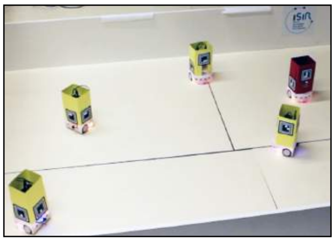
Swarm robotics

(1) Principles (2) Learning



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UE IAR - IA et Robotique
M2 informatique, parcours Androide
rev. 2019-11-29

- Outline of the course
  - Part 1 : principles of swarm robotics
    - Definitions and rationale (check also [Hamman, 2018] for a text book on swarm robotics)
    - Physics of swarms (check also [Bechinger et al., review of modern physics 2016])
    - (Trial&error) top-down approach [Mataric, 1992+][McLurkin, 2004+][Rubenstein, 2014][…]
    - (Bio-inspired) bottom-up approach [Bonabeau et al., 1999] for an introduction][Reynolds, 1984][…]
  - Part 2 : learning and optimisation
    - Brute force optimisation [Werfel et al., 2014][…]
    - Exact and approximate method in RL [Bernstein,2002][Amato, 2014][…]
    - Evolutionary algorithms for collective robotics [Trianni, 2008][…]
    - Lifelong learning for swarm robotics [Bredeche, 2018][…]

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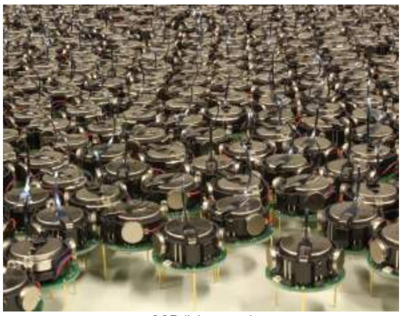
Kiva/Amazon


SSR/Harvard


LIS/EPFL

Collective robotics: multiple robots, acting together, to achieve a common goal.

Swarm robotics: collective robotics with large population of "simple" robots (i.e. *limited computation and communication capabilities*).

=> it is a *distributed* system.

- Applications (mostly prospective!)
  - Warehouse management, container management in ports
  - Mineral mining, agriculture, hazardous waste cleanup
  - Transportation, construction
  - Industrial and household maintenance
  - Search and rescue, security, SLAM and exploration
  - Medical applications: diagnostics, drug delivery
- Classic problems
  - Foraging and coverage
  - Flocking and formation
  - Cooperative manipulation, collective transportation
  - Multiagent observation
  - Traffic control and multi-robots path planning

from: Parker (2008) *Chapter on* Multiple mobile robot systems, *in:* Handbook of Robotics

- Class of problem [Nettleton et al., 2003], adapted from [Capitan et al. 2013]
  - Constraints
    - no central control
    - no common communication facility
    - no local knowledge of the team global topology
  - Expected
    - collective behaviours should emerge from local interaction

Advantages

- Robustness
  - “Fault-tolerance and fail-safety achieved by massive redundancy and the avoidance of single point of failure” [Hamman 2018, pp.6-8]
- Flexibility
  - Robots are interchangeable “due to the quasi-homogeneity, there is no specialisation in terms of hardware” [Hamman 2018, pp.6-8]
- Scalability
  - Each robot interacts with its local neighbourhood, therefore the swarm can “maintain its function while increasing size without the need to redefine the way its parts interact” [Dorigo, 2014, scholarpedia]
- Parallelisation
  - Robots are numerous. Therefore, accomplishing tasks, or learning how to, can be benefit from parallelisation. [Bredeche, 2018]

Tentative classification

Physical structure	**homogeneous**	*or*	heterogeneous
Control	~~centralized~~	*or*	**distributed**
Control design	**by hand**	*or*	**optimised**
Lifelong learning	**none**	*or*	adaptive

homogeneous physical structure does not mean similar behaviours

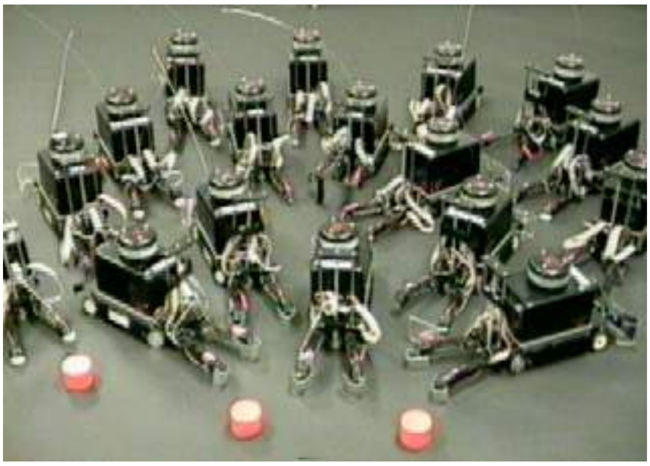
distributed control with full communication is not the same as centralised control

optimised control design covers off-line learning, planification, etc. (i.e. automatic process)

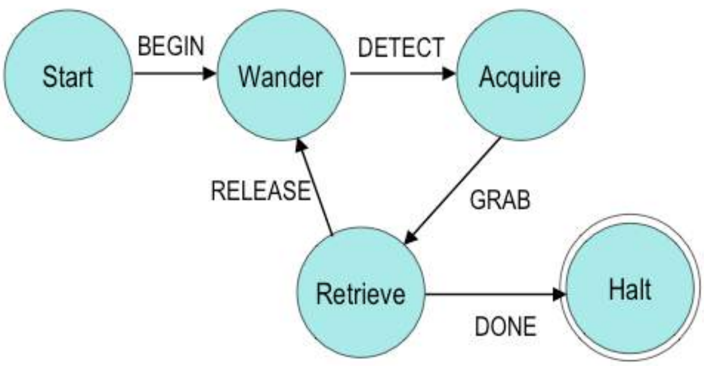
adaptive control at run-time means that response to a similar situation may change

in **bold**: most common cases

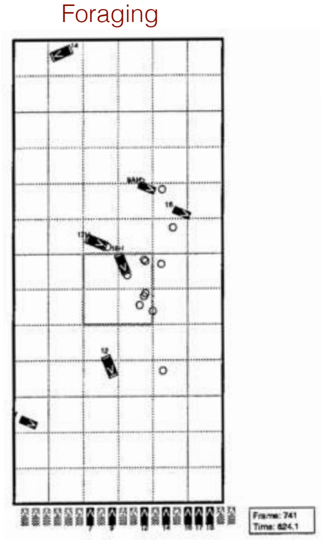
Physical structure	homogeneous
Control	distributed
Control design	by hand
Lifelong learning	none



Physical structure	homogeneous
Control	distributed
Control design	by hand
Lifelong learning	none



Foraging



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Control	distributed
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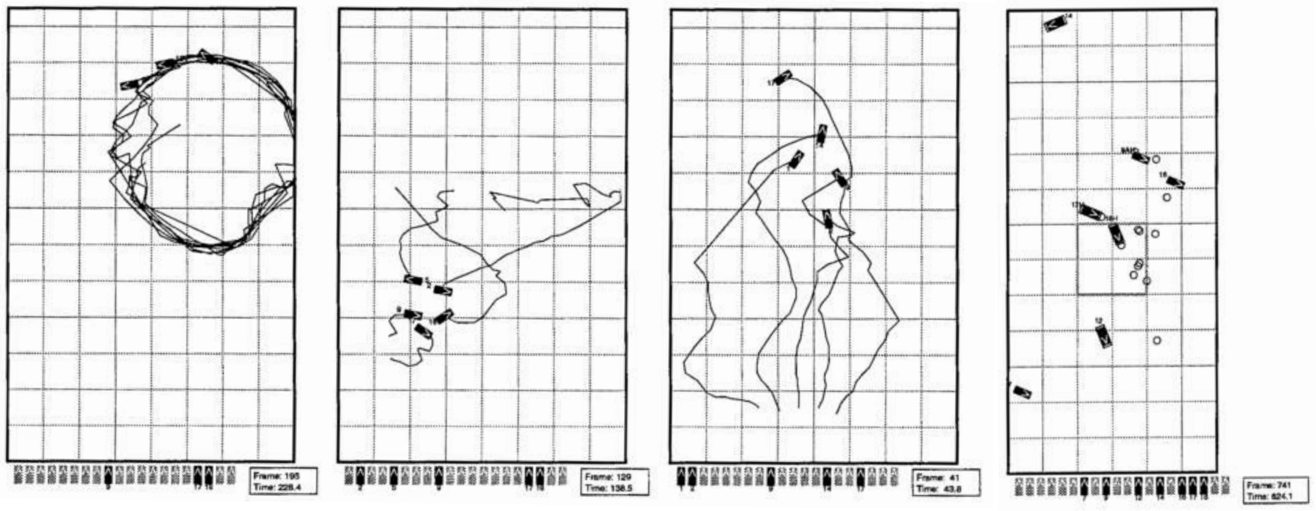
Lifelong learning	none

Following Homing Flocking Foraging



Mataric (1994) Ph.D. Thesis

Physical structure	homogeneous
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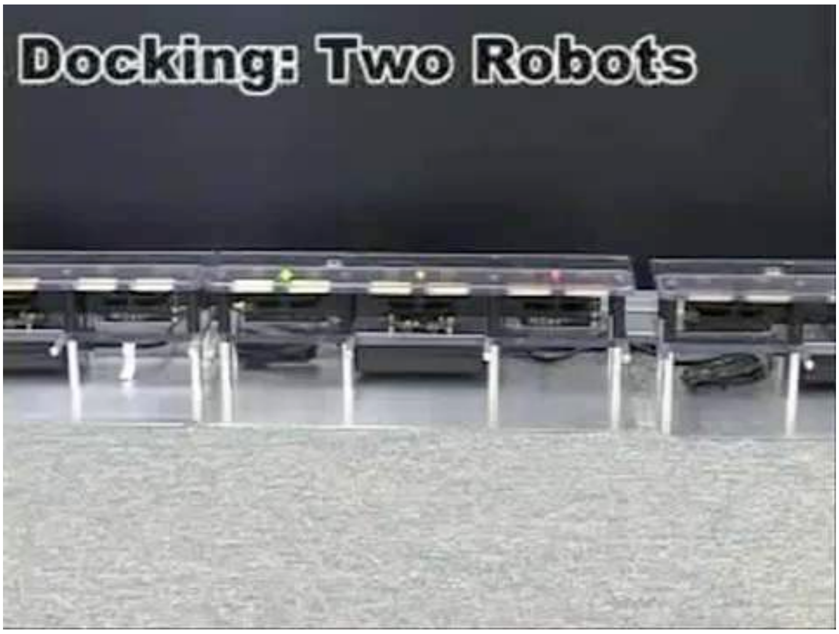


MIT's Swarmbot
James McLurkin, early 2000

Physical structure	heterogeneous
Control	distributed
Control design	by hand
Lifelong learning	none

Definitions and important concepts

How many?

$$3 < N < 10^{23}$$

"not as small as to be dealt with as a few-body problem."

"not as large as to be dealt with statistical averages"

Avogadro constant
$N_A \approx 6.02 \times 10^{23}$ 1/mol

Hamman (2018); Beni (2004)

Self-organization: a spontaneous process where global coordination arises out of local interactions between components of a system (e.g. *nest building in ants/termites/bees, coordinate movements in herd/swarm/schools*).
=> Out-of-equilibrium systems

Is there a benefit?

Self-organization: a spontaneous process where global coordination arises out of local interactions between components of a system (e.g. *nest building in ants/termites/bees, coordinate movements in herd/swarm/schools*).
=> Out-of-equilibrium systems

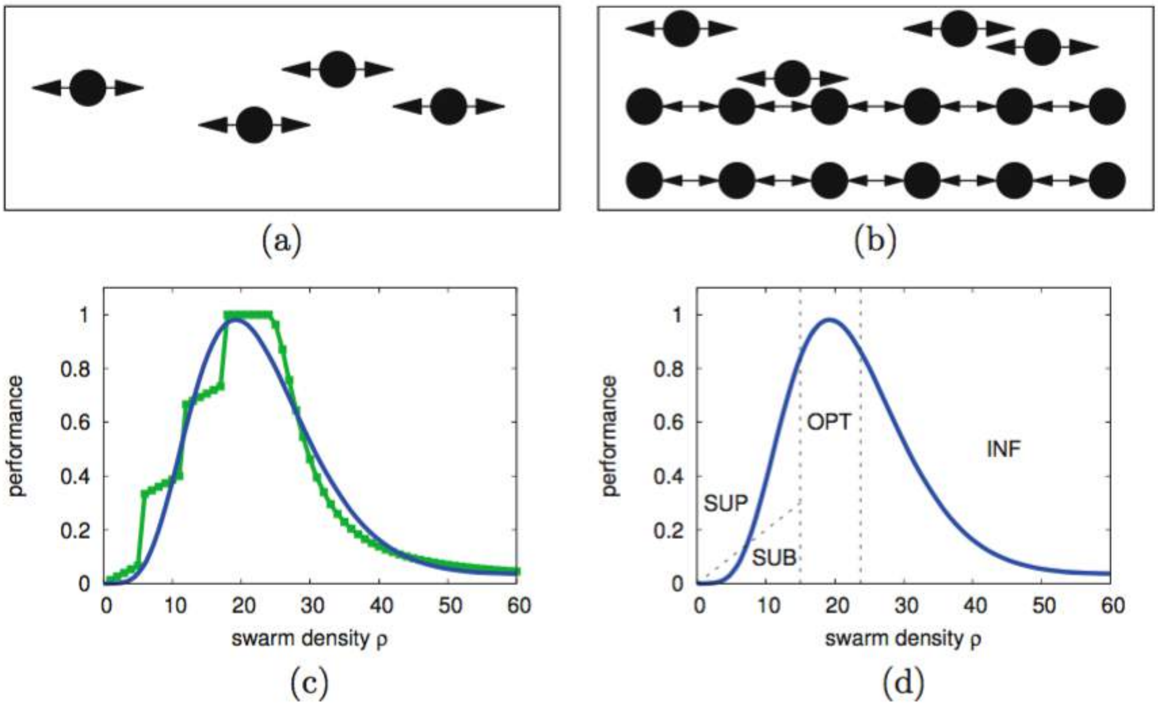
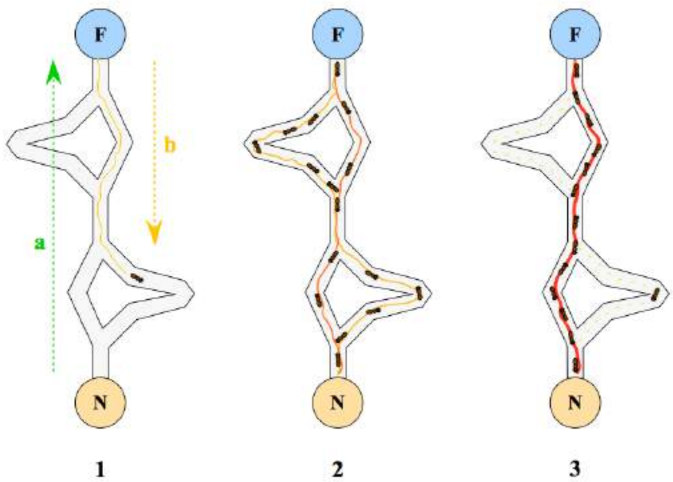


Fig. 1.5 Bucket brigade example for swarm performance (robots have to transport objects back and forth between the left and right side of the robot arena) and typical swarm performance function over swarm density $\rho = N/A$ for a fixed area $A = 1$ (without units). **(a)** Bucket brigade, $N = 4$ robots **(b)** Bucket brigade, $N = 16$ robots **(c)** Bucket brigade, performance. **(d)** Swarm performance showing four regions, SUP: super-linear, SUB: sub-linear, OPT: optimal, INF: **interference**

- Communication
  - explicit communication / signal (e.g. communication channel)
  - implicit communication / cue-based (e.g. stigmergy)
- Micro- and macro-level
  - “Lagrangian”: microscopic models, where individual properties are represented (e.g. velocity and orientation)
  - “Eulerian”: macroscopic models, where only group properties are represented (e.g. density of the swarm as PDE)

H. Hamman (2018) pp.14-15

Images: wikipedia

Stigmergy: indirect coordination between agents through a trace left in a shared environment (e.g. *pheromones*).

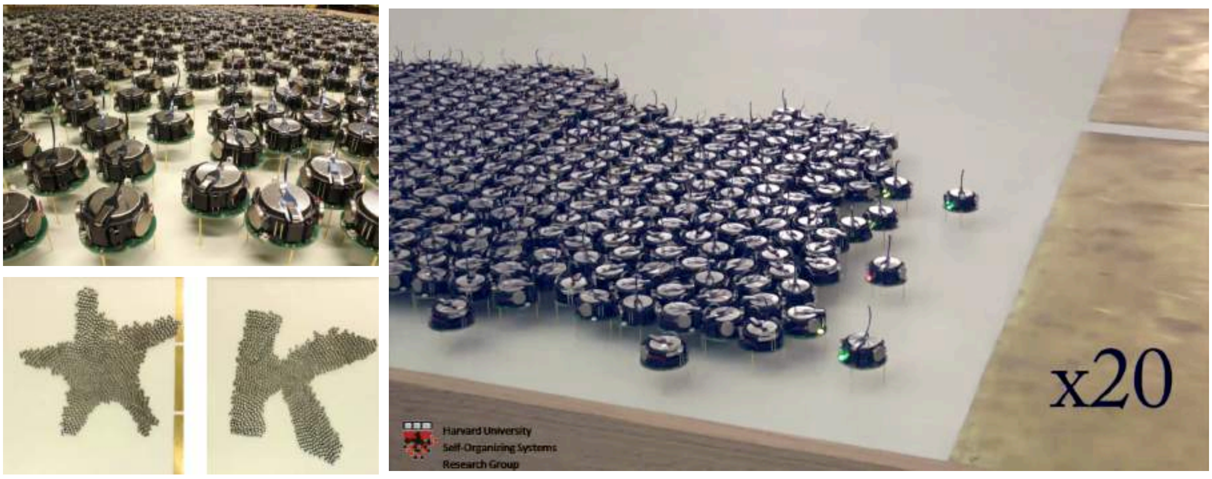
Dorigo et al. (1996) Ant system: optimization by a colony of cooperating agents

- Emergence
  - “the whole is greater than the sum of its parts” (Artistotle)
  - “ the behaviour of the complex system cannot be understood by examining only the components of the system” (Bayindir & Sahin, 2007)

Physical structure	homogeneous
Control	distributed
Control design	by hand
Lifelong learning	none

EU project Swarmbot

Physical structure	homogeneous
Control	distributed
Control design	by hand
Control at run-time	fixed



Science AAAS

Programmable self-assembly in a thousand-robot swarm
Michael Rubenstein *et al.*
Science **345**, 795 (2014);
DOI: 10.1126/science.1254295

self-assembly

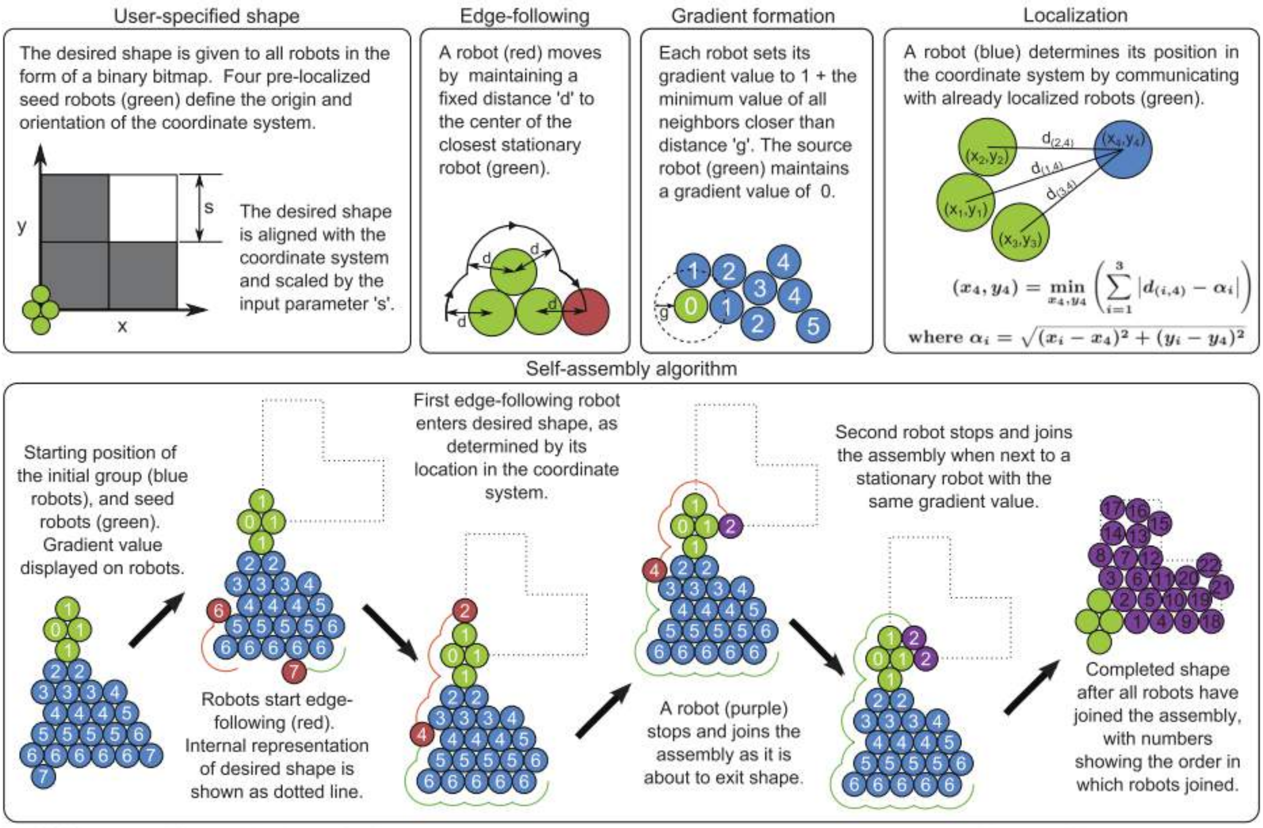
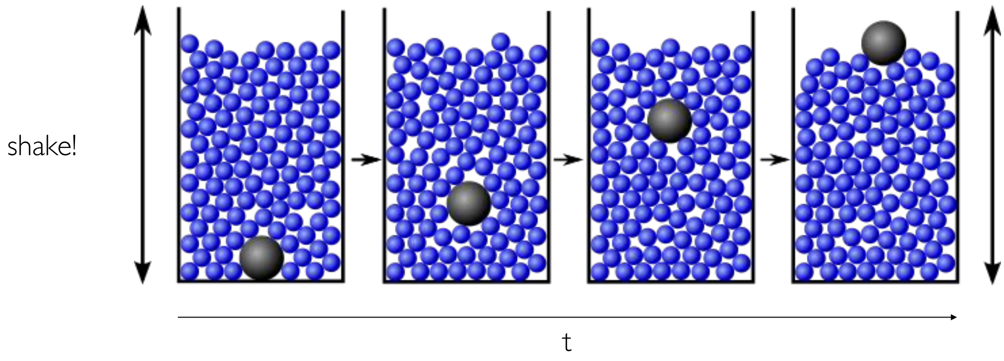


Fig. 2. Collective self-assembly algorithm. Top left: A user-specified shape is given to robots in the form of a picture. Top right: The algorithm relies on three primitive collective behaviors: edge-following, gradient formation, and localization. Bottom: The self-assembly process by which a group of robots forms the user-defined shape.

Granular convection



- Brazil nut effect (Möbius, Nature 2001)
  - sorting effect: big grains end up on top
  - How? small grains fill the gaps beneath big grains
  - See also: reverse Brazil nut effect (cone-shaped)

Collective sorting

Figure 1: A segregation pattern in a swarm of 20 e-puck robots. The robots have organized into a center-periphery pattern around a light bulb. Robots with green and red top markers emulate disks of radius 8 cm and 16 cm, respectively. Each robot's motion is governed by a combination of three components: (i) attraction towards the light bulb, (ii) random motion, and (iii) repulsion from nearby robots.

[Chen et al., AAMAS 2012]

Collective sorting

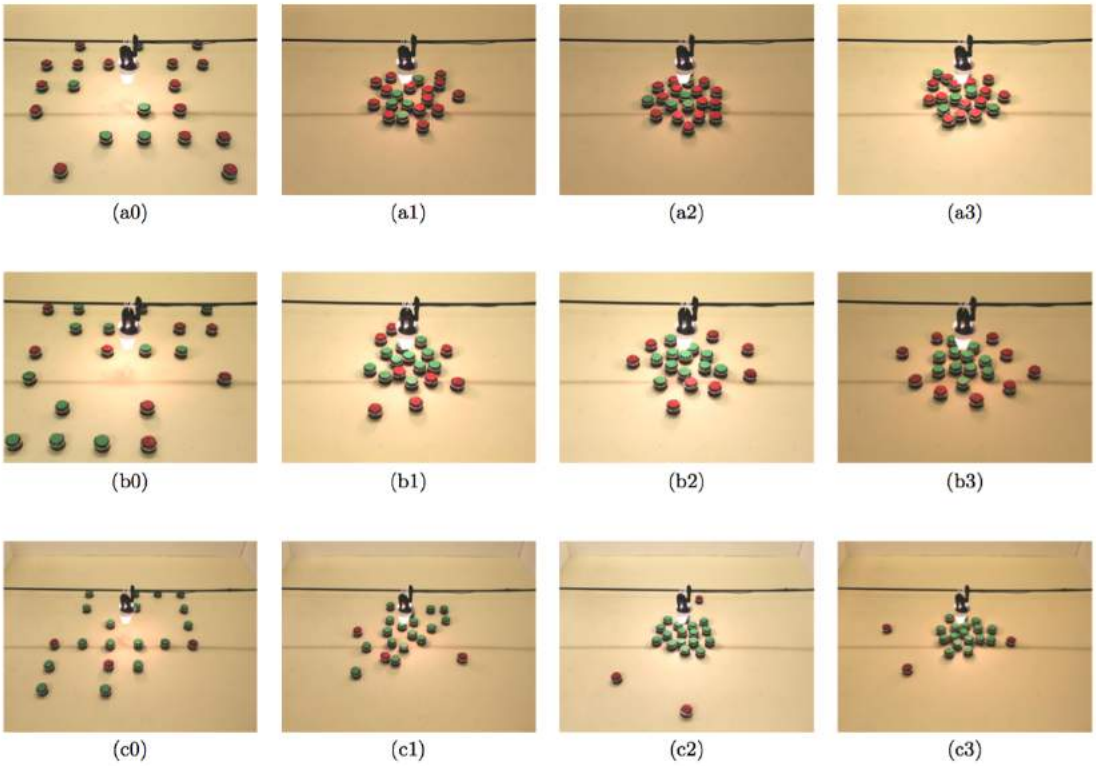


Figure 6: Sequences of snapshots taken during trials with radius factor b equal to 1 (top), 2 (center) and 4 (bottom). Robots with green markers represent disks of 8 cm radius. Robots with red markers represent disks of radius 8 cm (top), 16 cm (center) and 32 cm (bottom). The first and last images in each sequence (from left to right) show the initial and final configurations after 0 and 1200 s. The other two images show intermediate situations.

[Chen et al., AAMAS 2012]

Feedback loops

- Positive feedback
  - e.g. reinforcing alignement
  - limited by available resources
- Negative feedbacks
  - e.g. collision, breaking alignement

"1000's of sheep being herding by sheepdogs from one paddock to another"
credits: Tim Whittaker (www.tim.co.nz)

Sheep cyclone
(a youtube viral video)

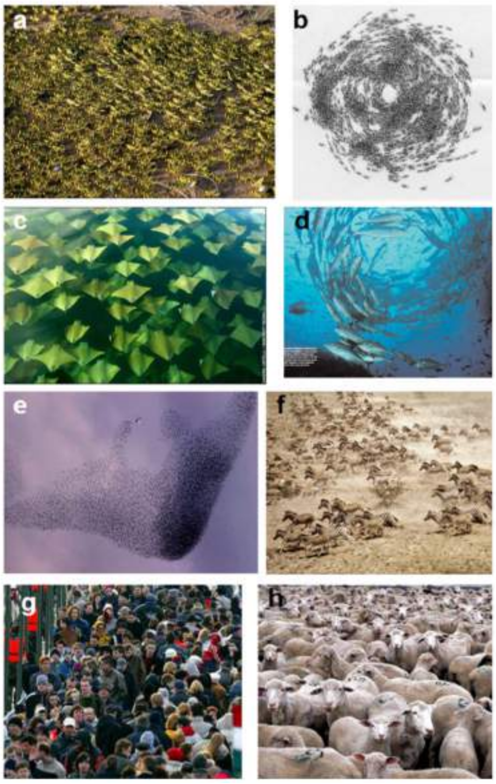


Fig. 1. (Color) A gallery of images related to collective behavior. Among others, it illustrates the possible existence of very general behavioral patterns. (a) Wingless Locusts marching in the field. (b) A rotating colony of army ants. (c) A three-dimensional array of golden rays. (d) Fish are known to produce such vortices. (e) Before roosting, thousands of starlings producing a fascinating aerial display. They are also trying to avoid a predator bird close to the central, finger-like structure. (f) A herd of zebra. (g) People spontaneously ordered into "traffic lanes" as they cross a pedestrian bridge in large numbers. (h) Although sheep are known to move very coherently, just as the corresponding theory predicts, when simply hanging around (no motion), well developed orientational patterns cannot emerge.

Active particles

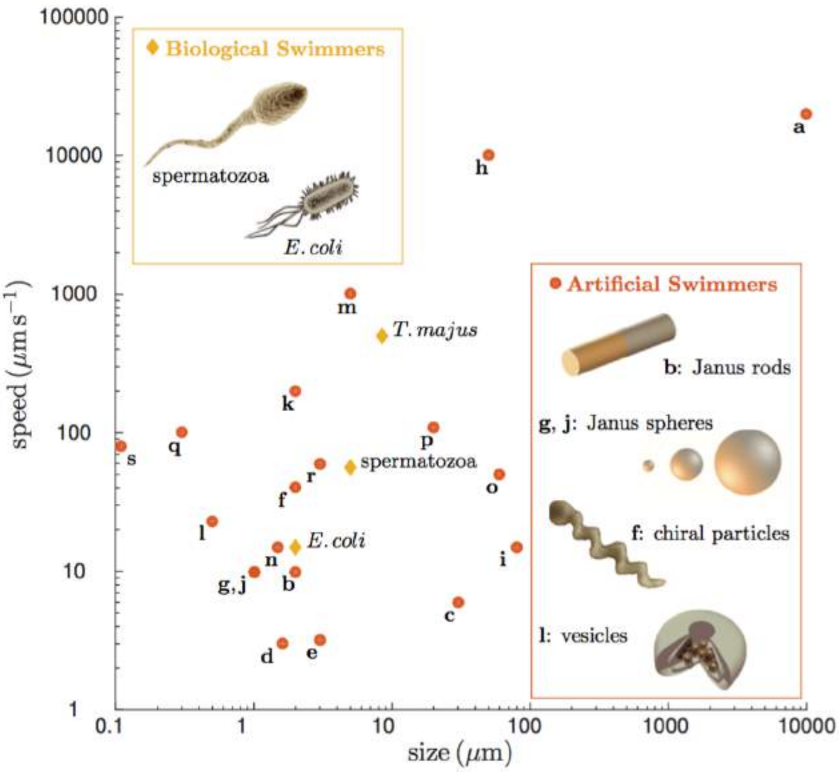


FIG. 1 (Color online) Self-propelled Brownian particles are biological or manmade objects capable of taking up energy from their environment and converting it into directed motion; they are micro- and nanoscopic in size and have propulsion speeds (typically) up to a fraction of a millimeter per second. The letters correspond to the artificial microswimmers in Table I. The insets show examples of biological and artificial swimmers. For the artificial swimmers four main recurrent geometries can be identified so far: Janus rods, Janus spheres, chiral particles, and vesicles.

Vicsek model

normalised random rotation
(uniformly distributed)

fixed

velocity

$$\mathbf{v_i}(t+\Delta t) = v_0 \; (\mathcal{R}_\eta \circ \vartheta) \left[\sum_{j \in \mathcal{S}_i} \mathbf{v_j}(t) \right]$$

particles within
spherical neighbourhood

$$\mathbf{r_i}(t+\Delta t) = \mathbf{r_i}(t) + \Delta t \; \mathbf{v_i}(t+\Delta t)$$

position

Hypotheses
constant speed
small perturbations

Equations from: Chaté et al. (2008) Modelling collective motion: variations on the Vicsek model

Vicsek model (cont.)

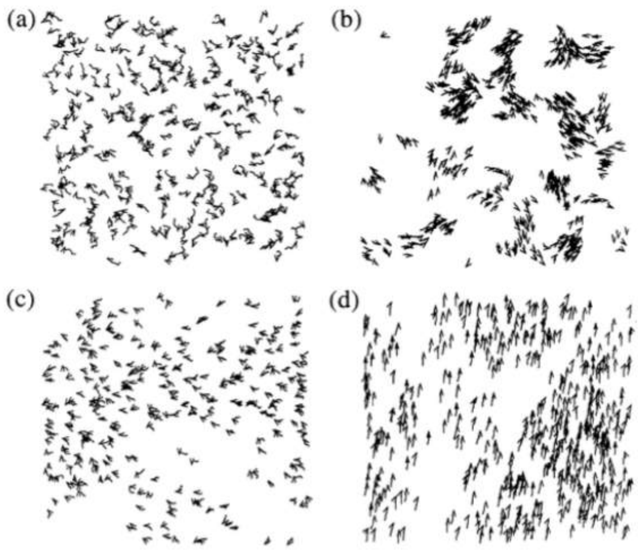


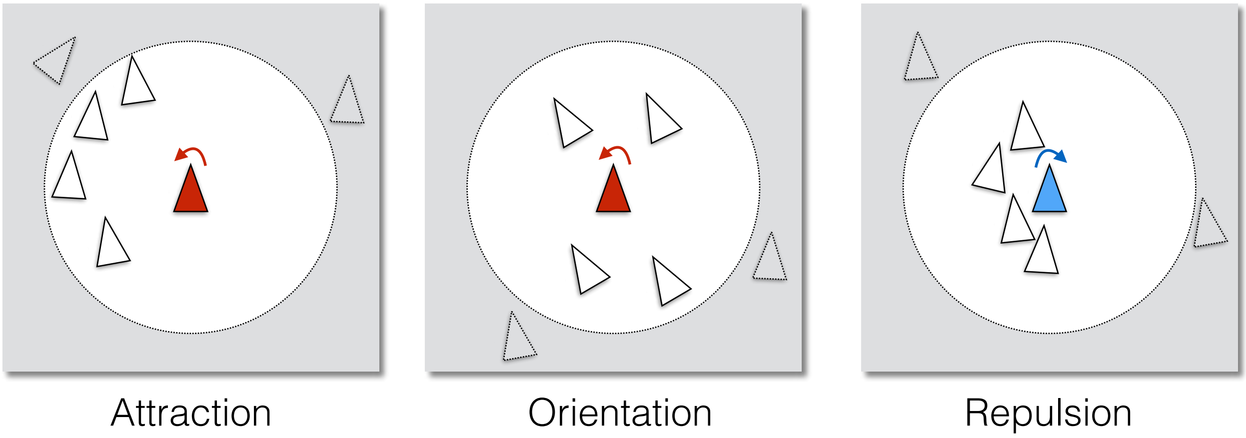
FIG. 1. In this figure the velocities of the particles are displayed for varying values of the density and the noise. The actual velocity of a particle is indicated by a small arrow, while their trajectory for the last 20 time steps is shown by a short continuous curve. The number of particles is $N = 300$ in each case. (a) $t = 0$, $L = 7$, $\eta = 2.0$. (b) For small densities and noise the particles tend to form groups moving coherently in random directions, here $L = 25$, $\eta = 0.1$. (c) After some time at higher densities and noise ($L = 7$, $\eta = 2.0$) the particles move randomly with some correlation. (d) For higher density and *small noise* ($L = 5$, $\eta = 0.1$) the motion becomes ordered. All of our results shown in Figs. 1–3 were obtained from simulations in which v was set to be equal to 0.03.

Seminal model from [Vicsek, 1995]:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t)\Delta t$$
$$\theta(t+1) = \langle \theta(t) \rangle_r + \Delta\theta$$

Orientation noise (Δt)
- in: $[-\eta/2, \eta/2]$

Density $\rho = N/L^2$
- N = 300
- L = 7 or 25 or 5

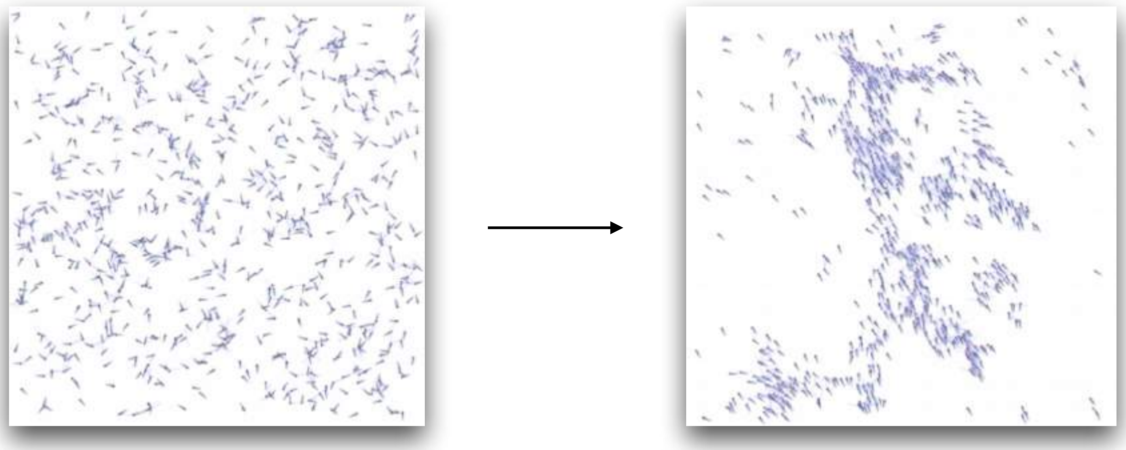


Positive and negative feedbacks
positive feedback: *attraction and orientation rules*
negative feedback: *repulsion rule*

Remark: assume constant speed and limited scope

 Reynolds (1987) Flocks, herds and schools: a distributed behavioral model

Phase transition



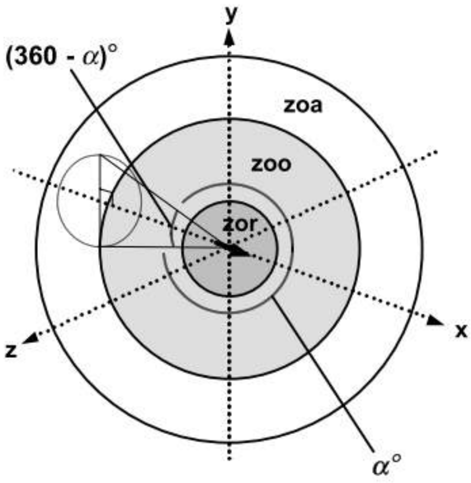
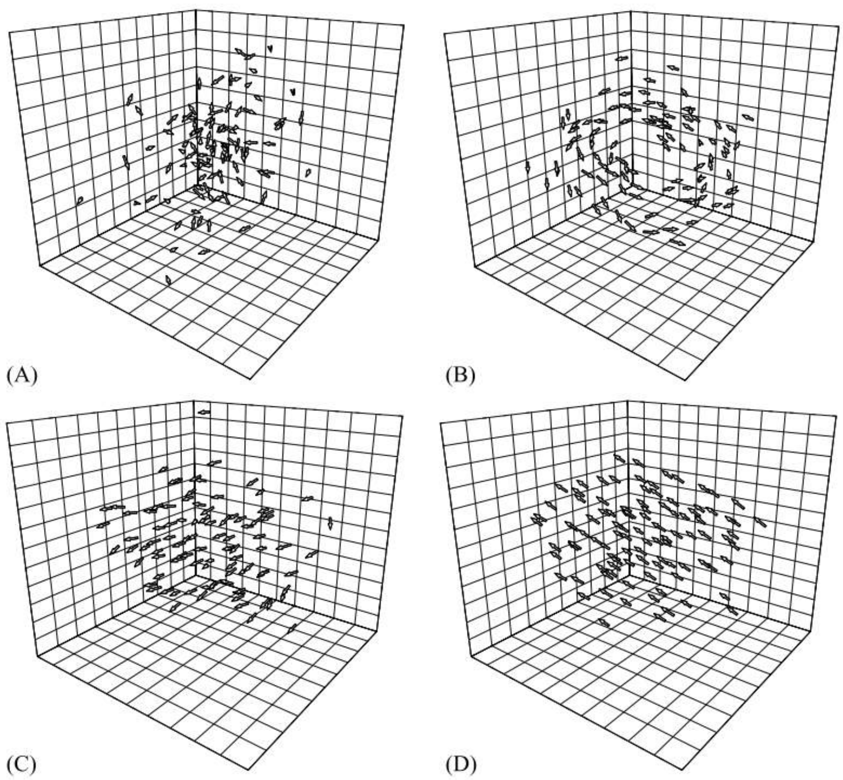


FIG. 1. Representation of an individual in the model centred at the origin: *zor* = zone of repulsion, *zoo* = zone of orientation, *zoa* = zone of attraction. The possible "blind volume" behind an individual is also shown. α = field of perception.

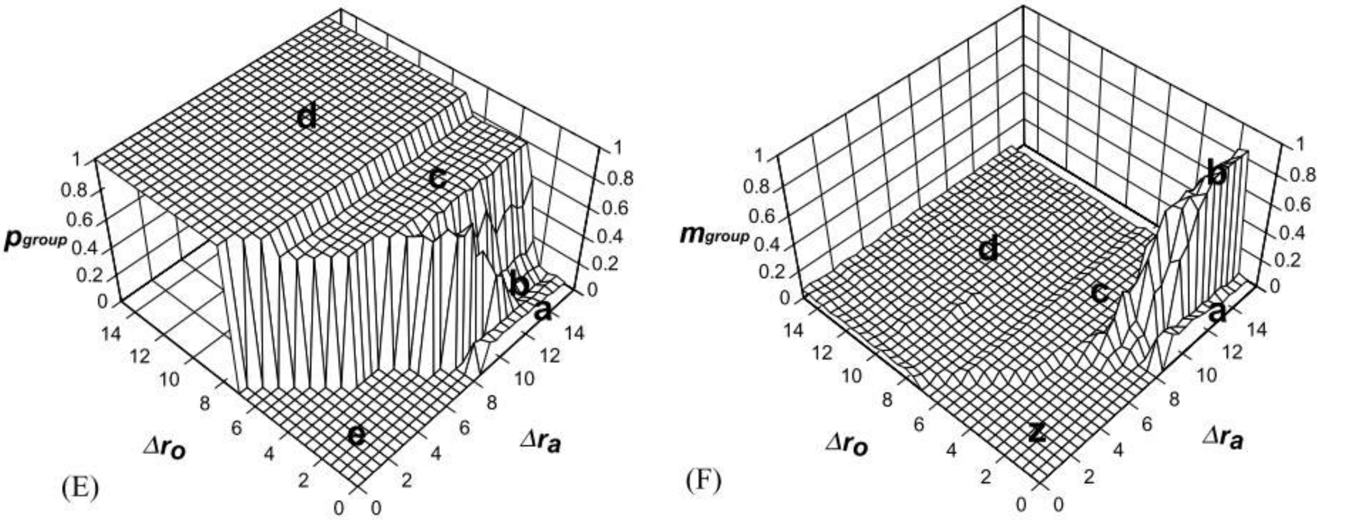
swarm

torus

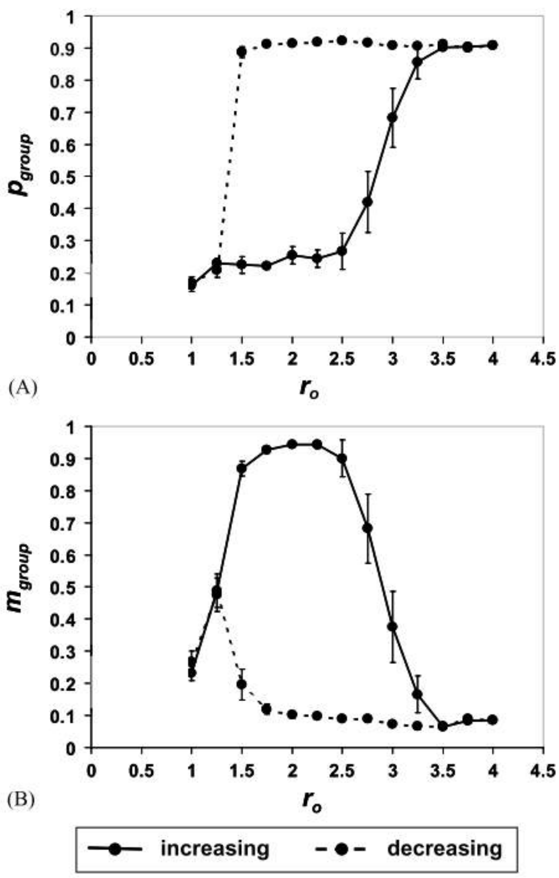


dynamic parallel group

highly parallel group



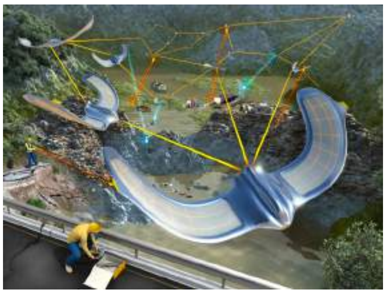
a:	swarm	p_group:	group polarization
b:	torus	m_group:	angular momentum
c:	dynamic parallel	δr_o:	zone of orientation
d:	highly parallel	δr_a:	zone of attraction



Hysteresis
The group patterns that form depend on the previous history of the group.

p_group:	group polarization
m_group:	angular momentum
δr_o:	zone of orientation
δr_a:	zone of attraction

Physical structure	homogeneous
Control	distributed
Control design	by hand ...using pre-evolved behaviours
Lifelong learning	none



Smavnet, EPFL

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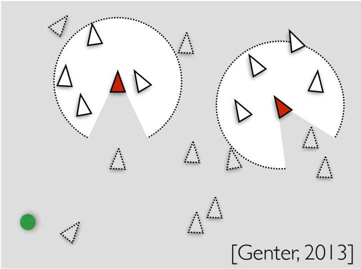
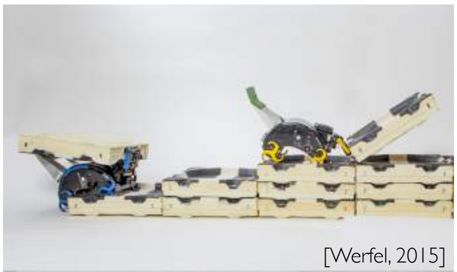
- Specific to autonomous robotic systems
  - open environment
  - incomplete perception
  - noisy action/sensing
  - size of the state and action spaces
  - size of the search space
- Specific to multi-robot systems
  - non-stationary environments (others move too)
  - joint states/actions
  - state transitions are asynchronous & externally induced
  - local utility vs. social welfare

Ad hoc autonomous agent teams problem


Robocup


[Genter, 2013]


[Werfel, 2015]

Problem setting:
N agents
Global utility function
No communication

Challenge: collaboration without pre-coordination

To create an autonomous agent that is able to efficiently and robustly collaborate with previously unknown teammates on tasks to which they are all individually capable of contributing as team members.

 Stone, AAAI 2010

Marginal contribution

Generalisation

Estimating the contribution of each agent in a coalition
cf. cooperative game theory: Shapley value and alike

$$\phi_i(v) = \frac{1}{\text{number of players}} \sum_{\text{coalitions excluding } i} \frac{\text{marginal contribution of } i \text{ to coalition}}{\text{number of coalitions excluding } i \text{ of this size}}$$

[Shapley, 1953]

Possible to estimate the marginal contribution of each agent
But nothing about how to do it in practical (computational cost, unavailability of replays, …)

Decision making in multiagent systems

- Decision making in multi-agent systems
  - Objective: learn the best policies w.r.t. the objective
  - Method: centralised planning for decentralised execution

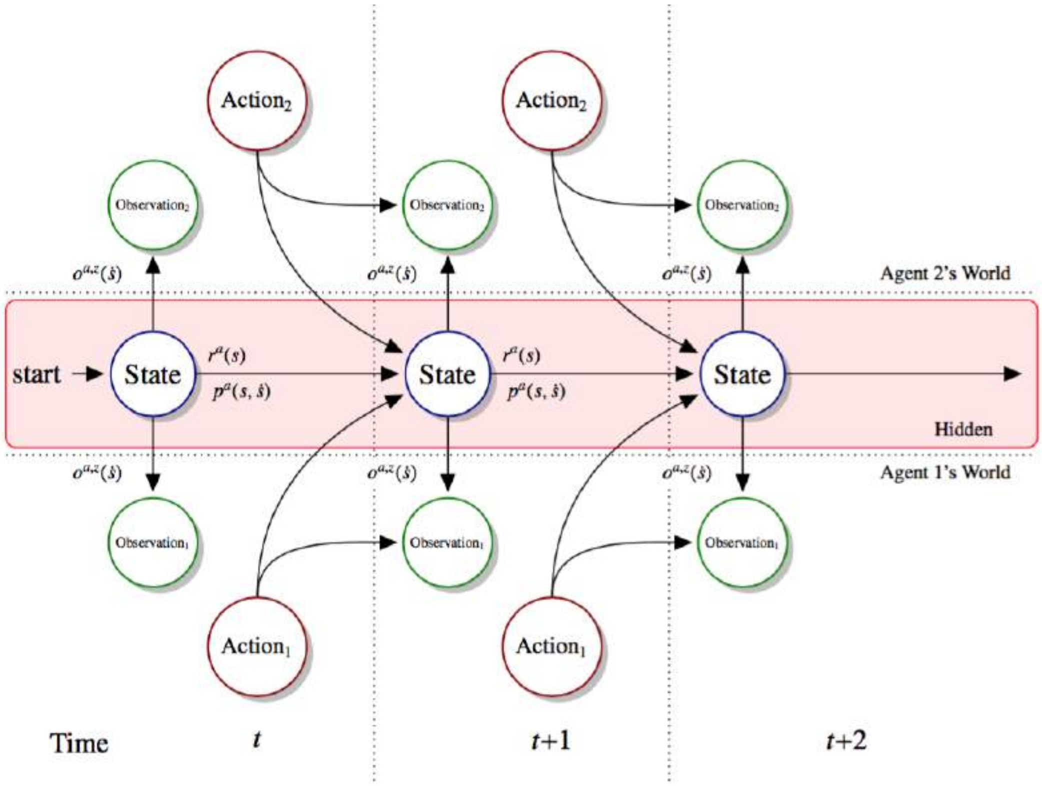


Figure 1: A graphical model of the two-agent Dec-POMDP model.

from: Dibangoye et al. (2016) JAIR

Decision making in multiagent systems

- Assumptions
  - Sequence of discrete « independent » decisions
  - Markovian environment
  - Stochastic models but: uncertainty (sensing/actions) can be accurately captured)
  - Objective encoding (cumulative rewards over time steps, or at least positive reward if success)

Classes of complexity

Observability	General Communication	Free Communication
Full	MMDP (P-complete)	MMDP (P-complete)
Joint Full	DEC-MDP (NEXP-complete)	MMDP (P-complete)
Partial	DEC-POMDP (NEXP-complete)	MPOMDP (PSPACE-complete)

- Observability
  - degree to which agents identify the current state
    - individual
    - collective ($O_1+\ldots+O_n$ uniquely identifies the state)
    - partial collective ($O_1+\ldots+O_n$ partially identifies the state)
- Communication
  - explicit message-passing
    - free: no cost
    - general: costly or limited

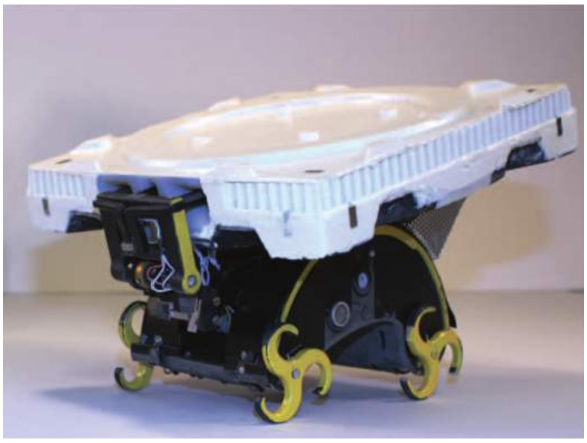
→ Solving a DEC-POMDP is NEXP-complete [Bernstein,2002]

table: AAMAS 2011 Tutorial from Doshi et al. ; original source from [Pynadath&Tambe, 2002]

Methods

- Model-based reinforcement learning
  - Exact & approximate method in MAS [Dibangoye, 2013, 2016][Amato, 2014] cf. UE COCOMA
- Direct policy search
  - Brute force optimisation in a well-chosen search space [Werfel et al., 2014][...]
  - Evolutionary algorithms for collective robotics [Nolfi&Floreano,2000][Trianni,2012]
  - Online distributed evolutionary learning algorithms [Watson,2002][Bredeche,2018]

Physical structure	homogeneous
Control	distributed
Control design	optimized
Control at run-time	fixed



Self-Organizing Systems Research Group

VE RI TAS

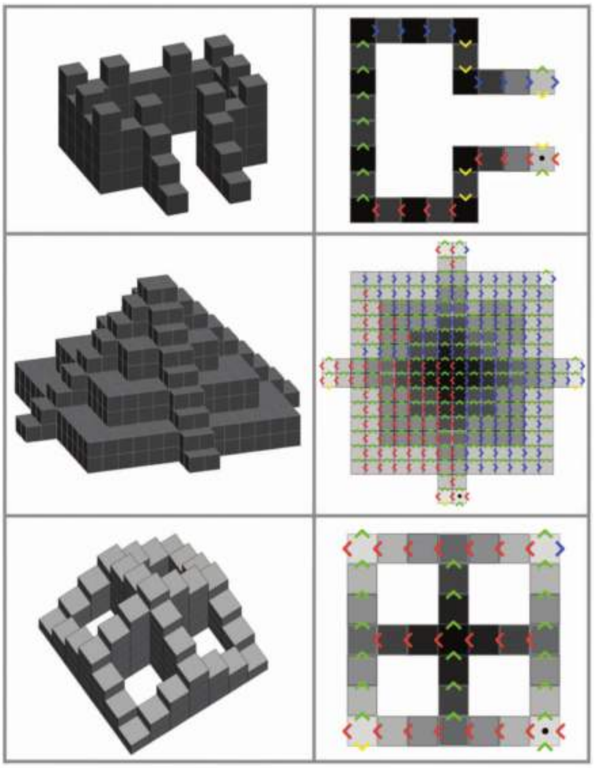
WYSS INSTITUTE

Harvard University
School of Engineering and Applied Sciences
Wyss Institute for Biologically Inspired Engineering

Science AAAS

Designing Collective Behavior in a Termite-Inspired Robot Construction Team
Justin Werfel *et al.*
Science **343**, 754 (2014);
DOI: 10.1126/science.1245842

Fig. 3. Target structures and corresponding structpaths. For each predefined target structure at left, the corresponding structpath representation at right is generated by the offline compiler (*19*). From top to bottom: a simple structure with a unique structpath if the seed location is given; the temple of Fig. 2C, showing one of many possible structpaths; a structure enclosing internal courtyards. Sites in the structpath are shaded according to height (darker = higher); a dot marks the seed brick. Directions are color-coded to clarify flows (red, left; blue, right; green, up; yellow, down).



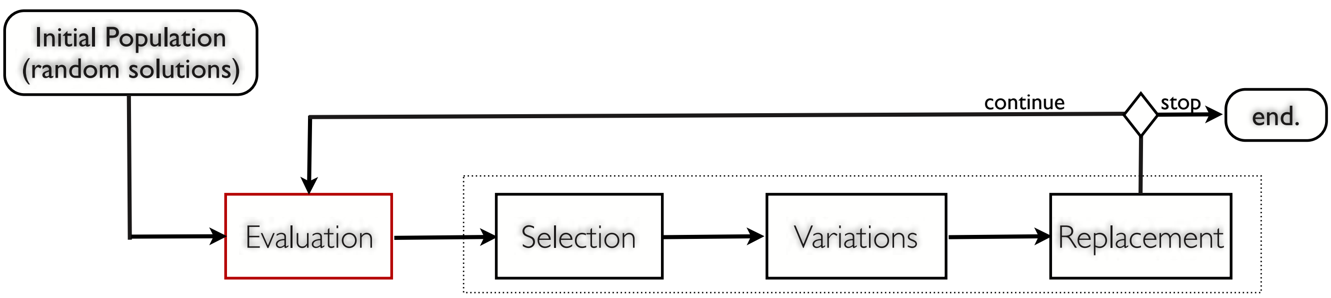
targets *« structpaths »*

Evolutionary swarm robotics

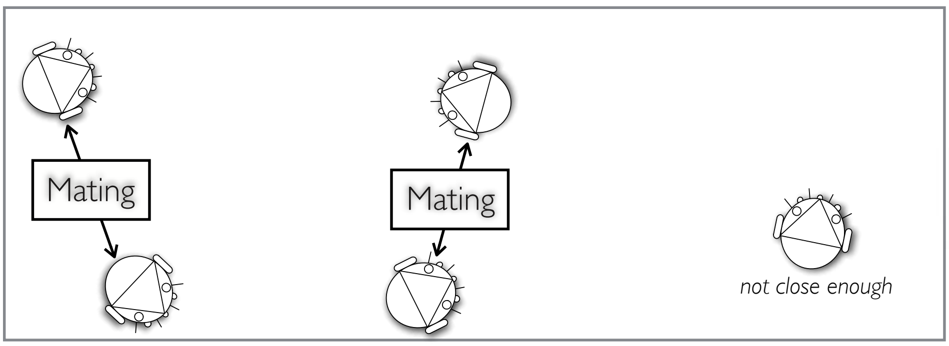
Evolving self-organizing behaviors

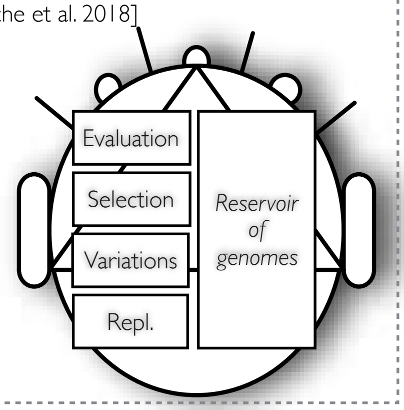
Dual methods

(Off-line) classic evolutionary robotics [Nolfi, Floreano 2000][Trianni et al. 2012]



(On-line) embodied evolution [Watson et al. 2002][Bredeche et al. 2018]



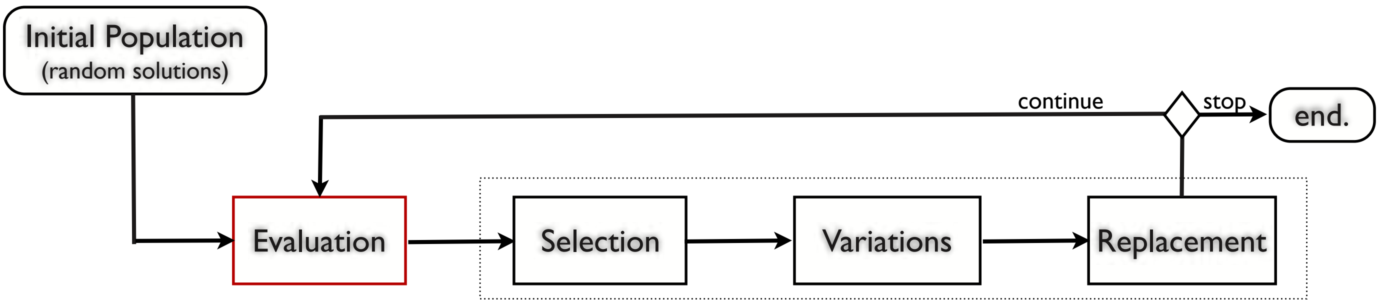


ER as an optimisation method for collective robotics

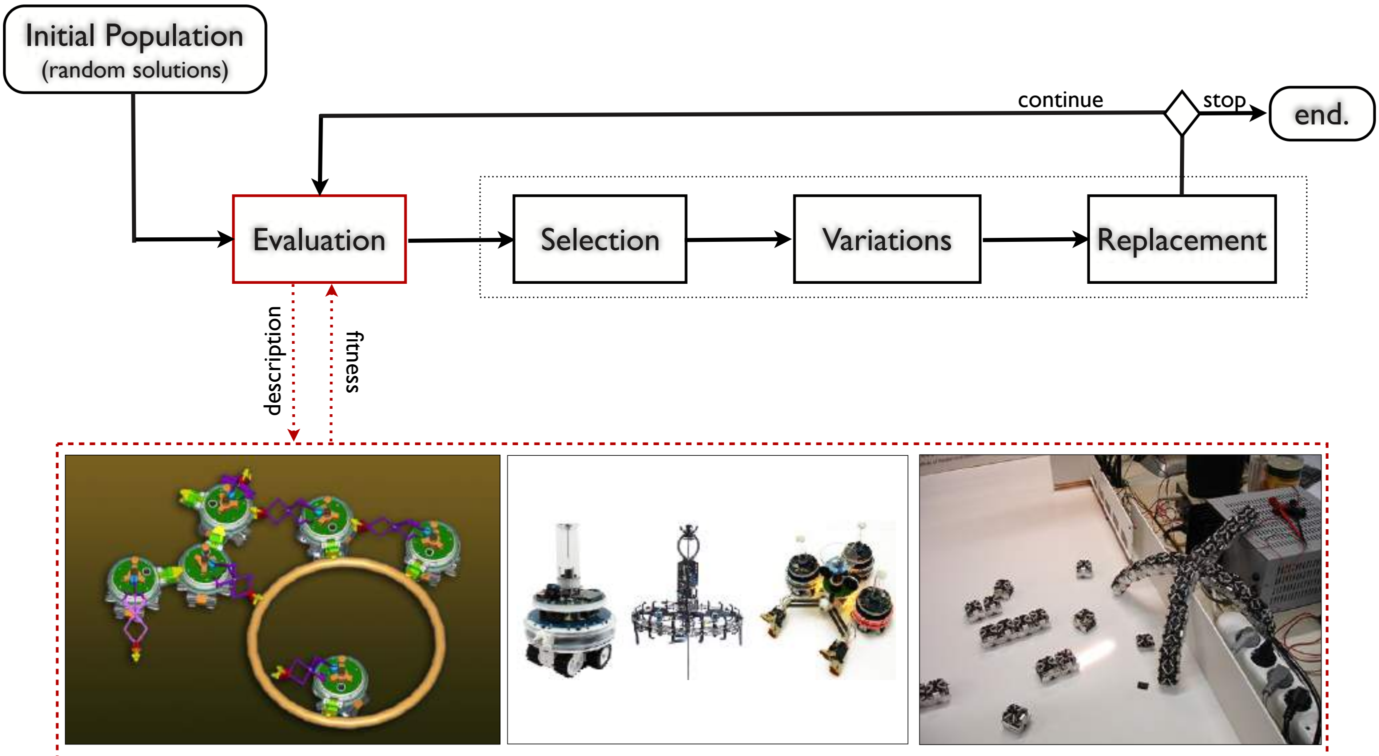
"classic" evolutionary robotics

Optimisation for collective robotics

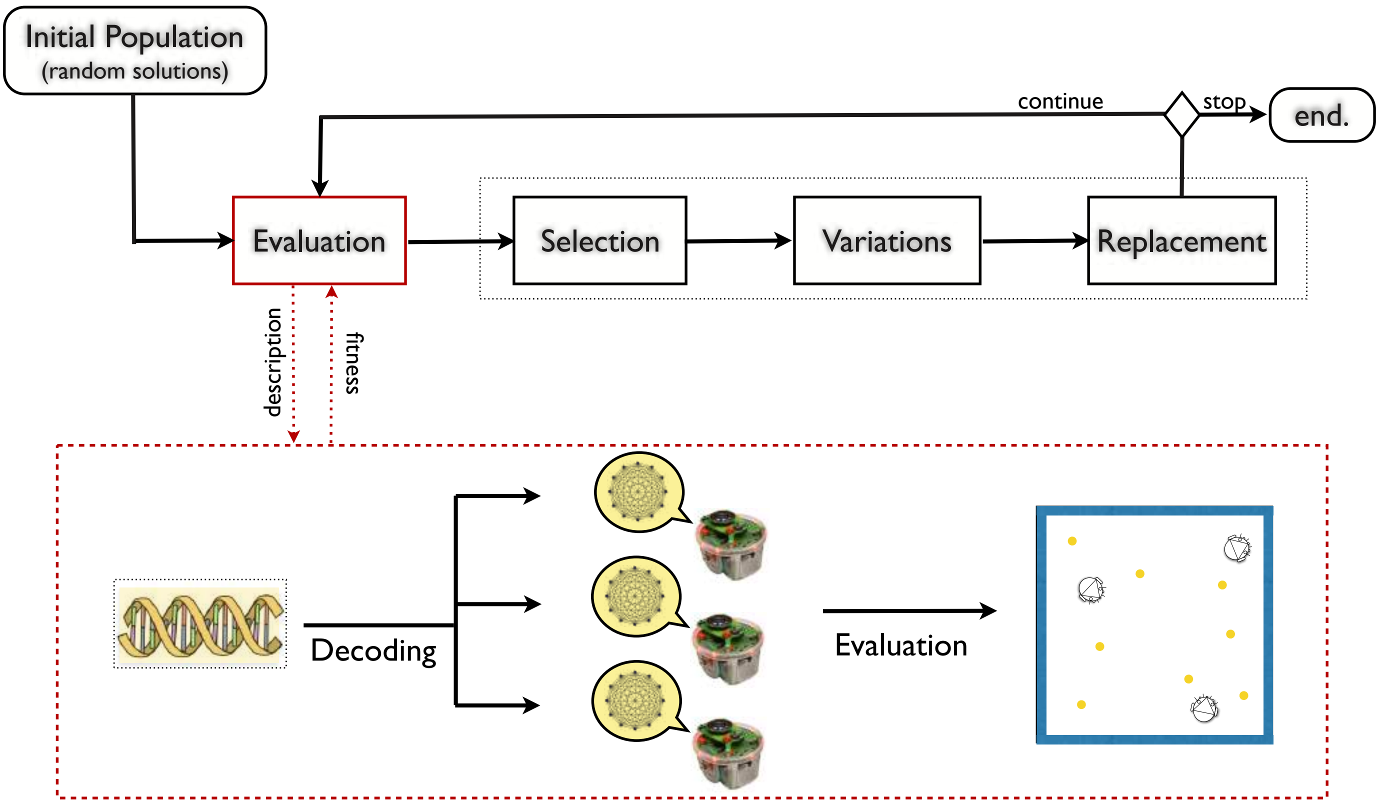
[Nolfi, Floreano 2000][Doncieux et al. 2015]

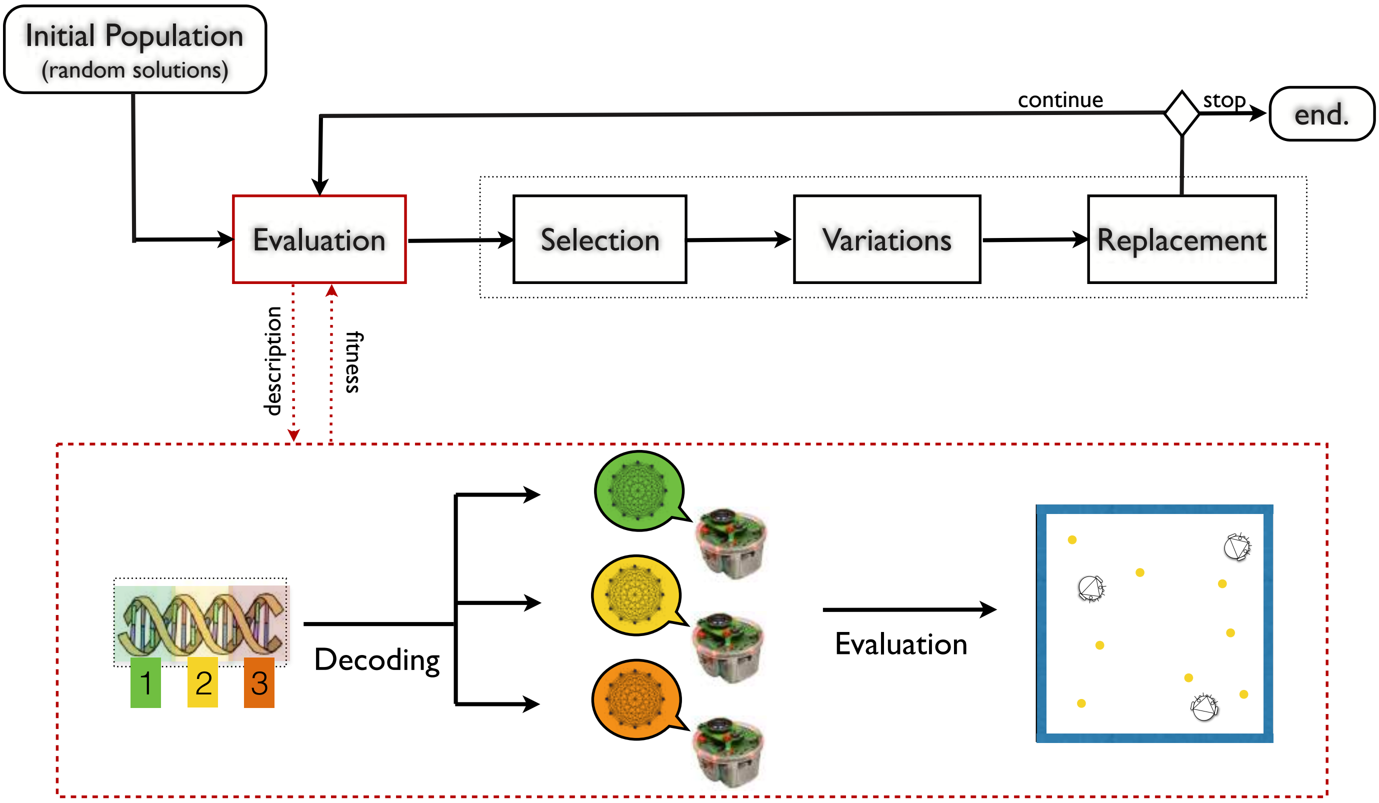


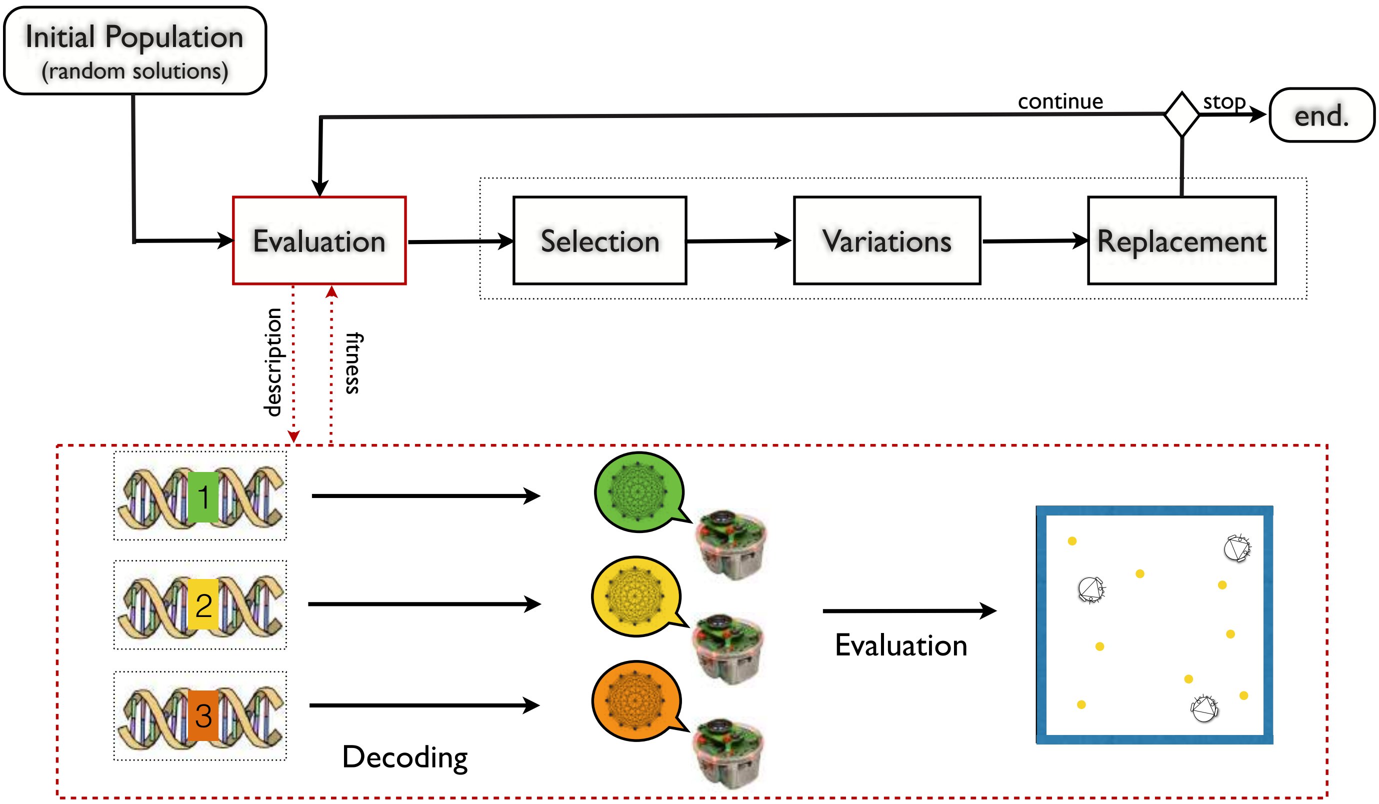
- What?
  - Off-line design method : classic "**evolutionary robotics**" method
  - Optimize in centralized fashion, then used in a distributed fashion
- Expected result
  - A set of <u>policies</u> (*possibly similar*) that can be used within a population of robots to solve a task



Swarm-bots, 2001-2005 Swarmanoid, 2006-2010 Symbrion and Replicator, 2008-2013




Initial Population
(random solutions)
continue
stop
end.
Evaluation
Selection
Variations
Replacement
description
fitness
1
2
3
Decoding
Evaluation


Initial Population
(random solutions)
continue
stop
end.
Evaluation
Selection
Variations
Replacement
description
fitness
1
2
3
Decoding
Evaluation

- Genetic team composition
  - (genetically) homogeneous team
    - easy to use [Baray, 1997][Trianni, 2006], fast to evaluate [Luke, 1997][Richards, 2005]
    - more robust, scale easily [Bryant, 2003]
  - (genetically) heterogeneous team
    - more flexible (e.g. specialists) [Bongard, 2000][Quinn, 2002][Baldassare, 2003][Bernard, 2016]
- Level of selection
  - Team-level
  - Individual-level

Task specialisation with homogeneous team

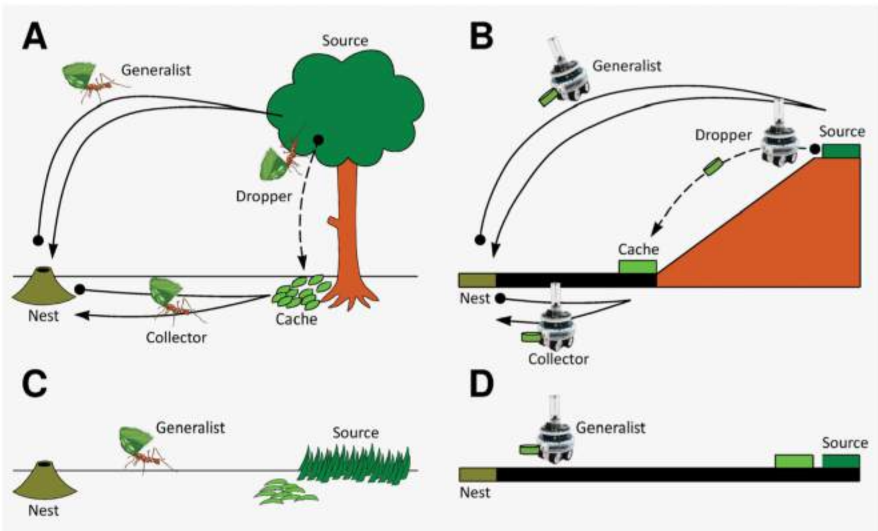


Fig 1. Task partitioning in insects and robots. (a) Task partitioned retrieval of leaf fragments, as found in most *Atta* leafcutter ants that harvest leaves from trees [7,43]. Dropper ants cut leaves which then accumulate in a cache, after which the leaves are retrieved by collectors and brought back to the nest, where they serve as a substrate for a fungus which is farmed as food. Ants also occasionally use a generalist strategy whereby both tasks are performed by the same individuals. (b) Analogous robotics setup, whereby items have to be transported across a slope using the coordinated action of droppers, collectors and possibly generalists. (c) Grass cutting leafcutter ants cutting leaf fragments in a flat environment without task partitioning, using a generalist foraging strategy [49]. (d) Analogous robotics setup, with robots being required to collect items in a flat arena.

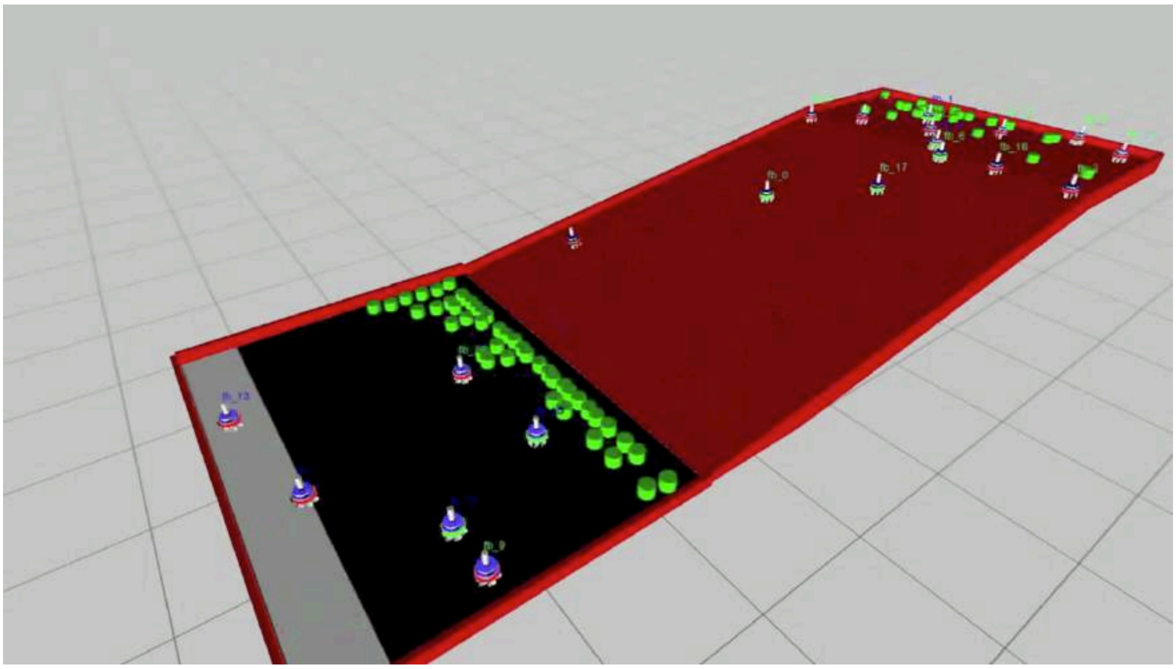
PLOS | COMPUTATIONAL BIOLOGY

Evolution of Self-Organized Task Specialization in Robot Swarms

Eliseo Ferrante[1]*, Ali Emre Turgut[2], Edgar Duéñez-Guzmán[1], Marco Dorigo[3], Tom Wenseleers[1]

DOI:10.1371/journal.pcbi.1004273 August 6, 2015

Experimental setup
Homogeneous team of 4 robots
100 teams, 2000 generations
3 evaluations per team
team fitness: #foraged_items



Selection gradient w/ and w/o slope

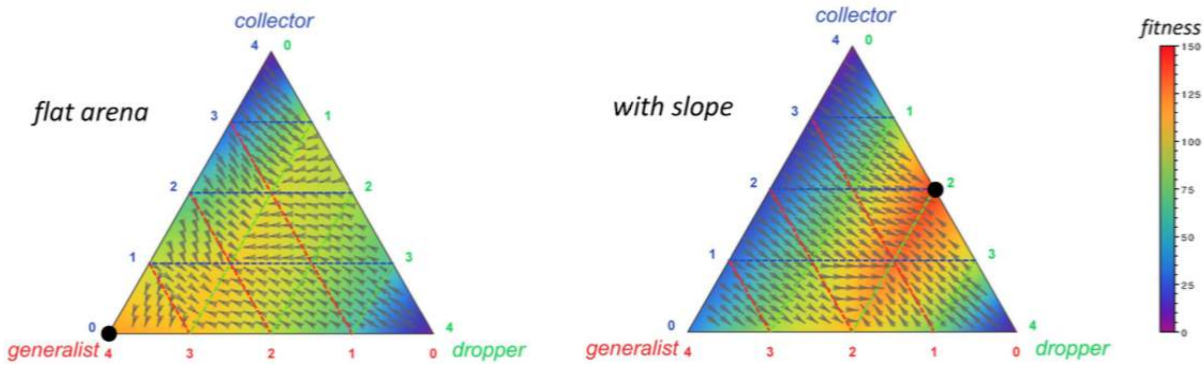


Fig 3. Optimal group composition in 4 robot teams using pre-adapted dropper, collector or generalist foraging strategies (cf. hand-coded rules shown in S1 Table). Ternary plots show group performance (total number of items retrieved to the nest over a period of 5,000 simulated seconds averaged over 10 simulation runs, color coded) as a function of the number of collectors (blue), droppers (green) and generalist foragers (red) in the 4 robot teams (black dot = optimum). In a flat environment **(a)**, teams of generalist foragers achieve optimal performance (cf. S2 Video), whereas in a sloped arena **(b)**, a mix of 2 droppers and 2 collectors is most optimal (cf. S1 Video). Both of these optima are global attractors in their respective fitness landscapes (cf. vectors which represent the phase portrait).

- Conclusions from [Ferrante et al., 2015]
  - Homogeneous teams are capable of task specialisation

Take-home message for "classic" ER for swarm robotics

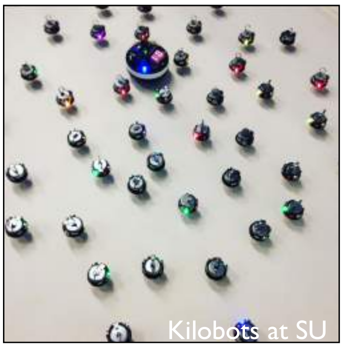
Team composition and level of selection matter
Homogeneous team are capable of specialisation

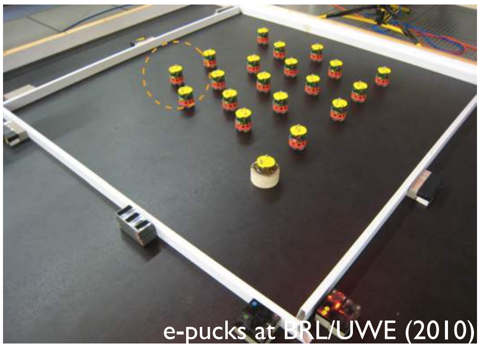
[Waibel et al., 2009, TEC]
[Nitschke et al., 2012, GPEM]
[Brambilla et al., 2012, SI]
[Lichocki et al., 2013, IEEE TEC]
[Tuci et al., 2014, Neural Comp. and Apps.]
[Gomez et al., 2015, AAMAS]
[Bernard et al., 2015, ECAL]
[Bernard et al., 2016, ALIFE]
(…)

ER as an on-line learning method for collective robotics

"embodied" evolutionary robotics

Class of problem





- Open environment
  - environment is unknown prior to deployment, it may change after
  - no «teacher» oversight, robots are “truly” autonomous (learn and move)
- High-level definition of the objective (e.g. maximise foraging)
  - a metric w.r.t. expected result (but no hint w.r.t. expected behaviour)
- Limited capabilities
  - limited computation power (embedded system)
  - limited communication capability (peer-to-peer, low bandwidth)

Objective

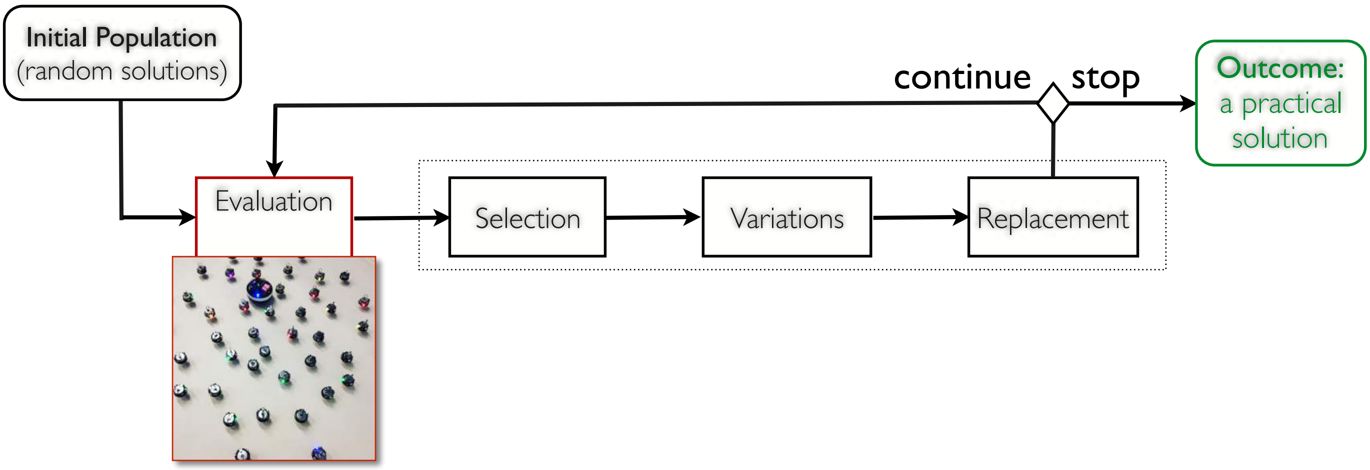
To design distributed on-line learning algorithms

for swarms of simple* autonomous robots

facing open dynamic environments

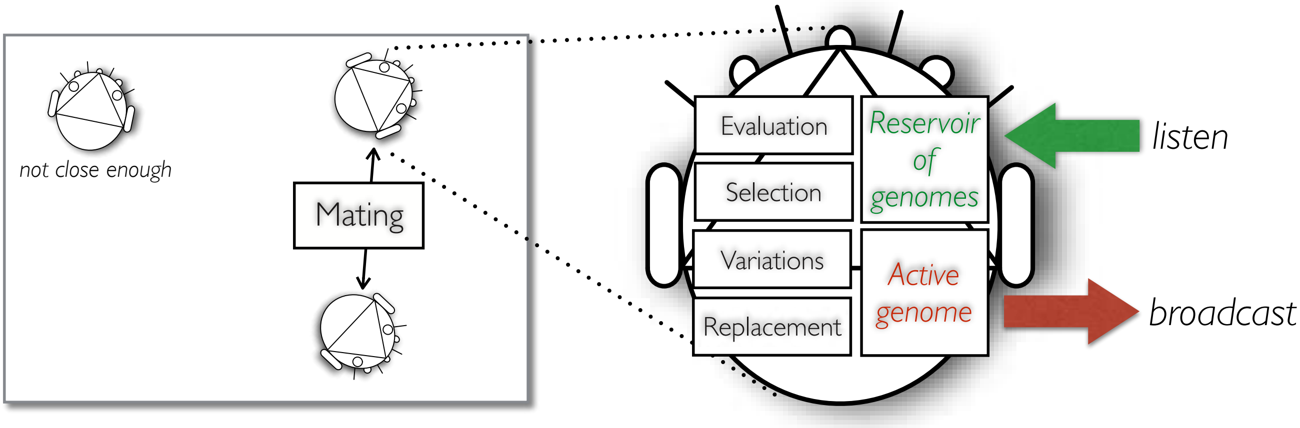
(* i.e. *with limited computation and communication capabilities*)

- Evolutionary robotics [Nolfi, Floreano 2000][Harvey et al., 1997]



- Relevance as a stochastic optimisation method
  - Black-box optimisation
  - Versatile wrt. nature of the search space & objective formulation
  - Process: design <u>then</u> deploy

- Embodied evolutionary robotics [Watson, 2002]



- Relevance as an distributed on-line learning method
  - Each robot encapsulates an evolutionary algorithm
  - “Mating” is constrained by communication capab. (~island model)
  - Process: design the algorithm, deploy, *then* learn


frontiers in Robotics and AI
Embodied Evolution in Collective Robotics: A Review
Nicolas Bredeche, Evert Haasdijk and Abraham Prieto
published: 22 February 2018
doi: 10.3389/frobt.2018.00012

Active genome

e.g.: *parameters in* $\mathbb{R}^n$

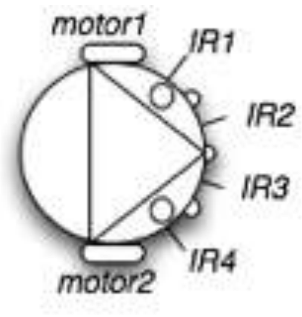
a = +0.31
b = +0.11
c = -1.42
d = +1.6
e = -0.14
f = 0.55
g = -1.17
h = +0.97

Robot controller

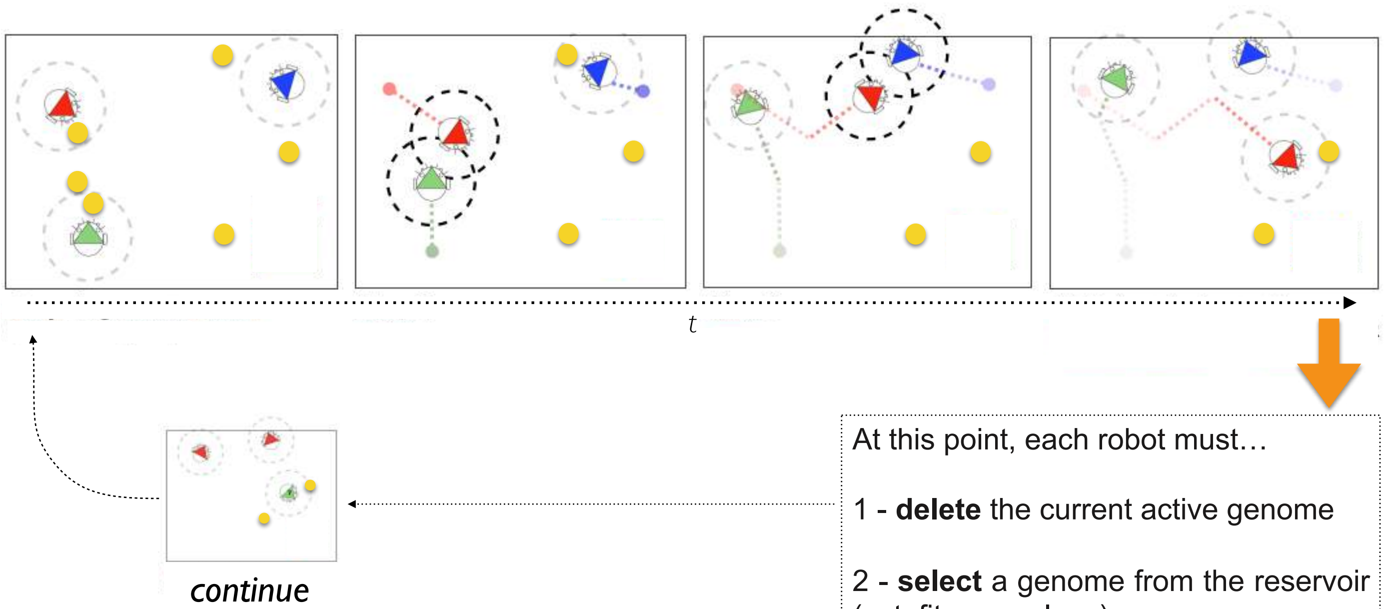
e.g.: *linear combination of sensory inputs and parameters*

motor1 = a*IR_1 + b*IR_2 + c*IR_3 + d*IR_4 + e

motor2 = f*IR_1 + g*IR_2 + h*IR_3 + i*IR_4 + j



IR = Infrared proximity sensors



At this point, each robot must…

1 - **delete** the current active genome

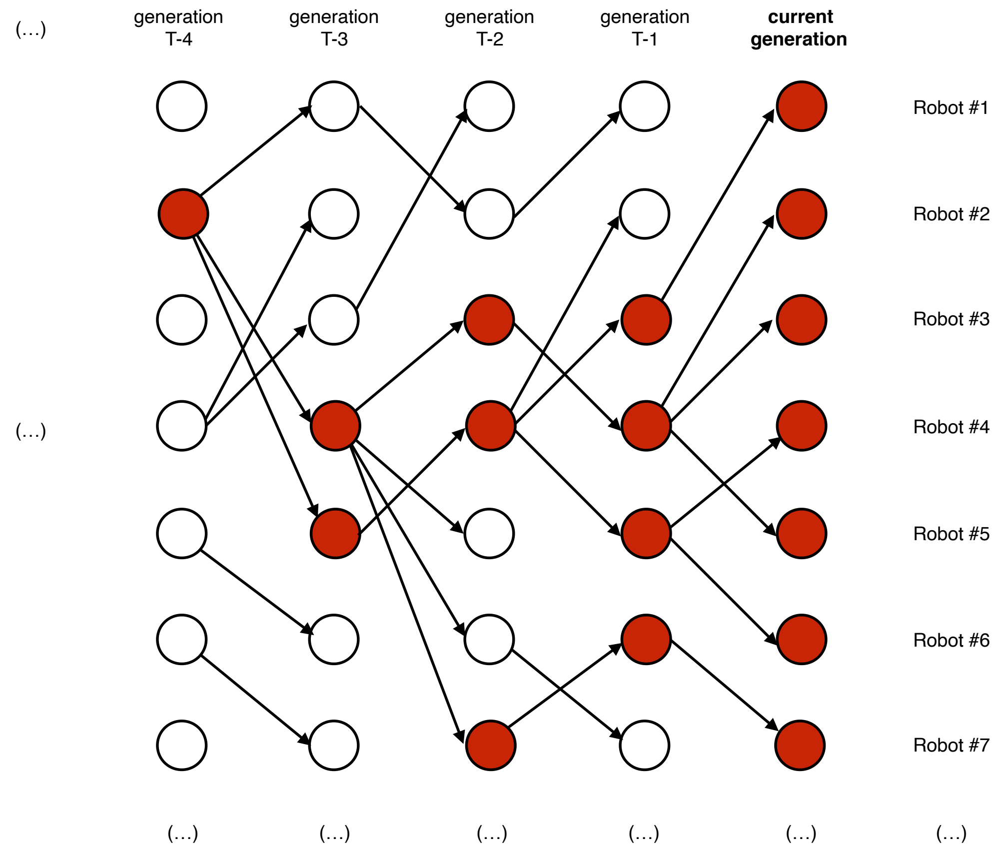
2 - **select** a genome from the reservoir (wrt. fitness values)

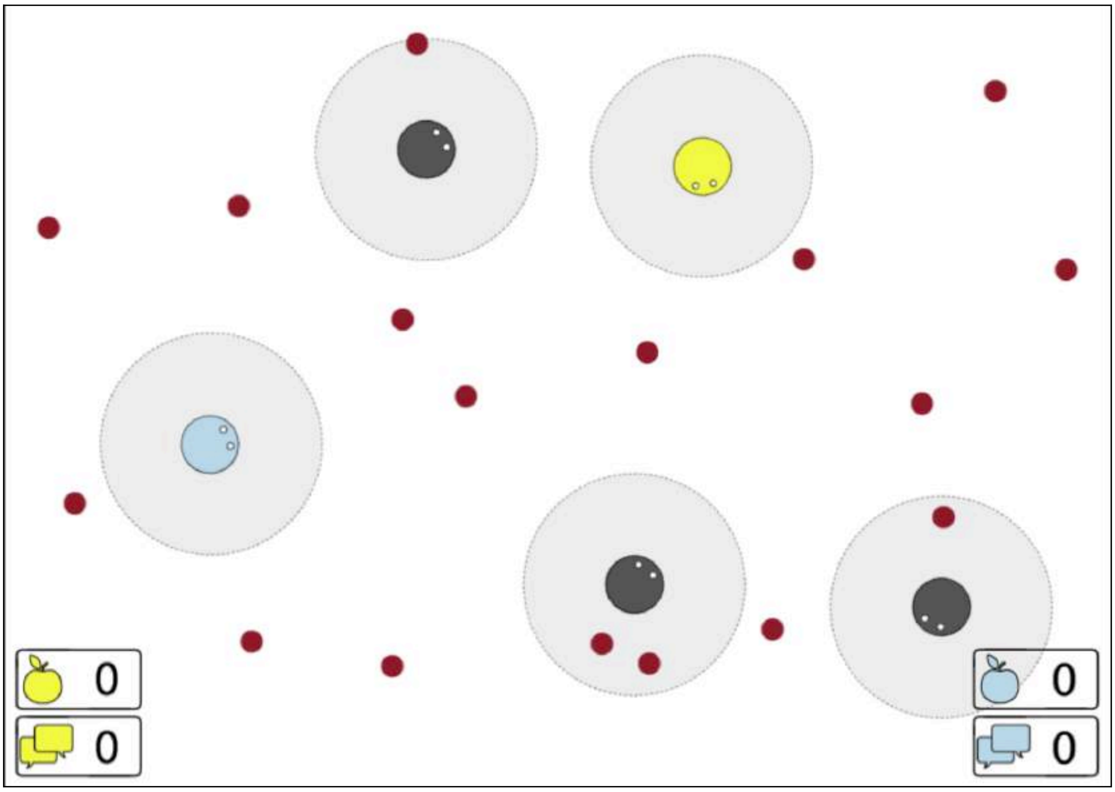
3 - apply **variation** (e.g. gaussian mutation) to the selected genome

4 - **activate** the new genome as active genome (and set up new controller)

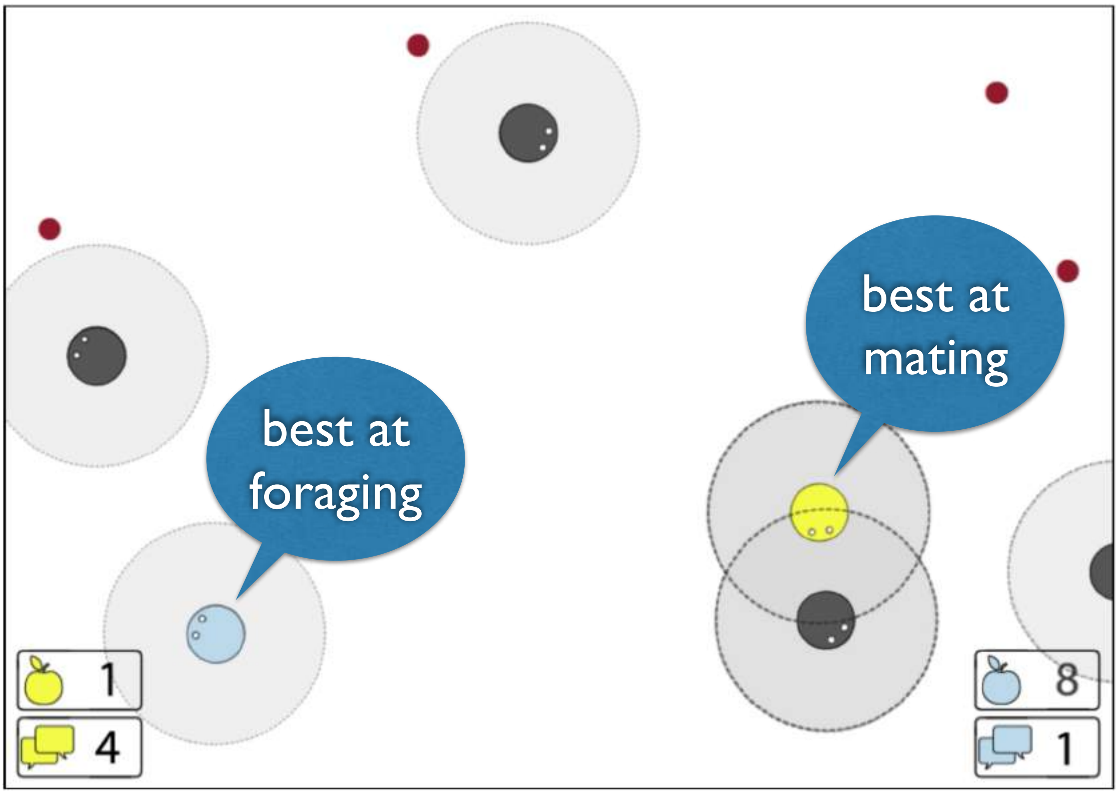
Example with a foraging task

fitness function is the number of foraged items



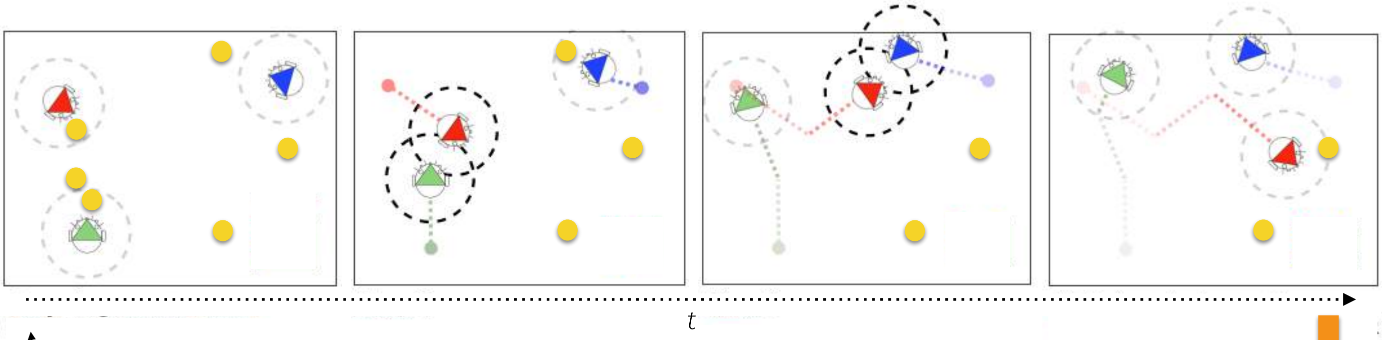


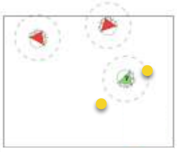
Embodied evolutionary robotics illustrated



Multiple selection pressures!

Selection pressure comes from the environment





continue

At this point, each robot must…

1 - **delete** the current active genome

2 - **select** a **random** genome from the reservoir

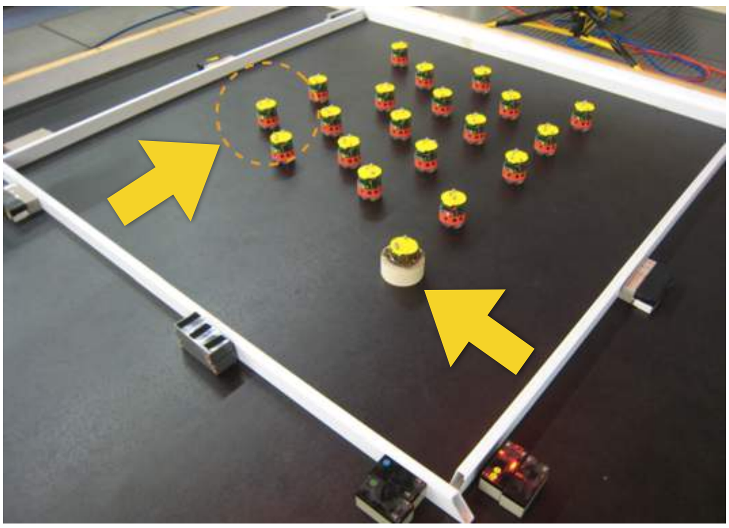
3 - apply **variation** (e.g. gaussian mutation) to the selected genome

4 - **activate** the new genome as active genome (and set up new controller)

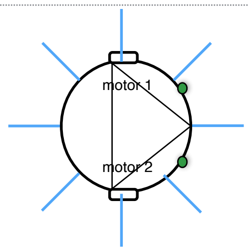
no explicit fitness function

Example with a foraging task

fitness function is the number of foraged items



~19 robots, limited communication, 1 landmark



inputs:
- 8 IR sensors
- 8 bumpets
- orientation wrt. landmark
- distance to landmark

outputs:
- left and right motor speed

control:
- perceptron (38 parameters)

Bredeche et al. (2012) *in:* Math. and Comp. Modelling of Dynamical Systems

http://www.youtube.com/watch?v=_ilRGcJN2nA

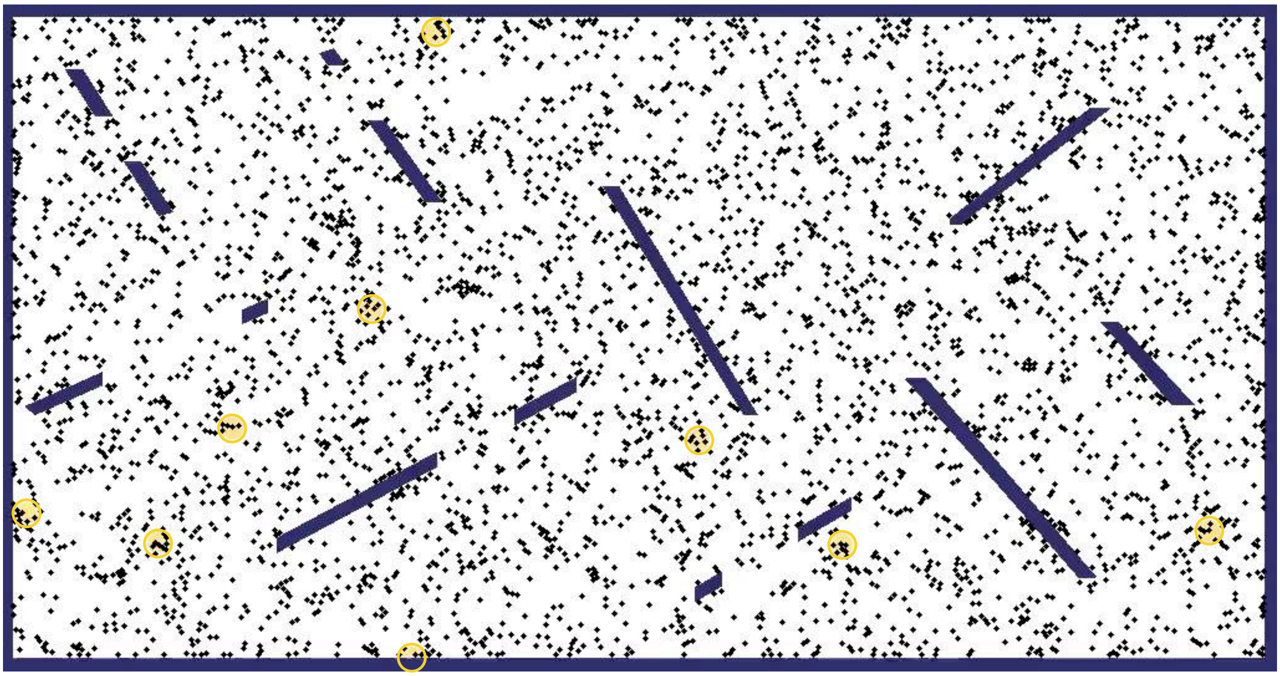
Environment-driven distributed evolutionary adaptation in a population of autonomous robotic agents

Nicolas Bredeche, J-M Montanier, W. Liu, A. F. Winfield

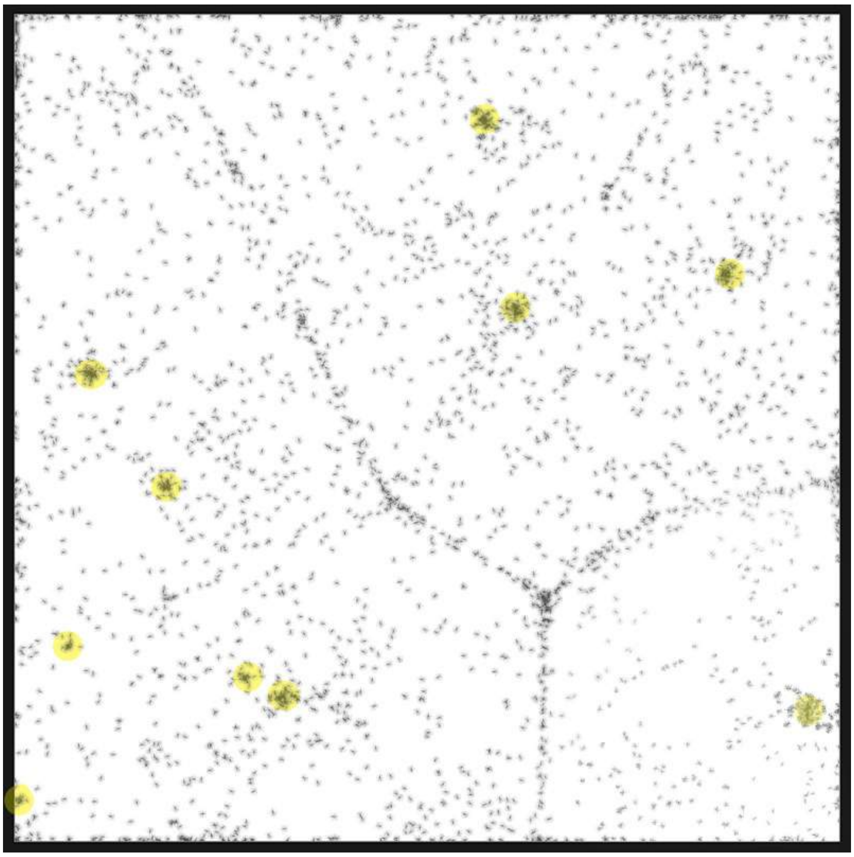
Mathematical and Computer Modelling of Dynamical Systems, Volume 18, Issue 1, 2012

[Bredeche et al., MCMDS 2012]

4000 robots in simulation

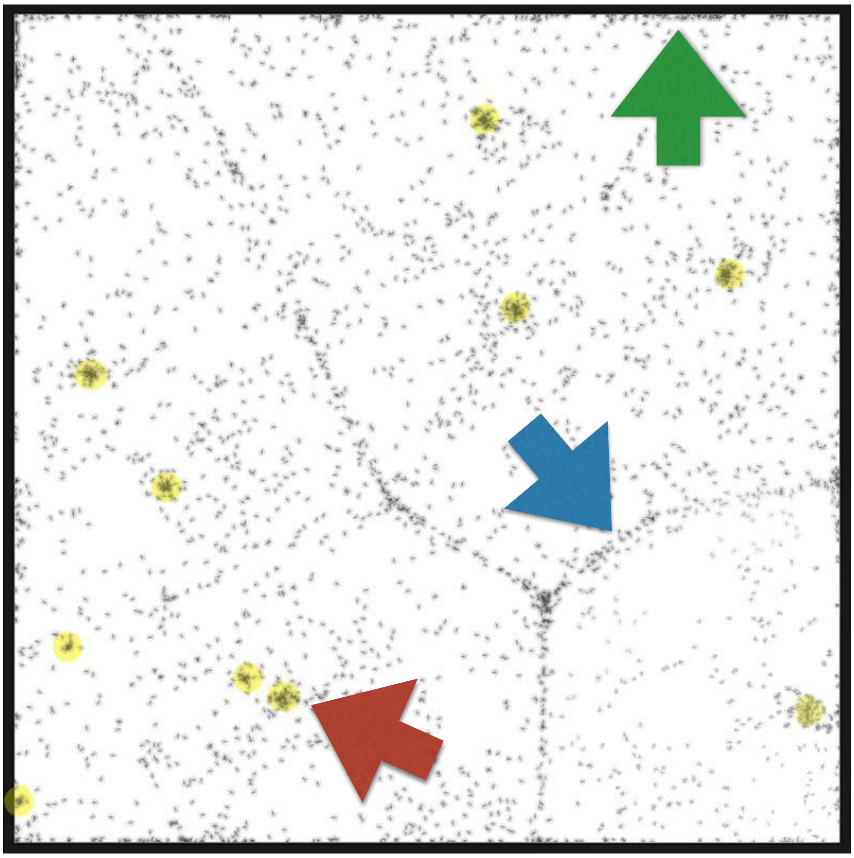


4000 robots in simulation



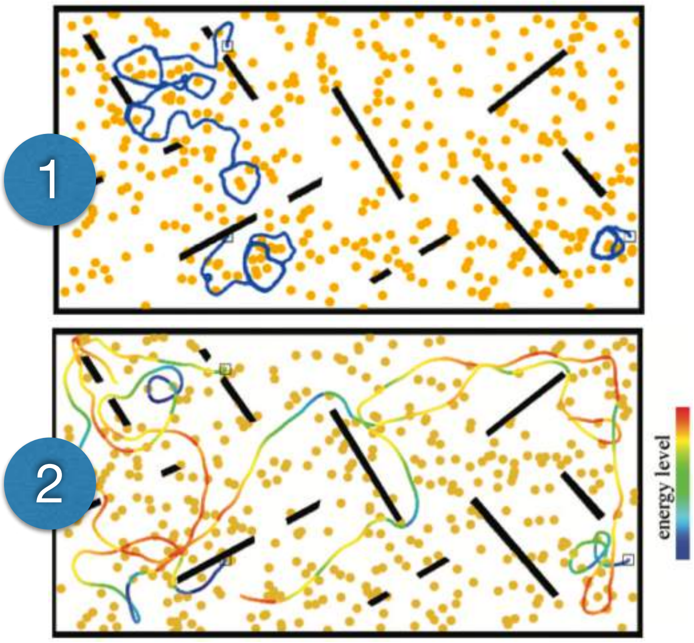
[Bredeche, ALIFE 2014]

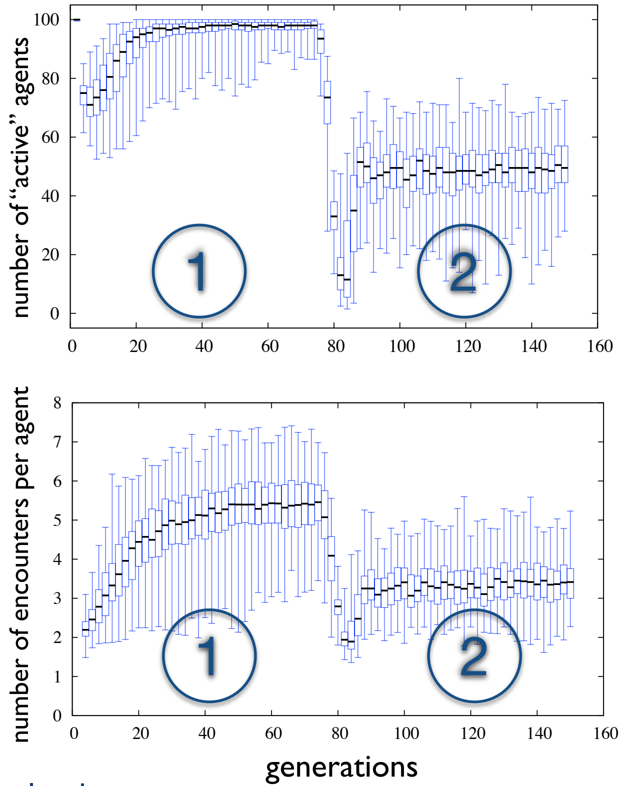
4000 robots in simulation



[Bredeche, ALIFE 2014]

Lifelong learning in a dynamic environment



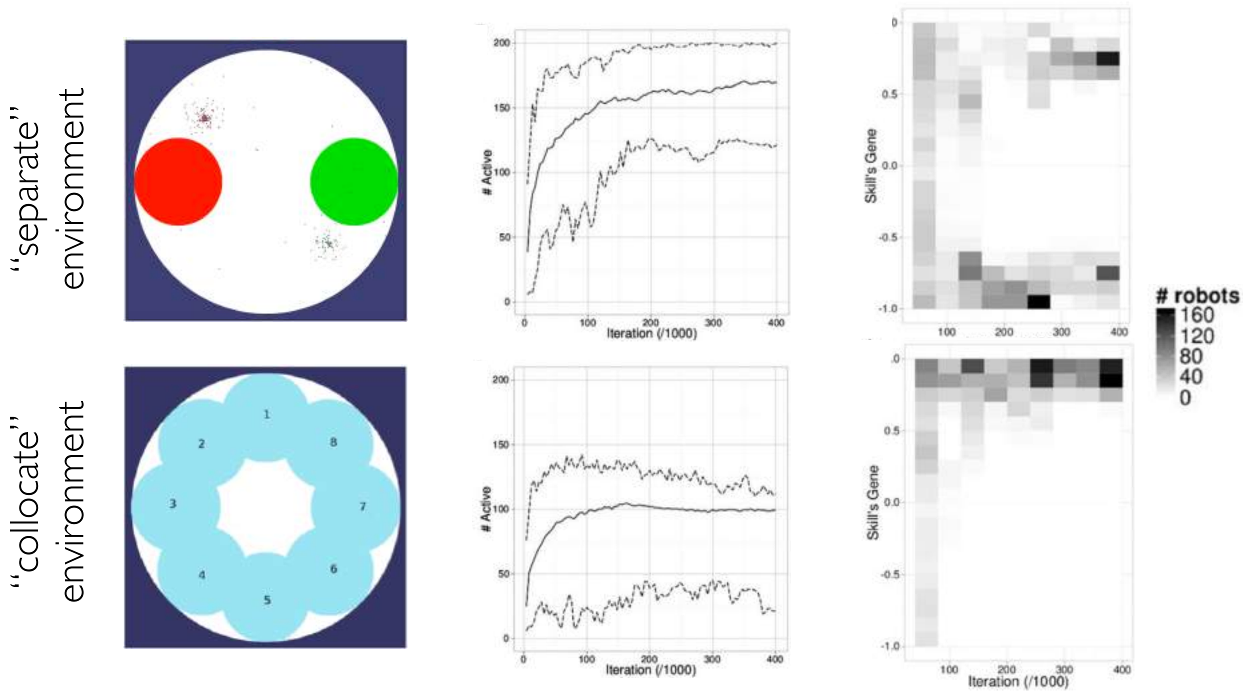


- Recovery from environmental change
- Trade-off between task and environment pressure

Division of labour

"separate" environment

"collocate" environment

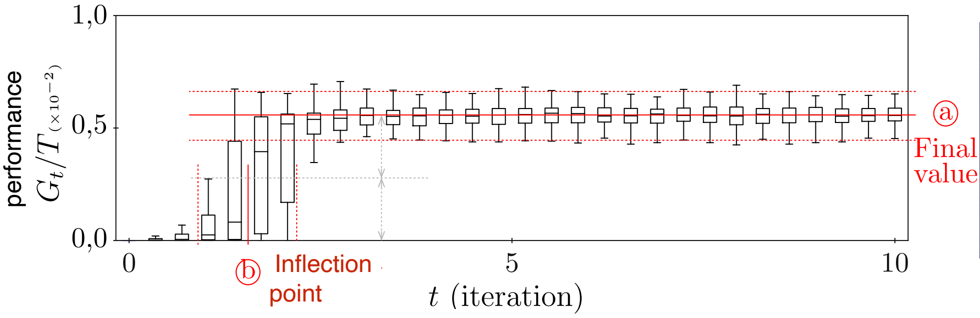


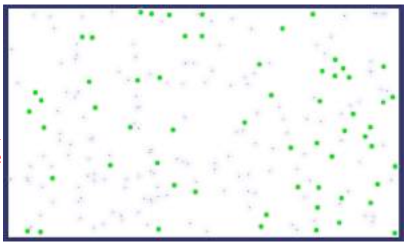
++ • geographical separation helps (but the environment is **not** a design choice…)

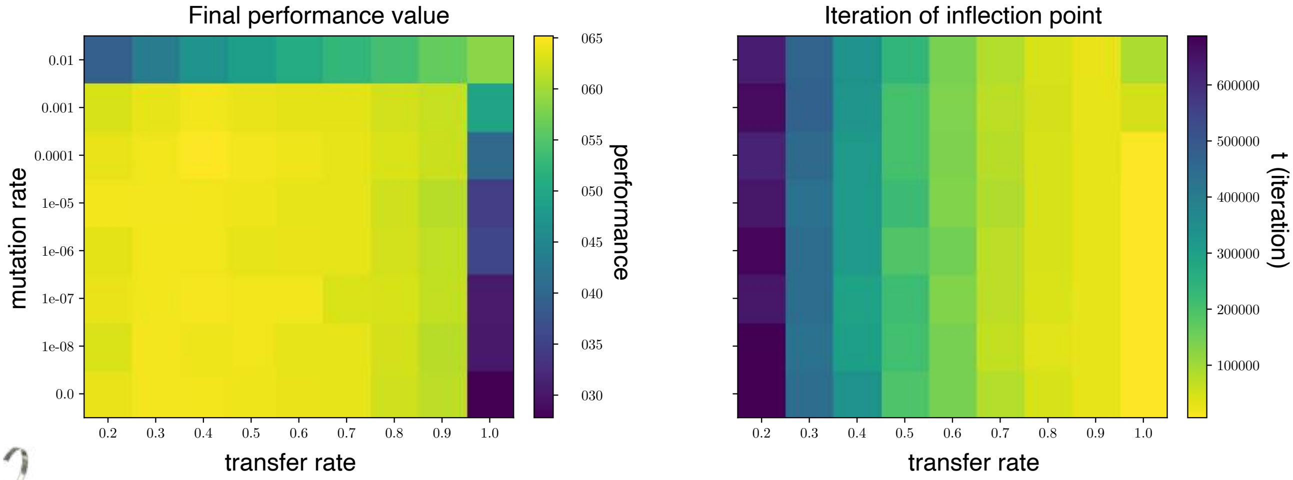
\+ • genetic polymorphism helps (random, fitness- & rank-proportionate)

\+ • a larger population size helps (but not always, e.g.: collocateEnv)

Running on limited hardware







- Horizontal Information Transfer (HIT) - social learning
- Self-adaptive horizontal transfer wrt. hardware limits

Take-home message for embodied ER

Selection pressure comes from both the environment and the task
Enabling genetic polymorphism always help

[Bredeche et al., 2010, PPSN]
[Haasdijk et al, 2014, Plos One]
[Hart et al., 2015, GECCO]
[Perez et al., 2015, ALIFE]
[Steyven et al., 2016, PPSN]
[Montanier et al., 2016, Frontiers in AI and Robotics]
(...)

Concluding Remarks

Thank you for your attention

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doi: 10.3389/frobt.2015.00004

Evolutionary robotics: what, why, and where to

Stephane Doncieux[1,2], Nicolas Bredeche[1,2], Jean-Baptiste Mouret[1,2] and Agoston E. (Gusz) Eiben[3]*

Swarm Intell
DOI 10.1007/s11721-012-0075-2

Swarm robotics: a review from the swarm engineering perspective

Manuele Brambilla · Eliseo Ferrante · Mauro Birattari · Marco Dorigo

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published: 22 February 2018
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Embodied Evolution in Collective Robotics: A Review

Nicolas Bredeche[1], Evert Haasdijk[2] and Abraham Prieto[3]*