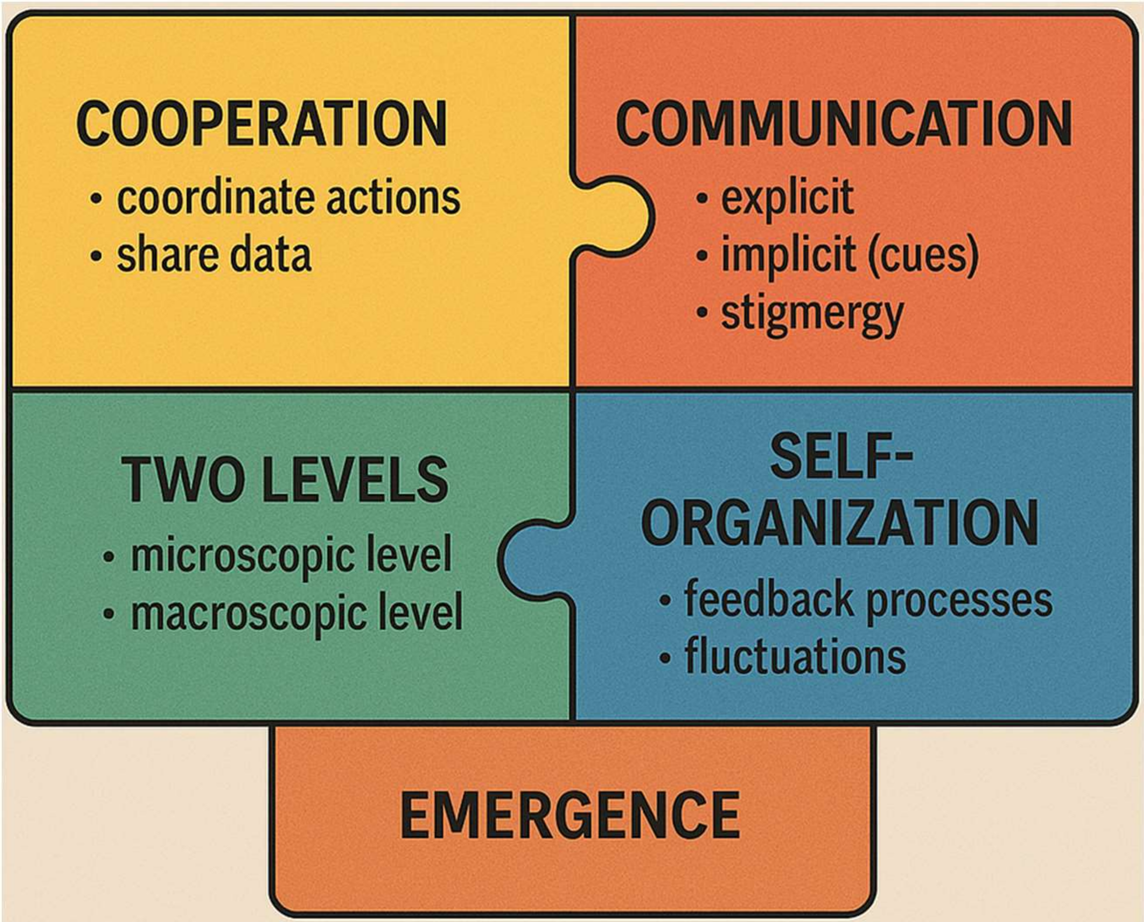
Form of cue-based communication

(it is said not to be intentional)

introduced by Pierre-Paul Grasse, (Grass ´ e, 1959) ´

Example: pheromone trails in ants

two levels


COOPERATION
• coordinate actions
• share data
COMMUNICATION
• explicit
• implicit (cues)
• stigmergy
TWO LEVELS
• microscopic level
• macroscopic level
SELF-ORGANIZATION
• feedback processes
• fluctuations
EMERGENCE

Microscopic level and macroscopic level (1/2)

micro-level: individual agent, local view, limited knowledge, limited sight distance, uncertainty, only primitive actions feasible

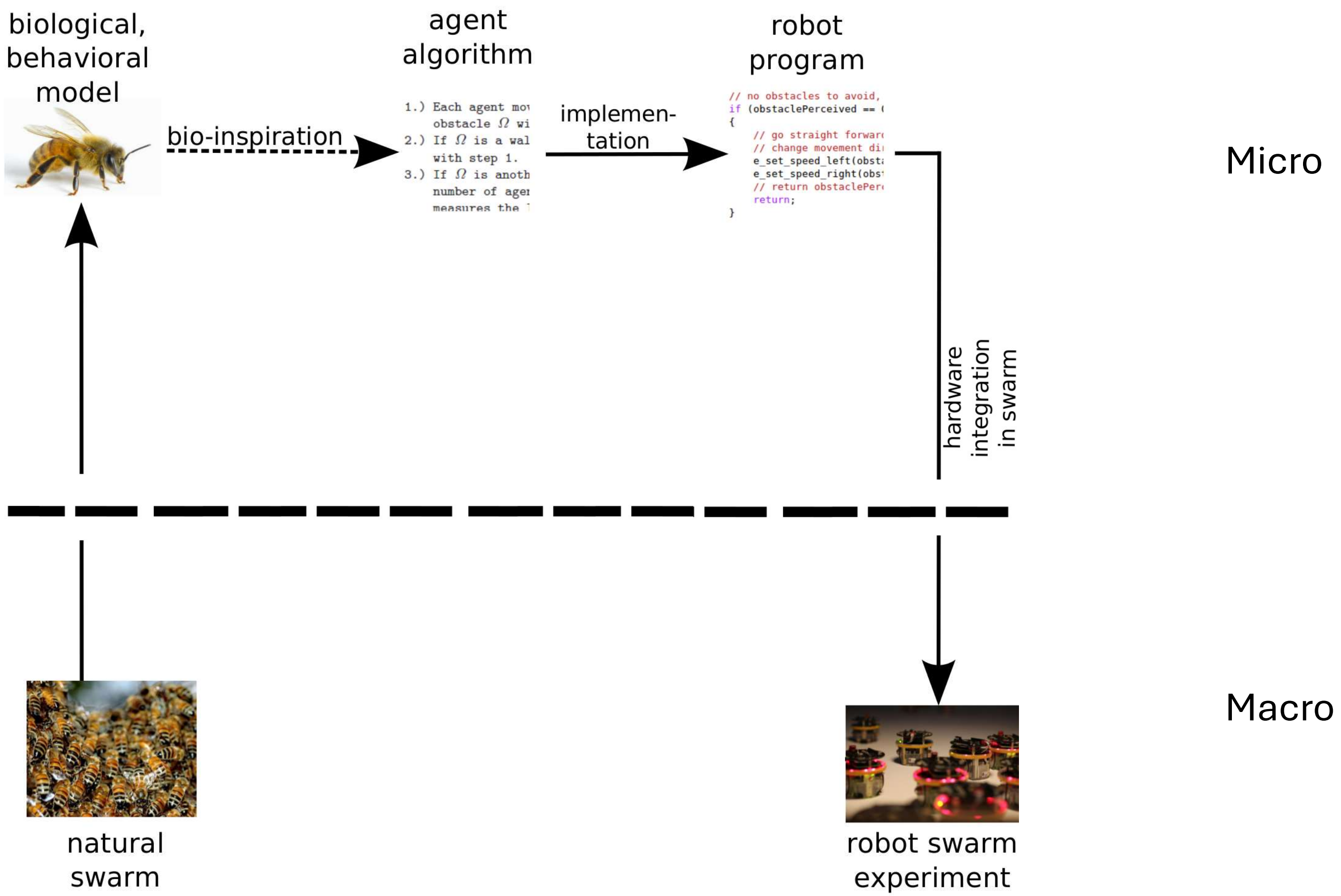
macro-level: swarm level, global view, all knowledge, full overview, overall task defined

challenge for design of swarm robotic systems:

- task defined on macro-level,
- implementation/programming on micro-level

note: macroscopic models abstract away microscopic details

Microscopic level and macroscopic level (2/2)



Micro/macro programming

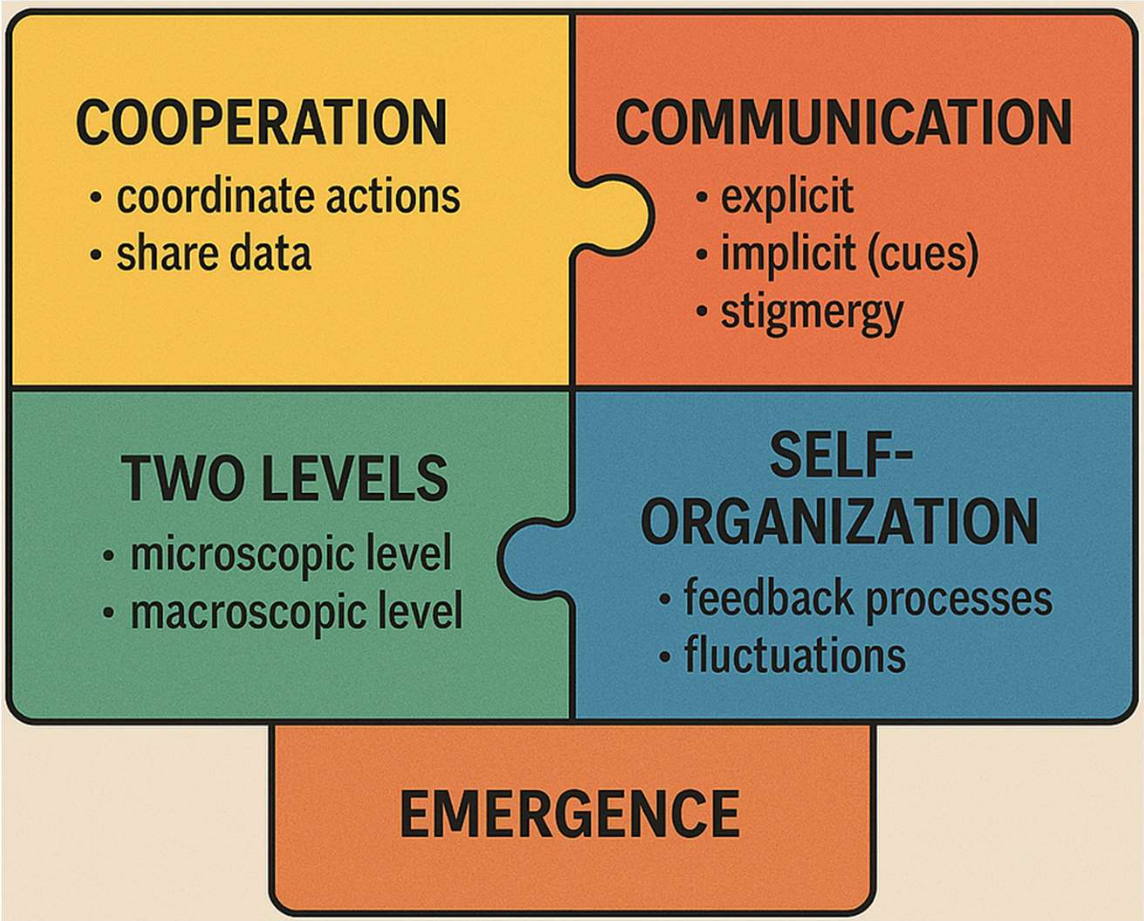
	computer	**single robot**	**swarm**
task ⇓	sort	explore	aggregate at optimal spot
algorithm design ⇓	quicksort	collision avoidance + X	move swarm to optimal spot and stop
implementation ⇓	C++, Objective-C, . . .	—″—	? swarm language? on each robot?
desired system	machine code + OS	—″—	machine code on each robot

Micro/macro programming – example

classical sorting on 1 CPU:
'global view' on data: (31, 15, 7, 1, 99, 43, 12, 2, 6)
clear what to do,
task definition and implementation on the same level

metaphorical, analogous example for swarm robots:
a robot has local view only: (7, 1, 99)
could be sorted locally + exchange of numbers with neighbors
but maybe it's even unclear which neighbor should get the bigger numbers. . .
⇒ micro-macro problem

self-organization



self-organization

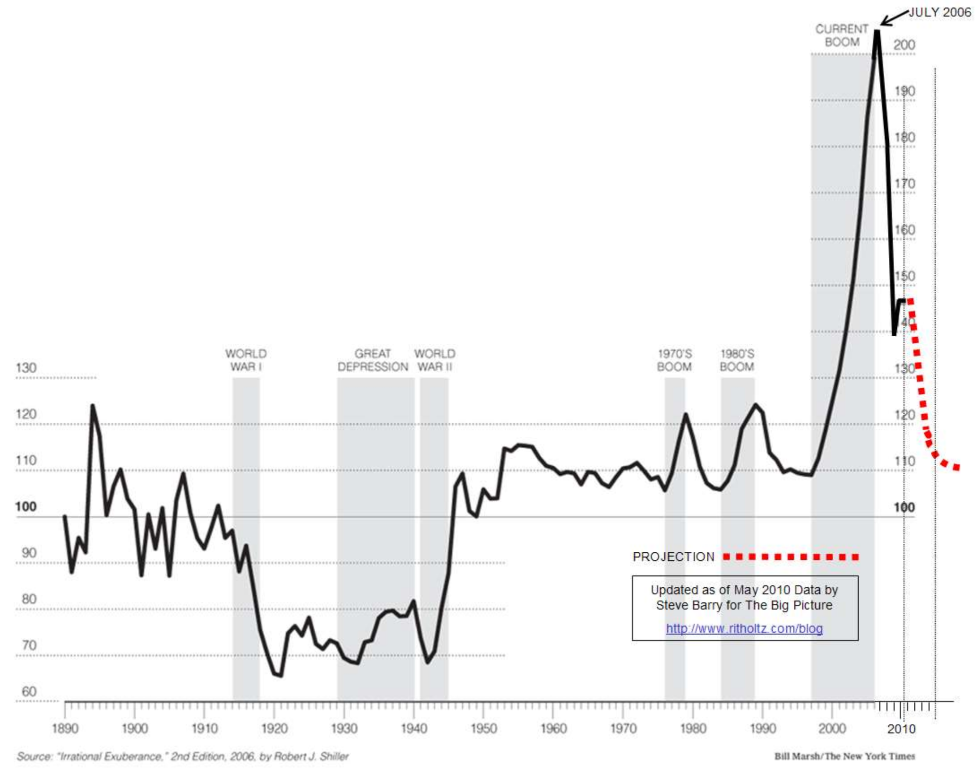
global order generated by local interactions
"order from noise"
spatial, temporal, spatiotemporal structures
in open systems driven away from thermal equilibrium

Self-organization is based on 4 components:

- positive and negative feedback (dynamical non-linearity)
- fluctuations (i.e., random events)
- multiple interactions
- balance of exploitation and exploration

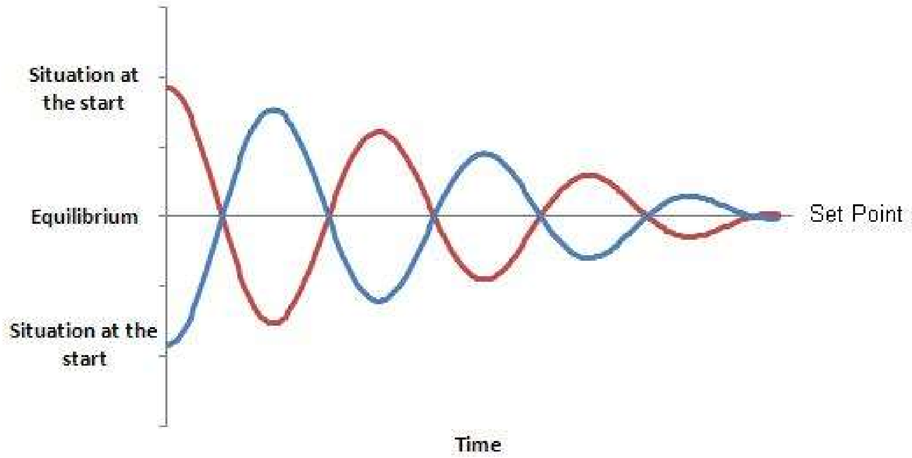
examples:
crystallization, convection cells (Rayleigh–Benard convection), pattern formation, ´
sorting

Positive feedback – example: market bubble



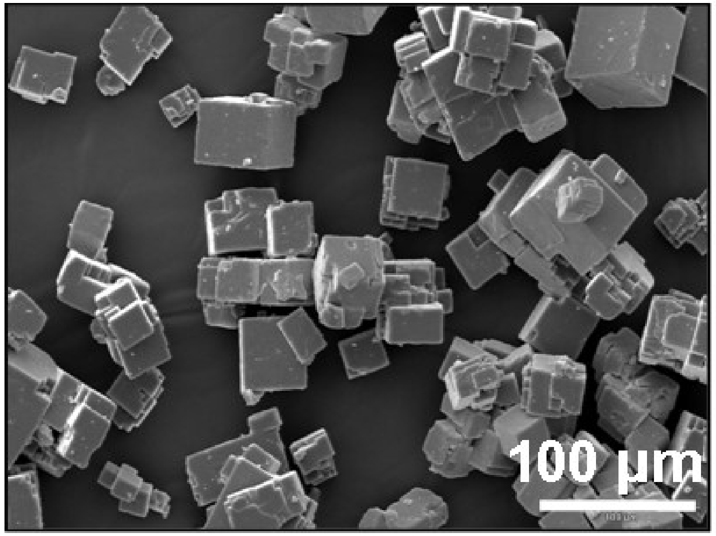
positive feedback
⇒ reinforcement of deviations

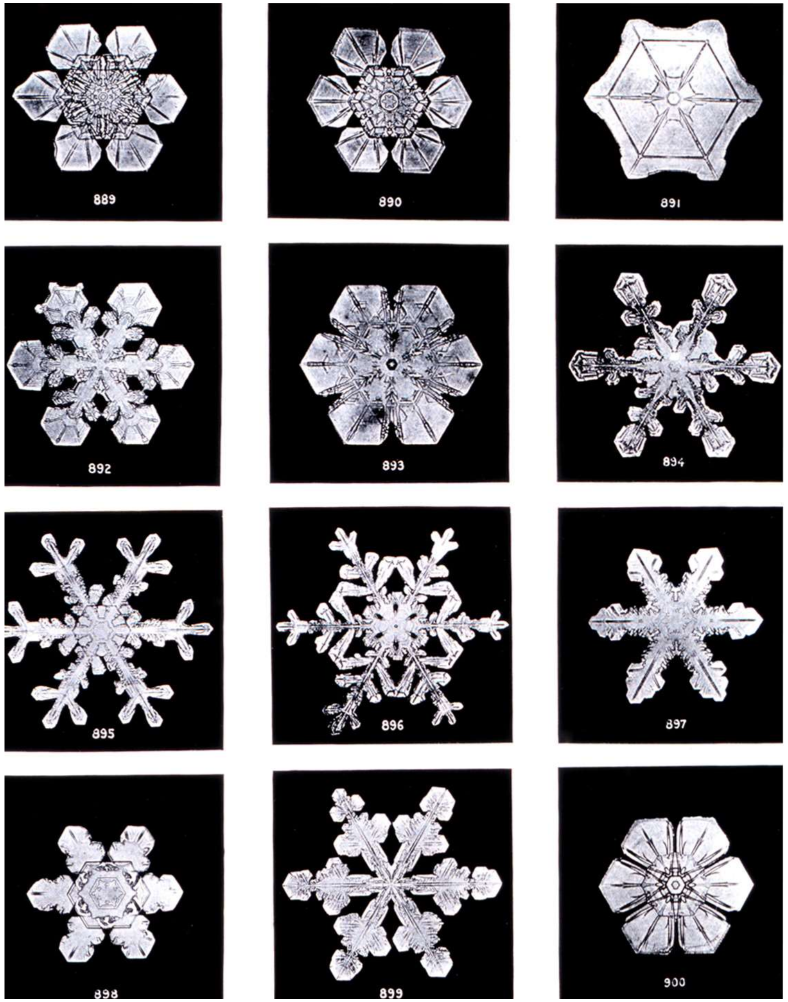
Negative feedback – example centrifugal governor



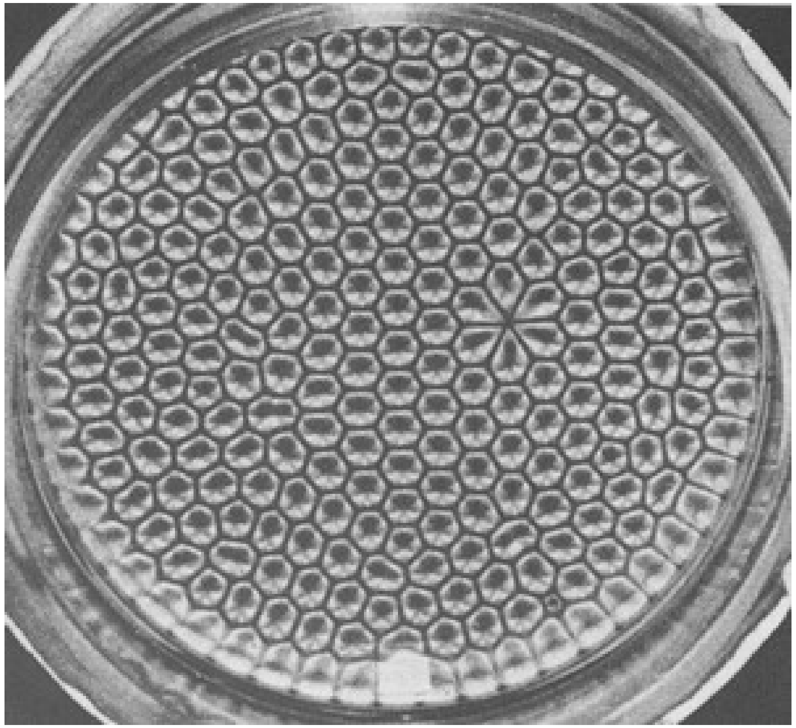
negative feedback
⇒ decrease of deviations

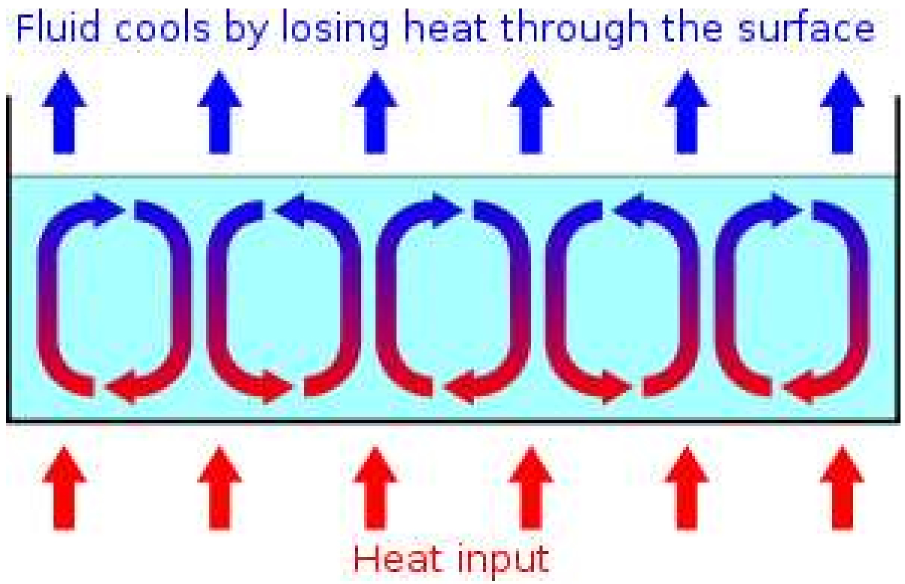
Self Organization– Crystallization



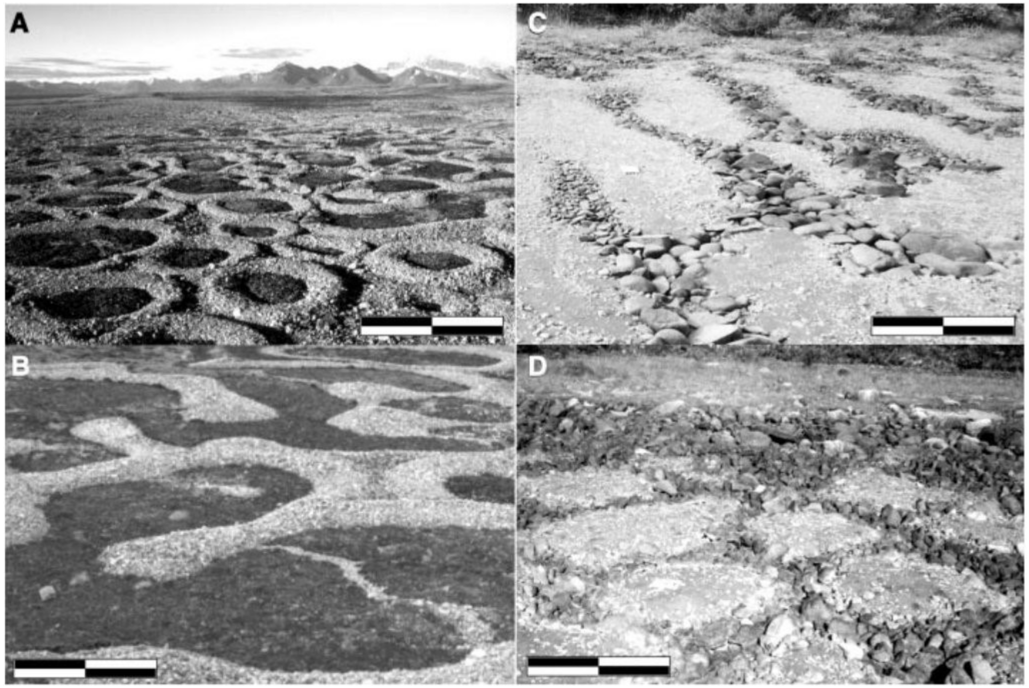


Self Organization– Rayleigh–Bénard convection





Self Organization–Pattern formation (1/2)

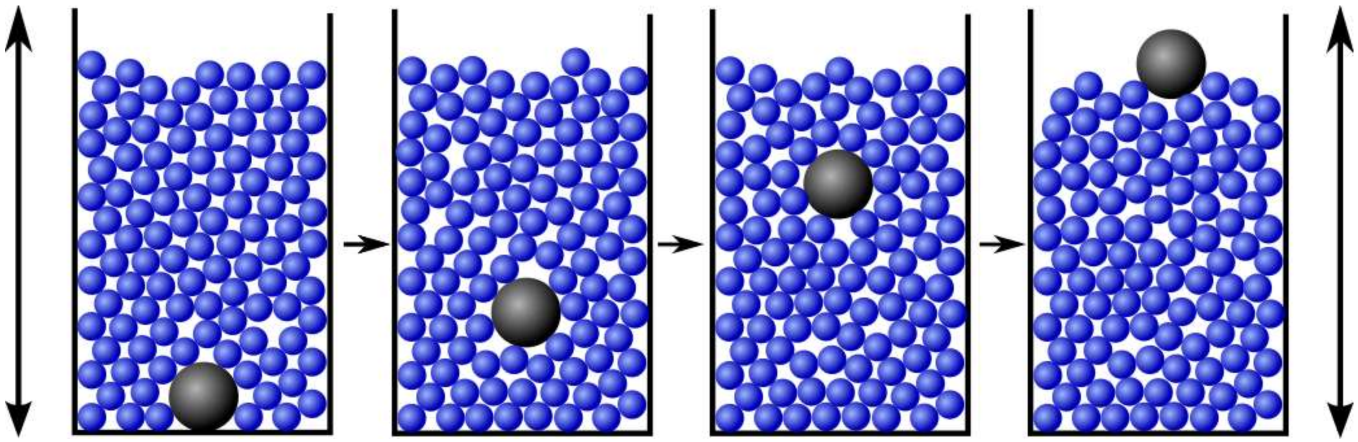


stone and salt patterns Kessler and Werner (2003)

Self Organization – Pattern formation (2/2)

defrosting permafrost (in Sakha, Russia)

Self Organization – Sorting



Brazil nut effect

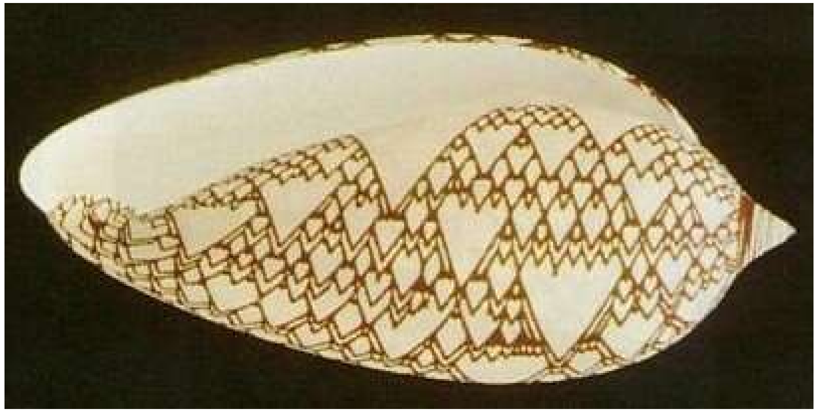
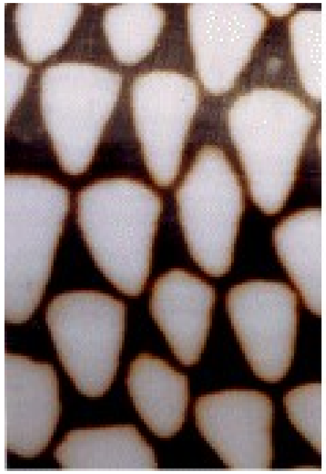
Biological Self-organization

examples from biology are

- pattern formation
- flocking
- morphogenesis
- homeostasis
- behaviors,
- e.g. of social insects

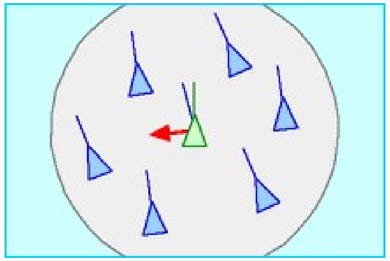
Self Organization – Biological pattern formation

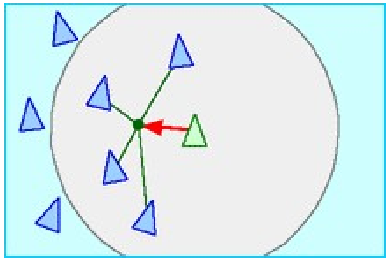


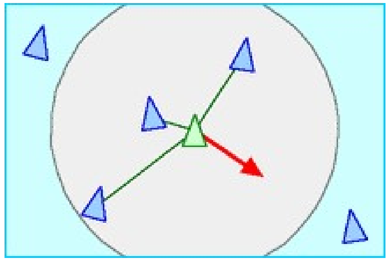





Self Organization – Flocking





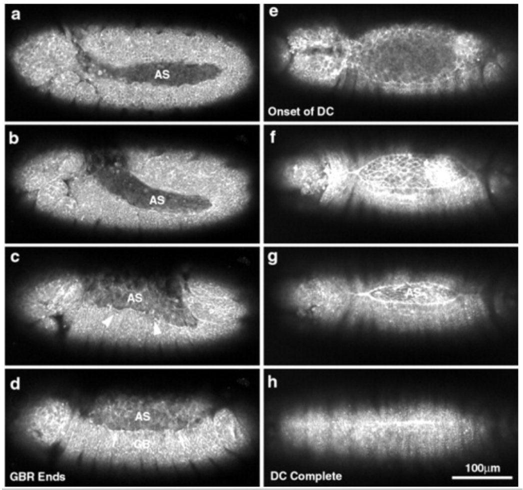


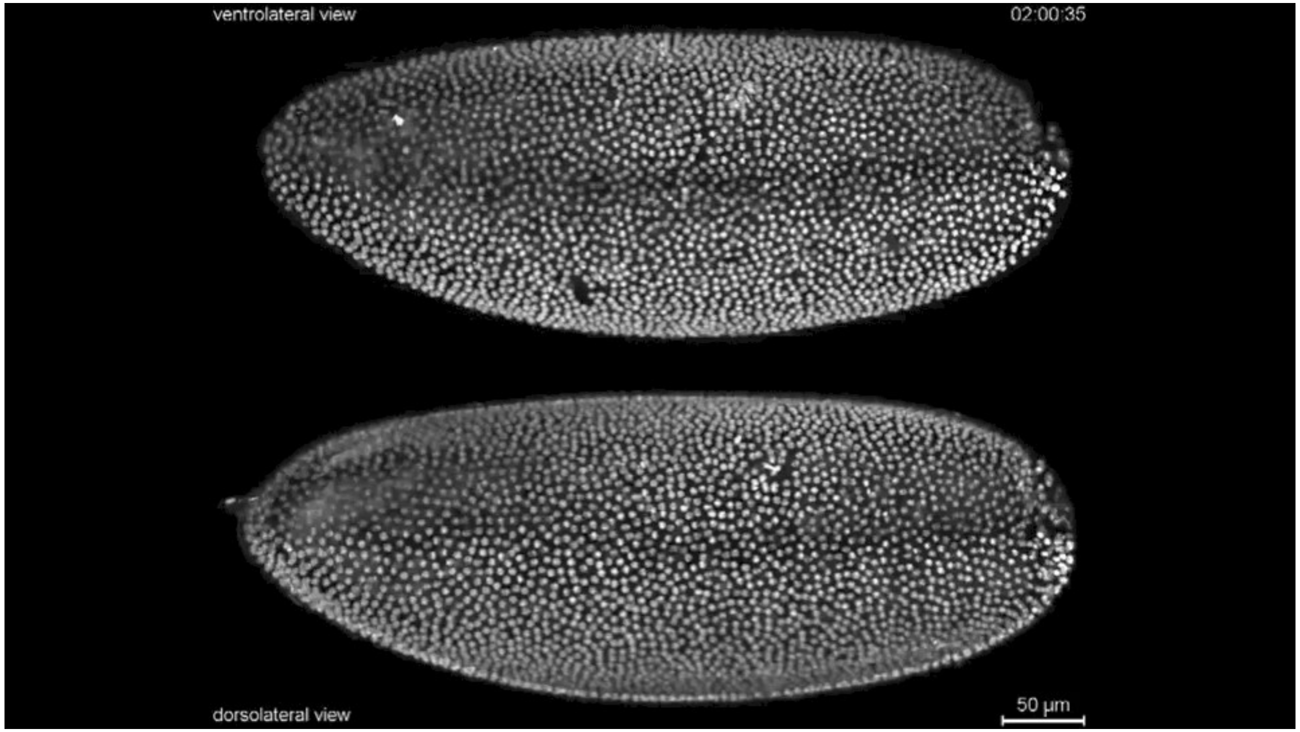
multiple interactions,
contraction of the whole swarm (positive feedback),
inflation of the swarm if too dense (negative feedback)

Self Organization – Morphogenesis

biological process that controls how the shape of an organism Develops

example:
Embryology of Drosophila

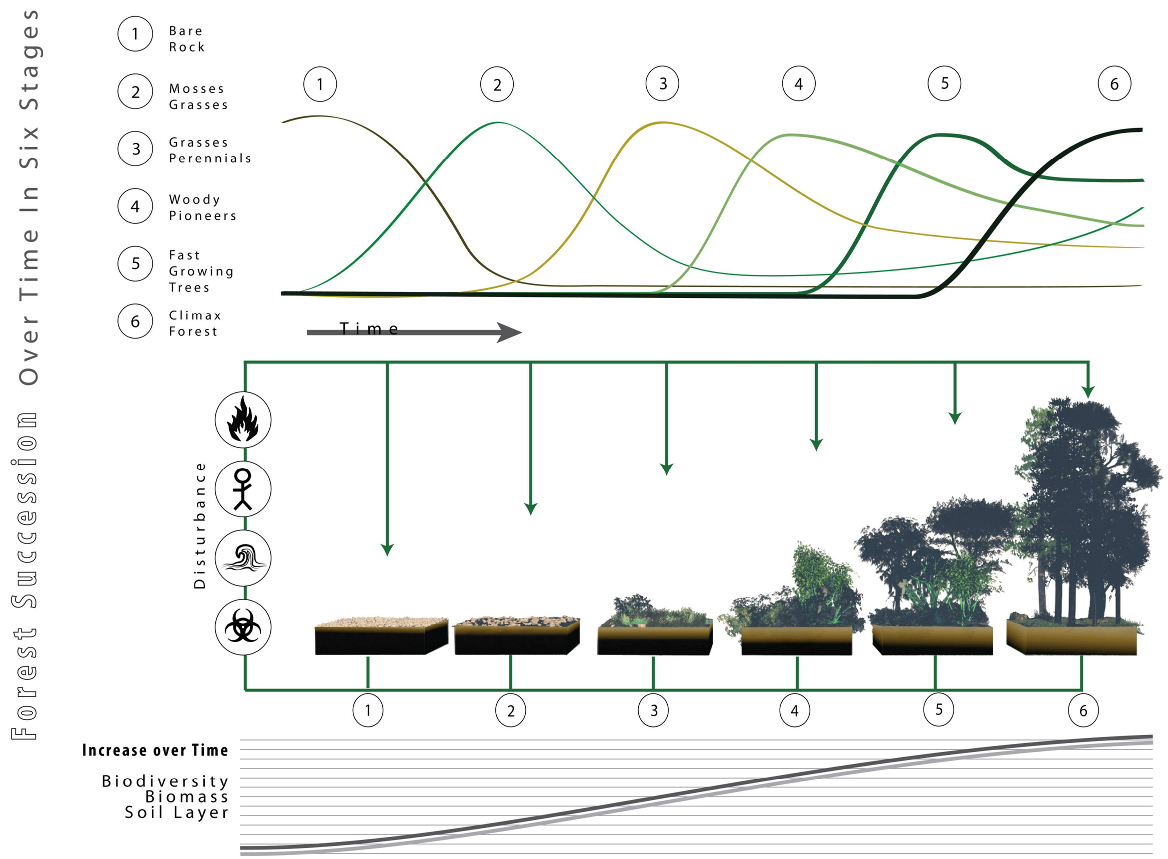




Self Organization – Homeostasis

Examples

- warm-blooded animals:
  control of body temperature (e.g., sweat, shiver)
- regulation of blood glucose with insulin and glucagon
- ecologies:
  disturbance, succession, homeostasis (distribution of species in forests)

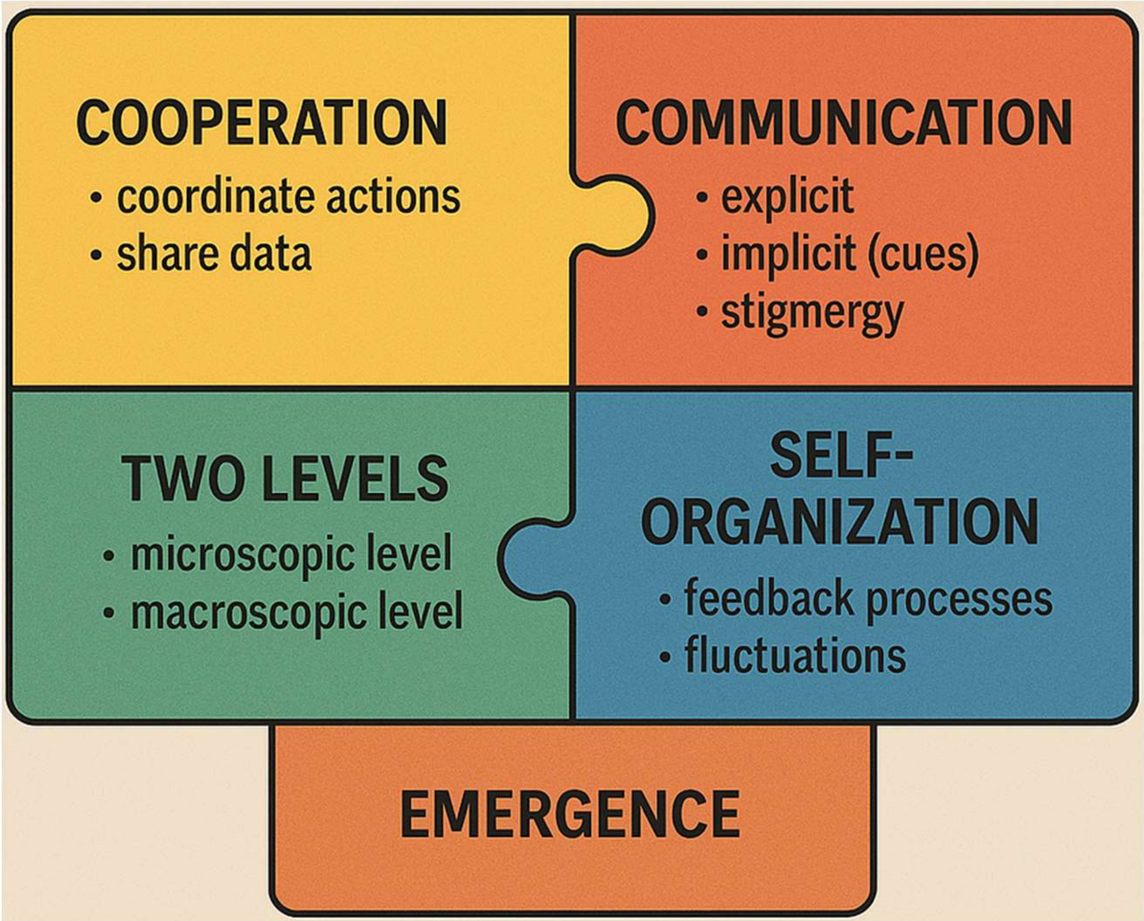


Self Organization – Behaviors – Social insects

- some simple behaviors could be genetically programmed but unlikely that it is many
- more plausible: evolution selects behavioral rules that capitalize on principles of self-organization
- behaviors result from interactions of individuals in a self-organizing process

Floreano and Mattiussi (2008)

Emergence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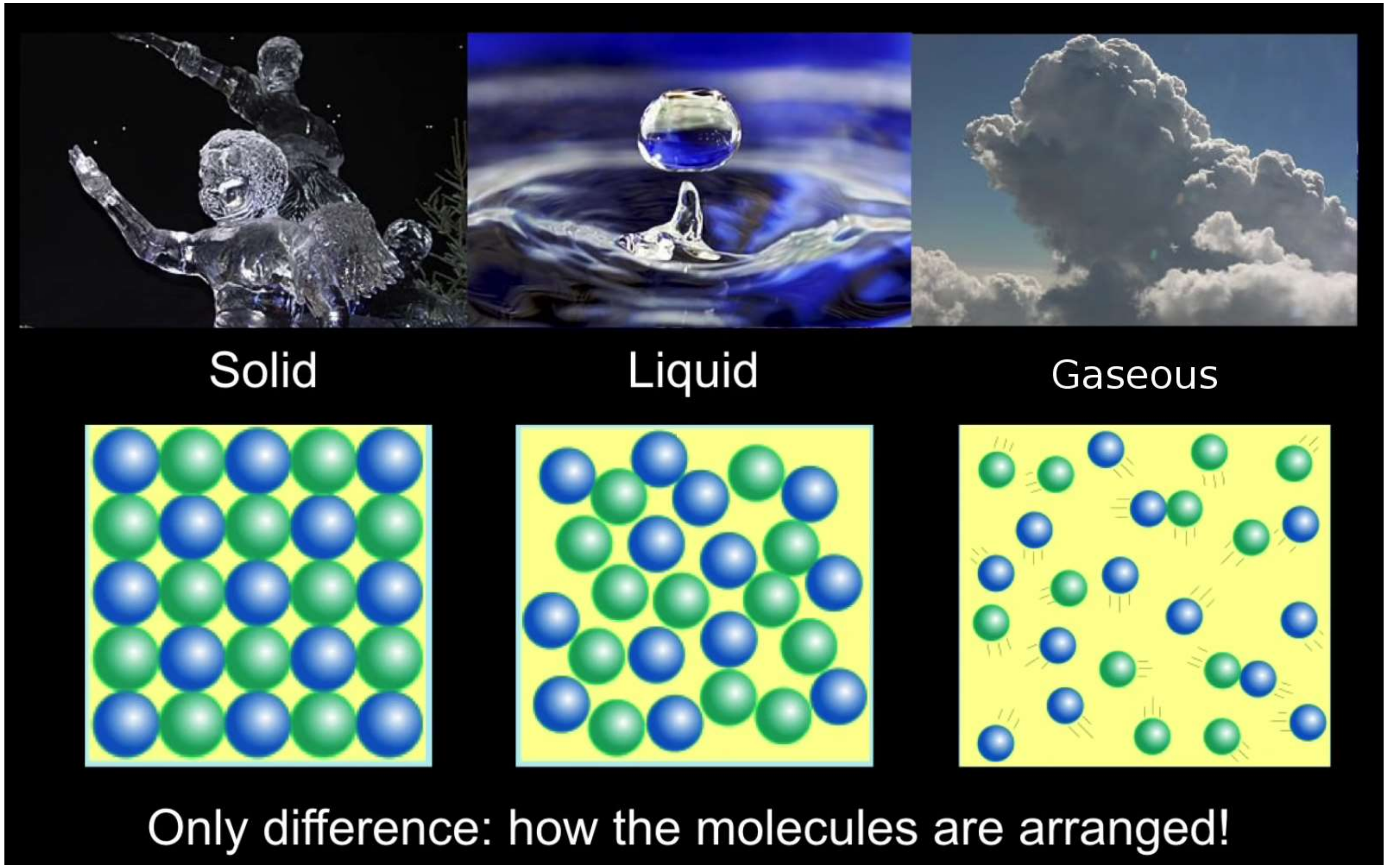


(slide by Max Tegmark)

Emergence

Difficult to define, vague philosophical concept:
new properties emerge on a higher level that cannot be described by the lower level (cf. also holism vs. reductionism)

Many definitions which use concepts such as:
"The whole is greater than the sum of its parts", surprise, fundamental novelty, unpredictability

"Solutions to problems faced by a colony are emergent rather than predefined." (Dorigo et al., 2000)

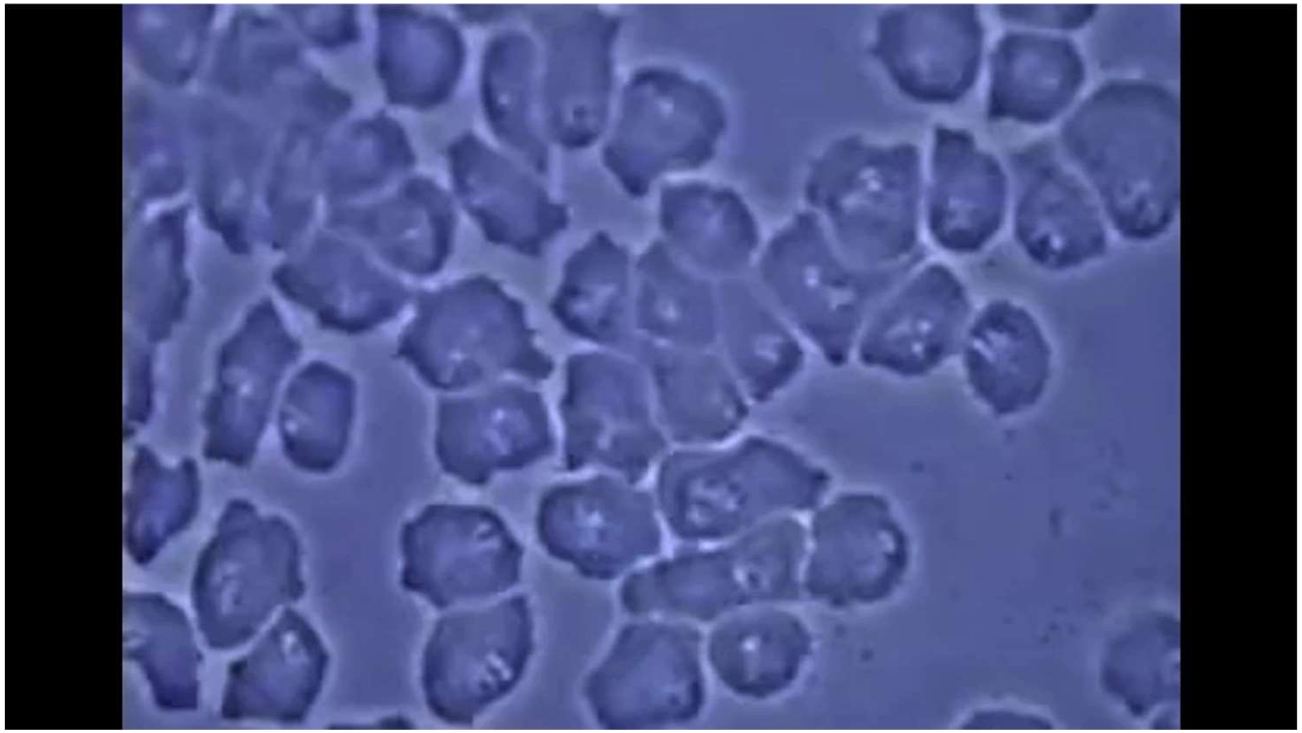
The engineer's dream:
construction of complex systems by an unproportionally small effort

Other sources of inspiration

- aggregation of amoeba into slime mold
- quorum sensing and communication in bacteria
- amorphous computing

Şahin (2005)

Sources of inspiration: Slime mold (1/2)



- (Dictyostelium discoideum and Dictyostelium mucoroides)
- (more details: https://youtu.be/spZwZLkMsYw)

Sources of inspiration: Slime mold (2/2)

features of interest:

- movement of singular cells
- taxis (movements directed by environmental stimuli)
- aggregation of organisms
- coordination and communication among cells

what slime molds do:

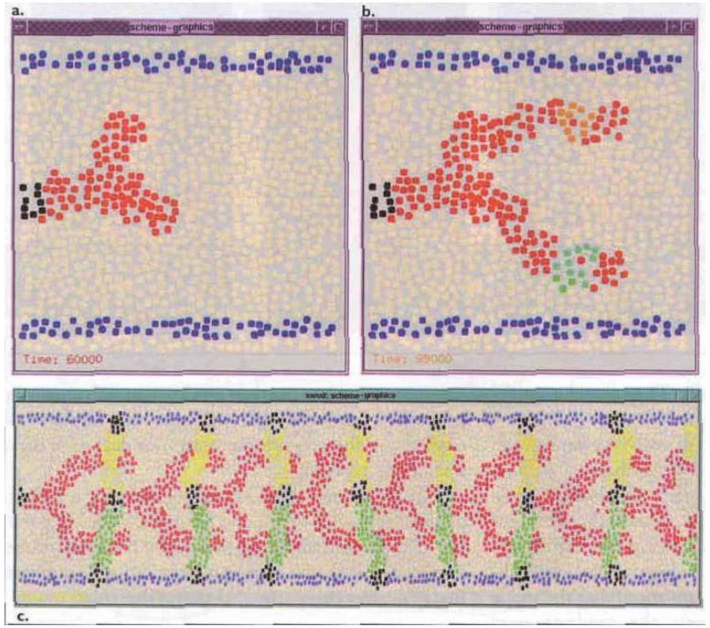
- excrete a chemical substance (cAMP) at small portions periodically
- if local environment exceeds a given threshold, it excretes a much higher amount of cAMP molecules
- amoebas walk uphill in local cAMP field
- trail-like formation towards the center of aggregation
- snail-like pseudo organism is formed, up to 105 cells, is called ‘slug’ state of slime mold

Sources of inspiration: Quorum sensing in bacteria

unicellular organisms measure the cell density of the population

used for coordination of processes that are only efficient if many do it at the same time

Sources of inspiration: Amorphous computing (1/2)



research of amorphous computing is focused on finding programming paradigms for a 'smart' medium composed of immobile particles

Sources of inspiration: Amorphous computing (2/2)

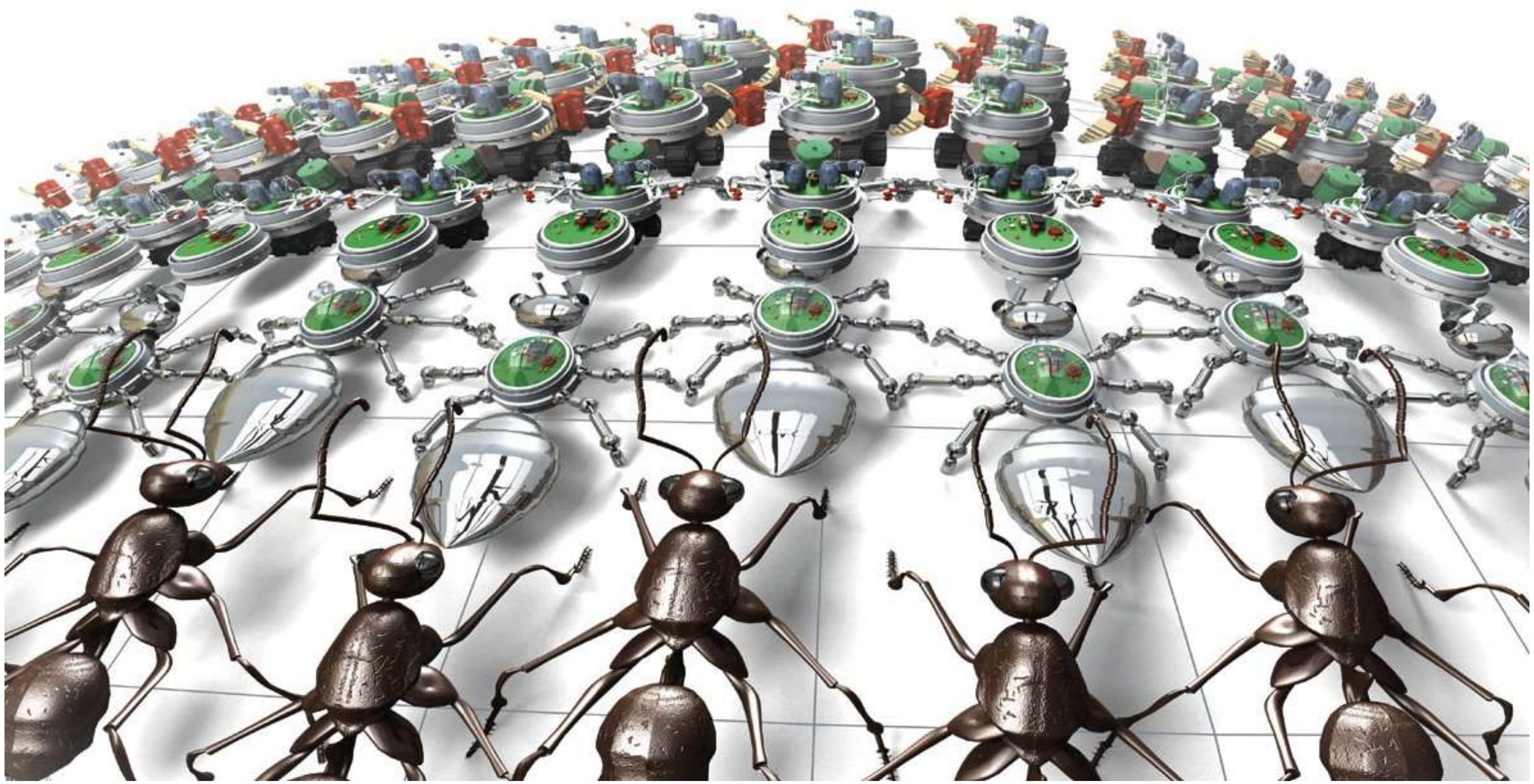
- biologically inspired by the cooperation of cells in natural organisms
- network topology is assumed to be unknown
- generation of self-organizing effects based on local interactions
- research on programming languages that are defined on the continuous
- medium abstraction
- challenge is to find compilers that translate these abstract description into
- executable code for the particles

Abelson et al. (2000)

Example tasks

- aggregation
- self-organization into a lattice
- deployment of distributed antennas or arrays of sensors
- covering of areas
- mapping of the environment
- deployment of maps
- creation of gradients
- goal searching / finding the source of a chemical plume
- homing
- foraging / prey retrieval
- cooperative transport
- mining (stick picking)
- shepherding
- flocking
- containment of oil spills

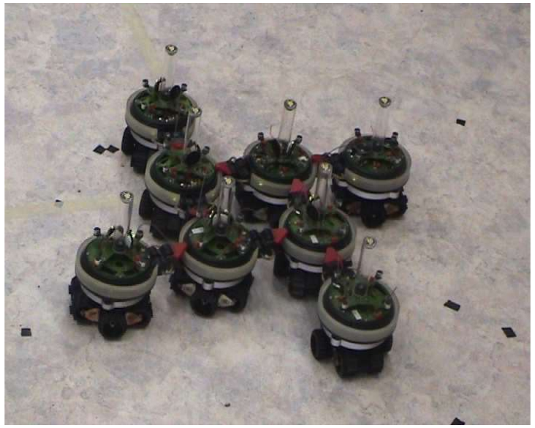
Project Swarm-bots



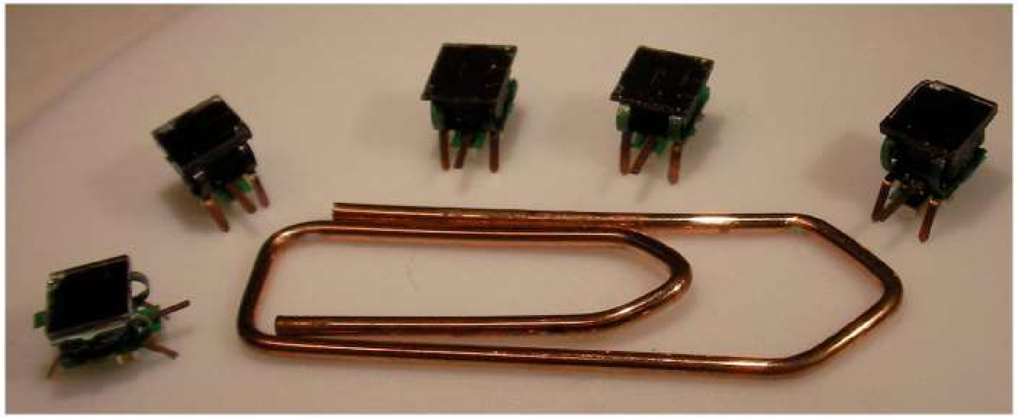
Project Swarm-bots – summary

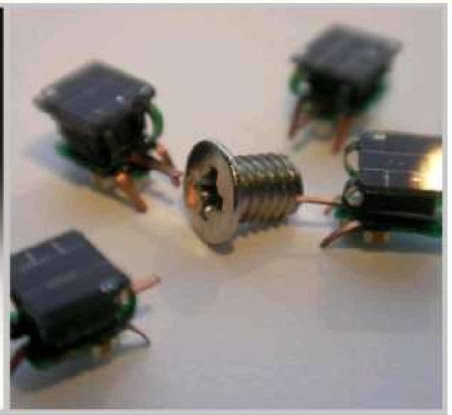
The main scientific objective of the Swarm-bots project is to study a novel approach to the design and implementation of self-organising and self-assembling artefacts. This novel approach finds its theoretical roots in recent studies in swarm intelligence, that is, in studies of the self-organising and self-assembling capabilities shown by social insects and other animal societies.
The main tangible objective of the project is the demonstration of the approach by means of the construction of at least one of such artefact. We intend to construct a swarm-bot. That is, an artefact composed of a number of simpler, insect-like, robots (s-bots), built out of relatively cheap components, capable of self-assembling and self-organising to adapt to its environment.

Project Swarm-bots – results



Project I-SWARM





Project I-SWARM – summary

The aim of the I-SWARM project is the realisation of a 'real' micro-robot swarm.

More than 100 micro-manufactured autonomous robots will be able for the collective execution of different tasks in the small world. This is achieved by:

the realisation of collective intelligence of these robots

- in terms of co-operation and
- collective perception
- using knowledge and methods of pre-rational intelligence, machine learning, swarm theory and multi-agent systems

The development of advanced micro-robot hardware

- being extremely small (size of a single robot: $3 \times 3 \times 2\ mm^3$)
- by integrating novel actuators for locomotion, miniaturised powering with
- micro solar cells and miniaturised wireless communication
- with ICs for on-board intelligence and
- an integrated tool for the manipulation in the small world.

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