Collective Robotics
Part 3: Scenarios

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A collection of common swarm-robotic behaviors

implementation ideas by example

aggregation, dispersion, clustering & sorting,
cooperative construction, cooperative transport,
cooperative manipulation, flocking, foraging

for an overview see Brambilla et al. (2013)

Aggregation – biological inspiration

Aggregation – overview

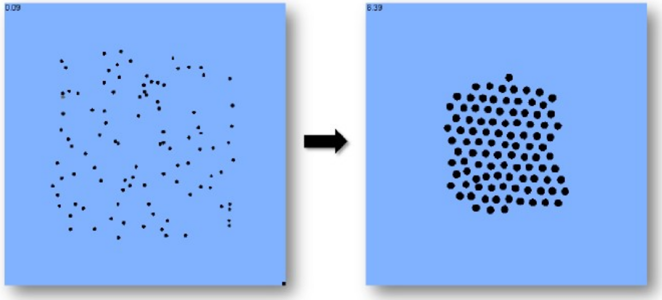
Task: robots position themselves close to each other by aggregating in one spot
⇒ minimization of distances between robots

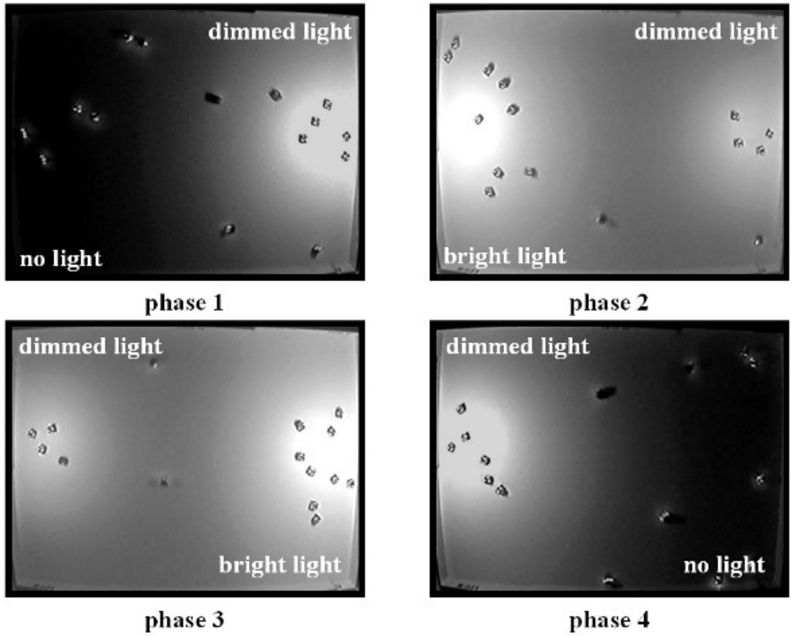
position of aggregation spot can be unspecified
⇒ robot swarm self-organizes to find a consensus position
(cf. decision making)

position of aggregation spot can be specified
(e.g., brightest/warmest spot)
⇒ each robot has to find that position and stop there

examples of biological systems:
honey bees, ladybugs, nest site selection in ants

Aggregation – aggregation with/without specified position





top left: aggregated ladybugs

left: aggregation with specified position of aggregation spot (BEECLUST algorithm)

Aggregation – global vs local information

global task: minimization of distances between robots

local task: position yourself close to as many robots as possible

simple case if GPS & global communication are available:

agree on spot and go there

with local knowledge only:

go to next neighbor? what if there is no one?

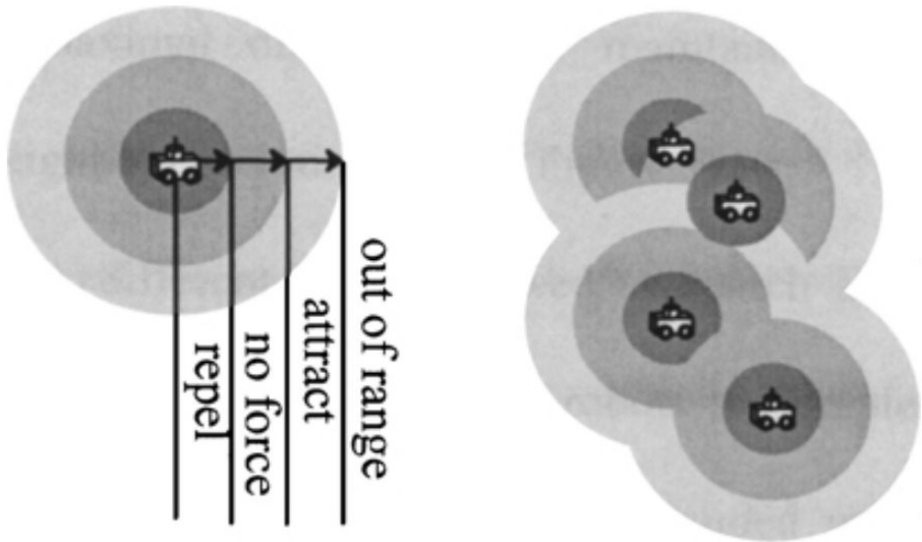
⇒ will be discussed later in detail

Aggregation – simple approach using potential fields

example: a potential field method to implement aggregation

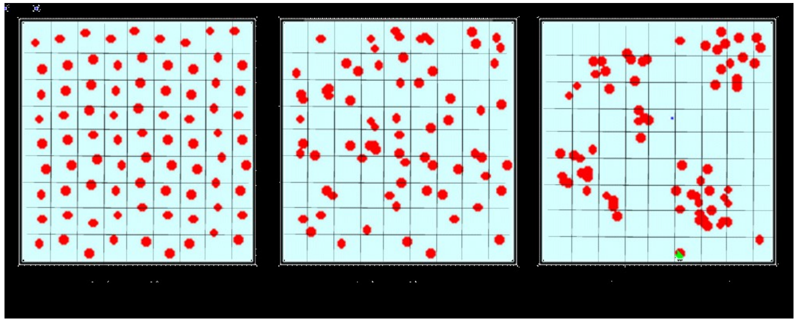
if neighbor is. . .

- too close then assign repelling force
- about at the right distance then do nothing
- too far away then assign attracting force
- out of range then is no reaction possible

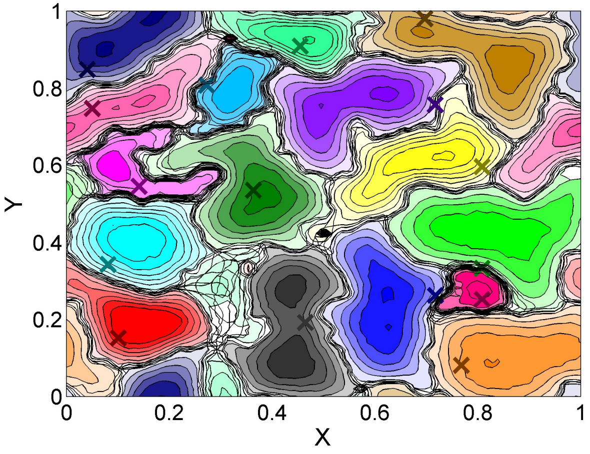


Dispersion – overview

Task: robots position themselves as far as possible from each other while staying in contact
⇒ maximization of distances between robots
examples of biological systems: territory selection

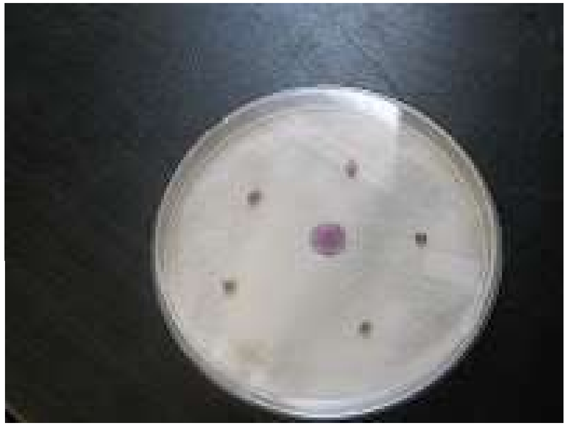


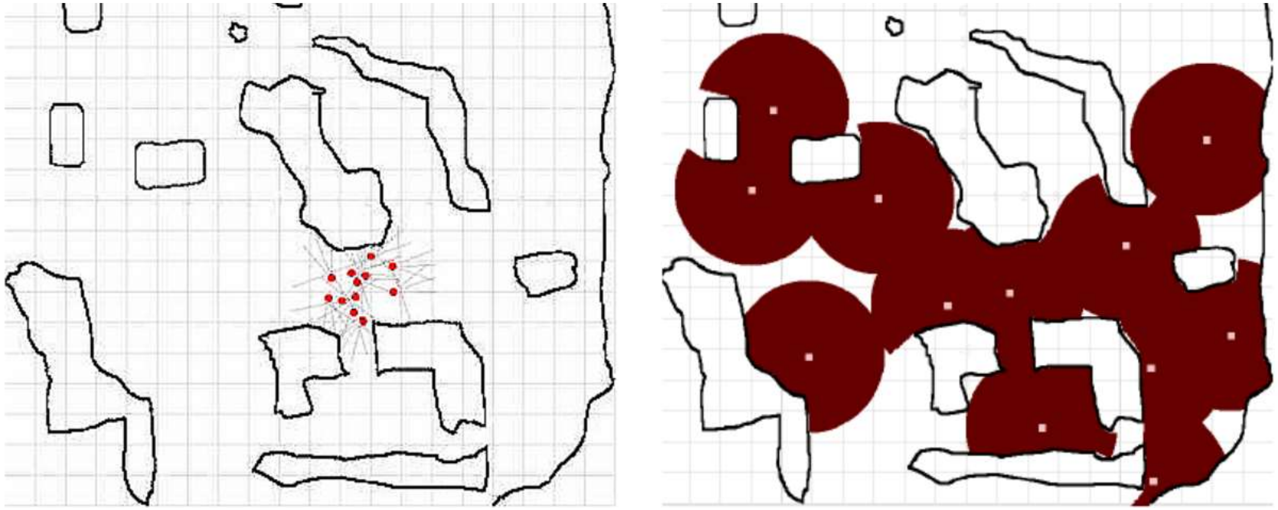
types of dispersion: uniform, random, clustered



Dispersion (2/3)

allelopathy: production of toxins that keep others from establishing nearby in plants and microorganisms

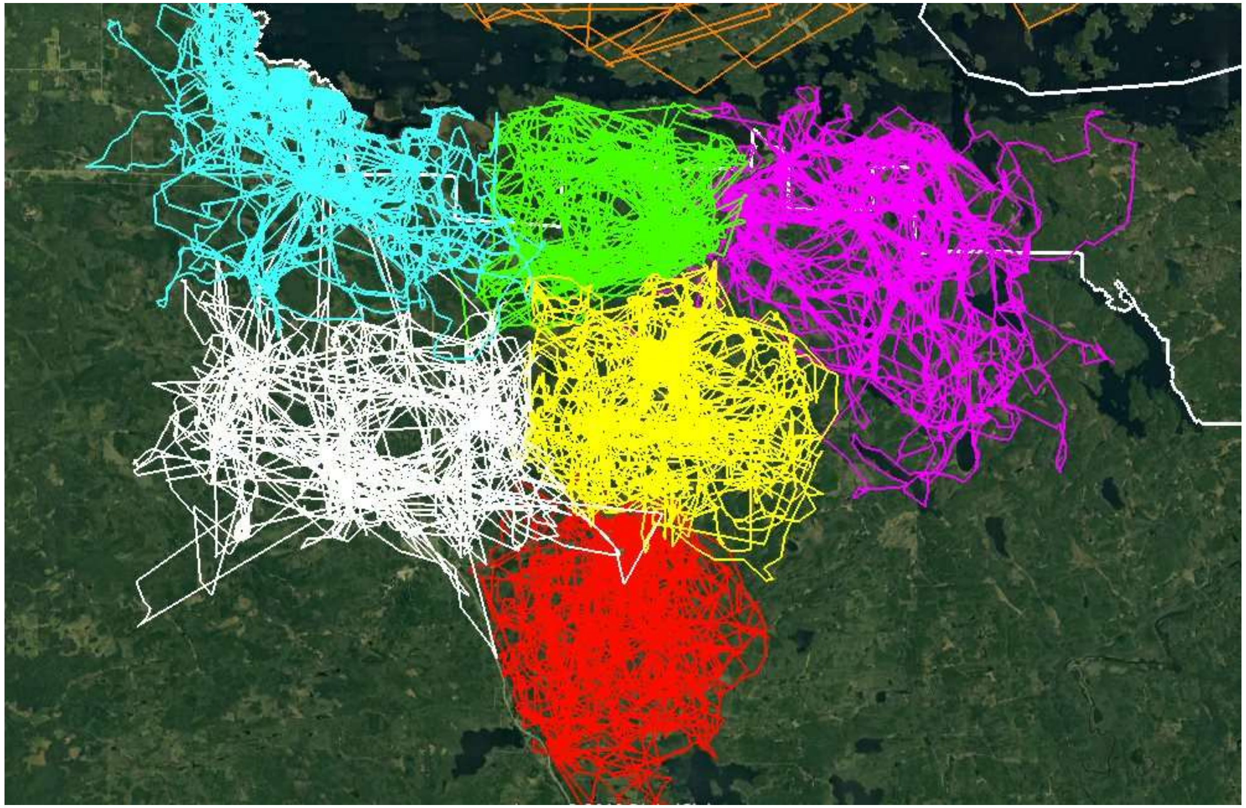




dispersion of robot swarm using wireless intensity signals
(Luke Ludwig , Maria Gini, 2006)

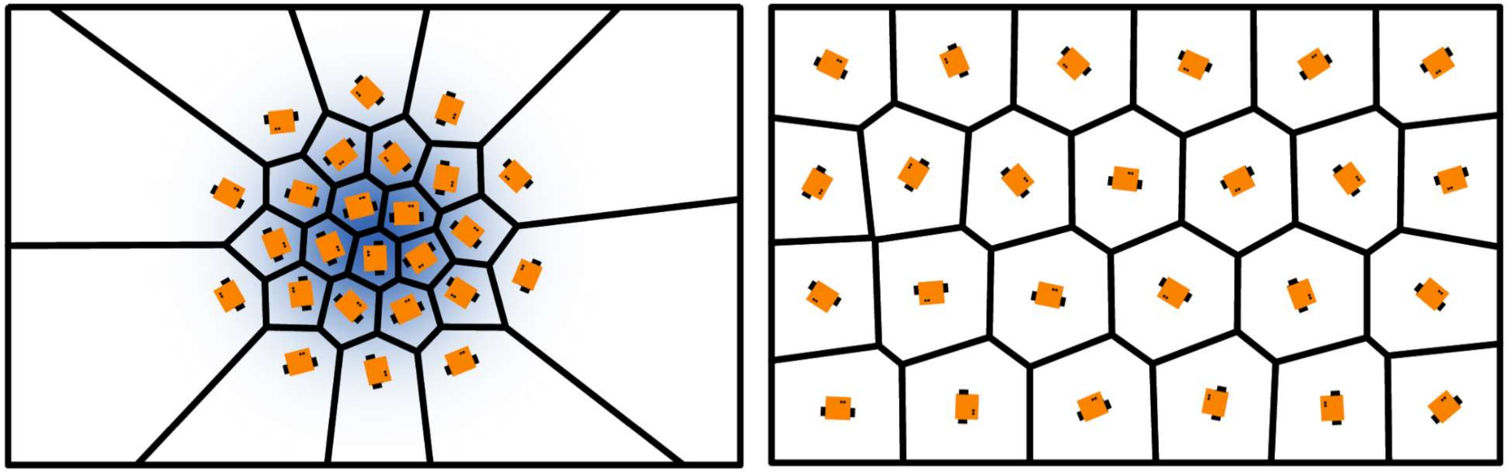
Dispersion (3/3)

“6 wolves from different adjacent packs move around their territories at the same time (based on GPS-collar locations)”



source: https://www.voyageurswolfproject.org/

Dispersion – with equal shares of resource



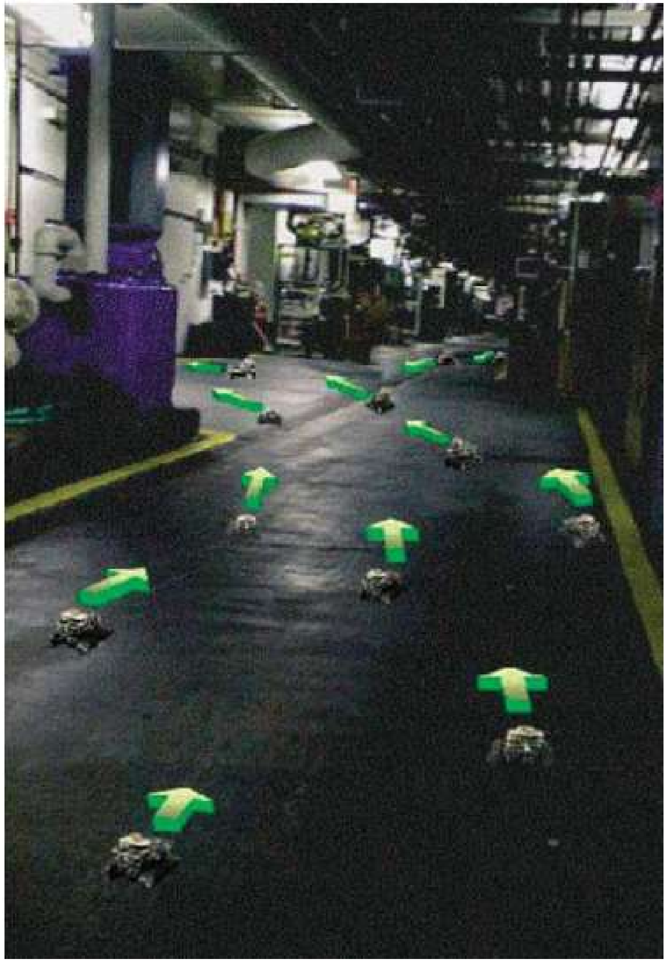
Centroidal Voronoi tessellation

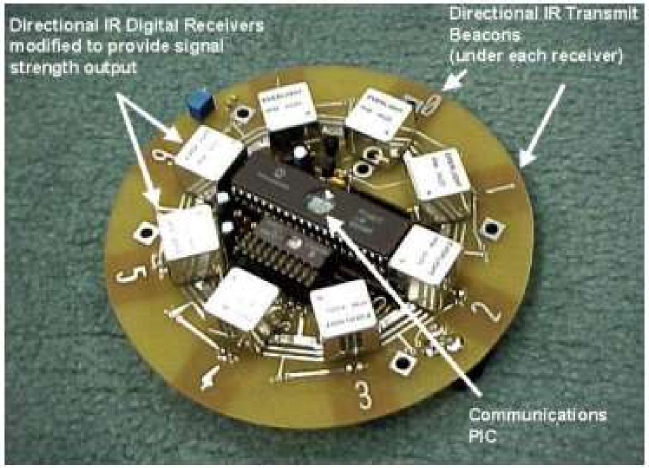
left: in a gradient (spatially centered Gaussian density function) such that each Voronoi cell contains the same amount

right: uniformly distributed resources across the domain

(Egerstedt, Robot Ecology, 2021)

Dispersion – Pheromone Robotics (1/2)





broadcast of optical signals (virtual pheromones)

used information:

- signal intensity
- hop count
- direction

(Payton et al., 2001)

Dispersion – Pheromone Robotics (2/2)

virtual pheromones are. . .

- broadcasted optical signals
- not faithful copies of chemical pheromones
- transmitted at a known intensity

a received signal indicates. . .

- existence of line of sight
- viable path toward source of signal
- signal identity
- hop count
- estimated distances on the basis of signal strength

received signals are tagged with direction and intensity

Clustering and sorting of objects – biological example

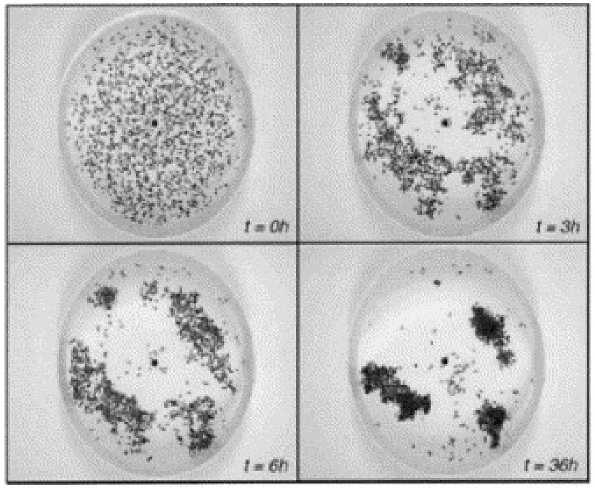
Task: robots position objects close to each other by clustering them in one spot ⇒ minimization of distances between objects

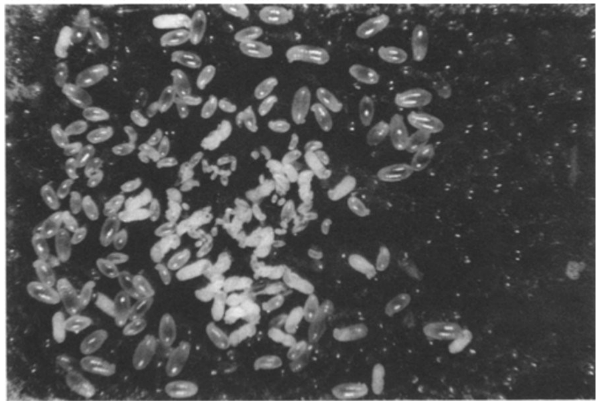
ants cluster. . .

. . . corpses of dead ants

. . . sand pellets to form a circular wall that protects the colony

. . . eggs of similar maturation





Clustering and sorting of objects – behavioral model

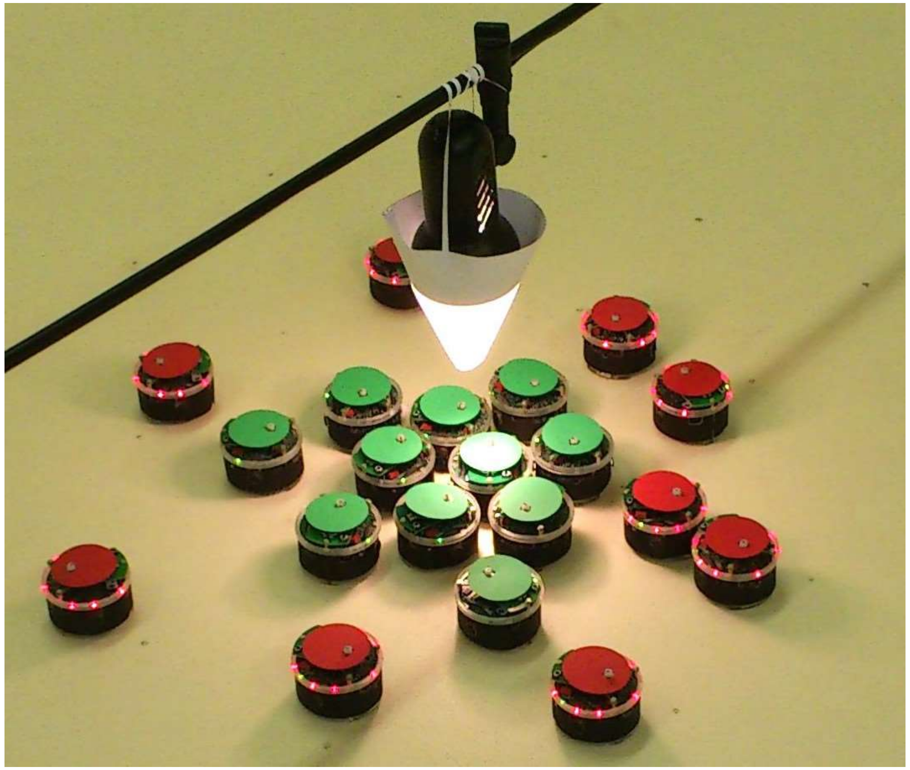
simple behavioral model of clustering:

- the probability, that an ant picks up an object, is inversely proportional to the
- number of objects it has experienced within a short time window (memory
- required)
- consequently the probability of picking up isolated objects is high
- removing objects from a cluster is unlikely
- the probability that an ant deposits an object is directly proportional to the
- number of perceived objects within a short time window

sorting may be explained by adding different response probabilities for different types of objects in the environment

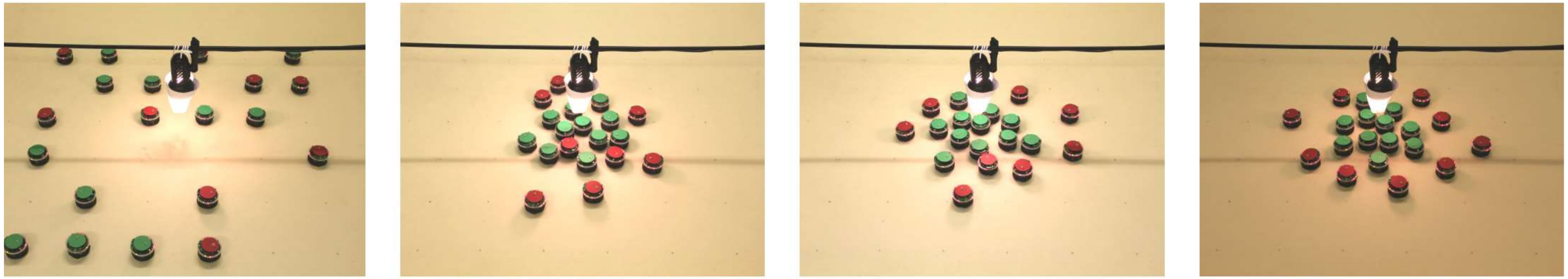
Floreano and Mattiussi (2008)

Clustering and sorting of objects – Brazil nut effect (1/2)



The Brazil nut effect as inspiration for robot segregation, Chen et al. (2012)

Clustering and sorting of objects – Brazil nut effect (2/2)



consider 2 groups of robots:

robots of group 1 represented disks of radius r1 = 8 cm,

robots of group 2 represented disks of radius r2 = 8b cm, with b ∈ {1, 2, 3, 4, 5}

for b > 1: group-1 robots (small nuts) basically ignore group-2 robots (big nuts) ⇒ sorting effect

Chen et al. (2012)

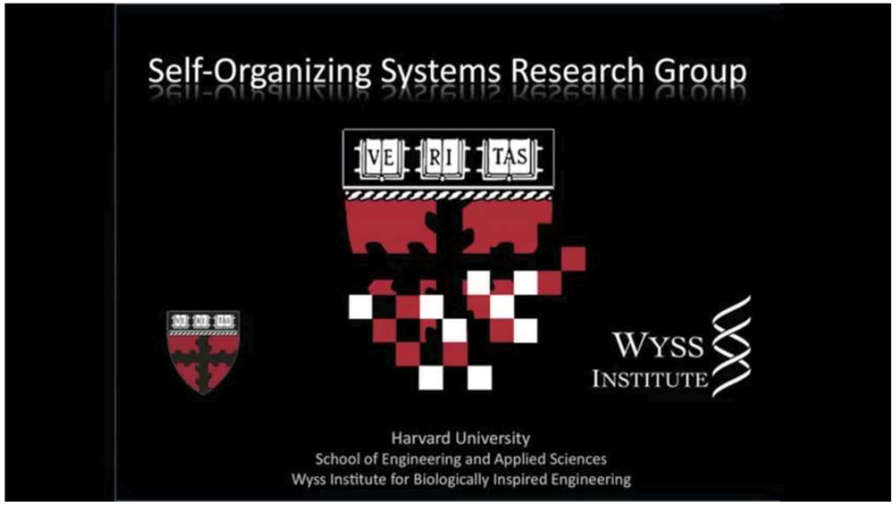
Recap

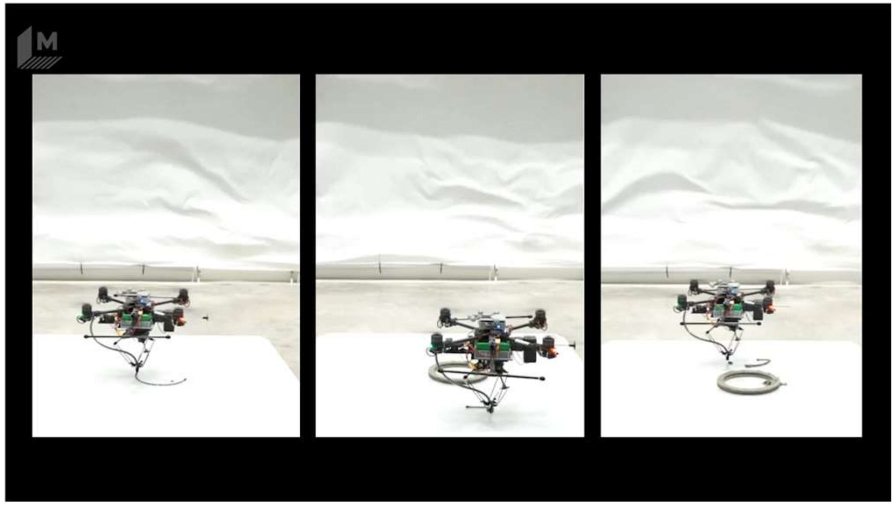
- What did you note from last time as what did you learn?
- What did you note from last lecture as challenging?

Cooperative construction (1/3)

Task: robots repeatedly position building blocks at appropriate positions to construct a particular architecture

example from biology: nest construction in wasps and termites





Cooperative construction (2/3)

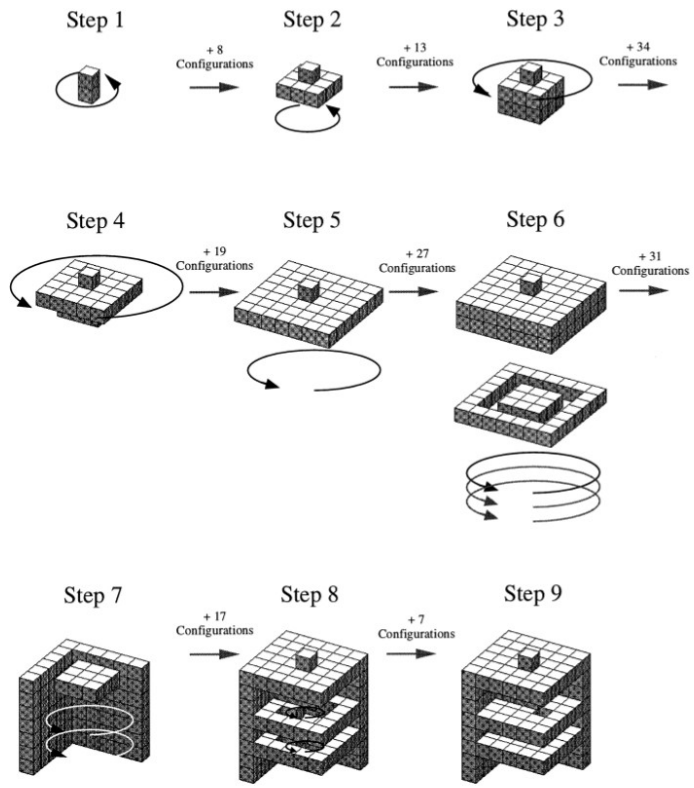
The architectural complexities exceed the perceptual and cognitive abilities of single individuals. Coordination between builders adds complexity.

Suggested models rely on stigmergic communication, specific construction behaviors are believed to be encoded genetically as stimulus–response associations.

Theraulaz and Bonabeau (1995); Floreano and Mattiussi (2008)

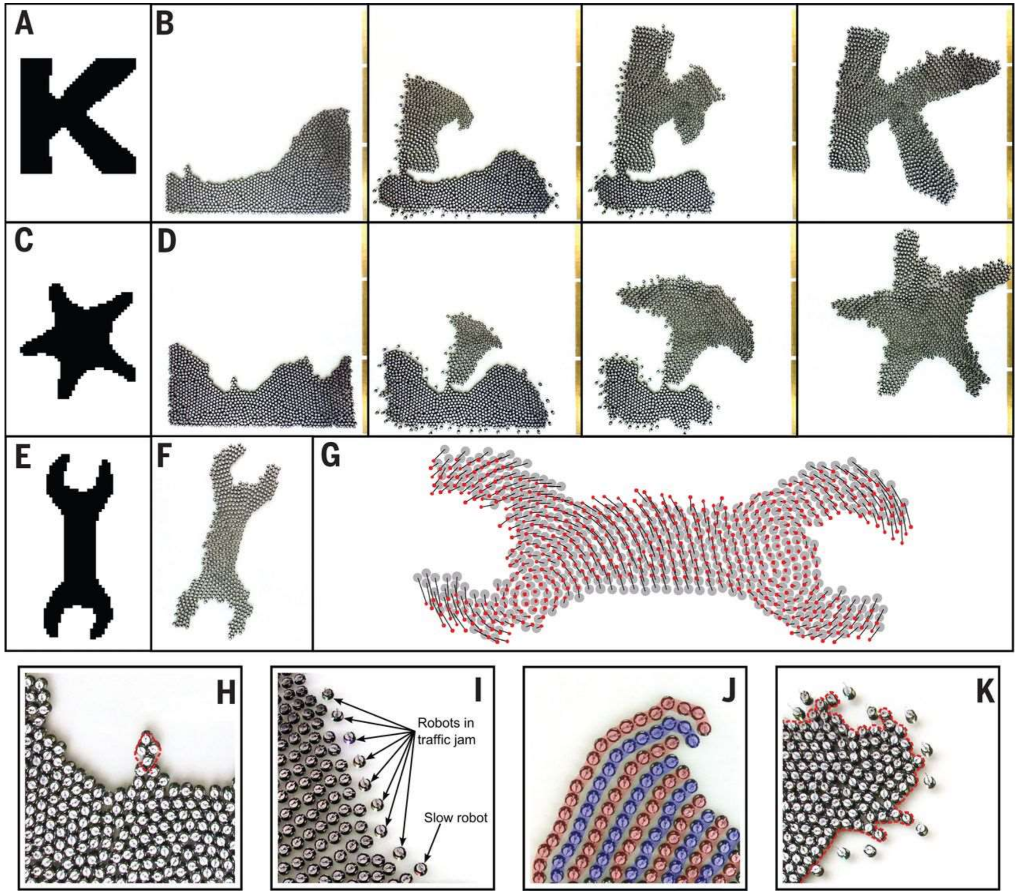
Cooperative construction (3/3)

A model by Theraulaz and Bonabeau operates like a cellular automaton; a local perception of the current construction site defines the next construction step.



Theraulaz and Bonabeau (1995)

Self-assembly



Emulation of self-assembly with Kilobots by Rubenstein et al. (2014)

1024 Kilobots

task: position robots to form predefined shapes (A, C, E)

four seed robots as anchor (H) to form a gradient as coordinate system, robots move along edge of aggregation in a line

challenge 1: error propagation using the gradient approach

challenge 2: time overhead as waiting times scale linearly with the swarm size (O(N))

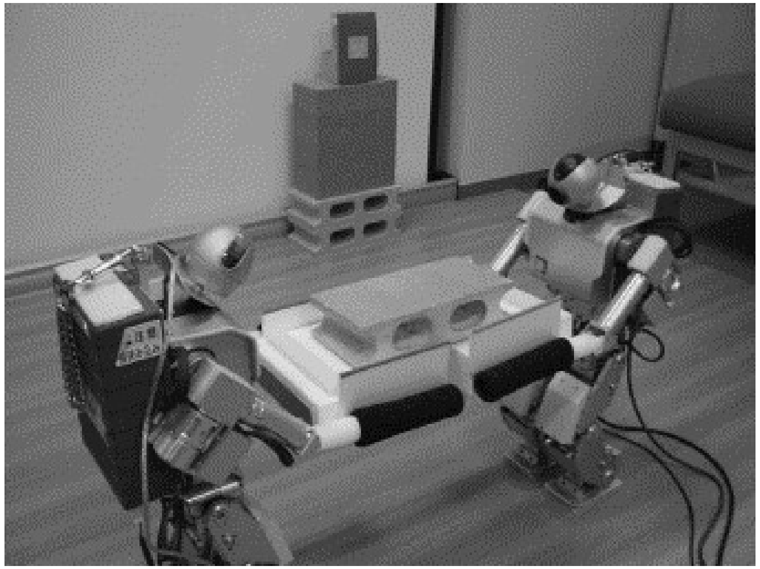
option: self-organized disassembly

Cooperative transport (1/2)

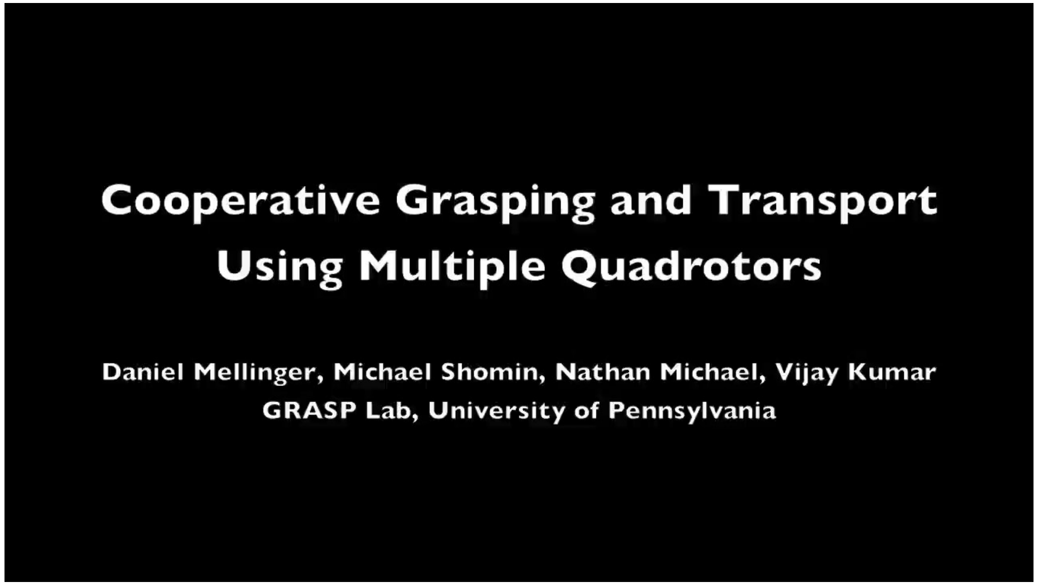
Task: robots cooperate in moving a heavy payload

subtasks: aggregation, synchronization, collective motion

example from biology: ants



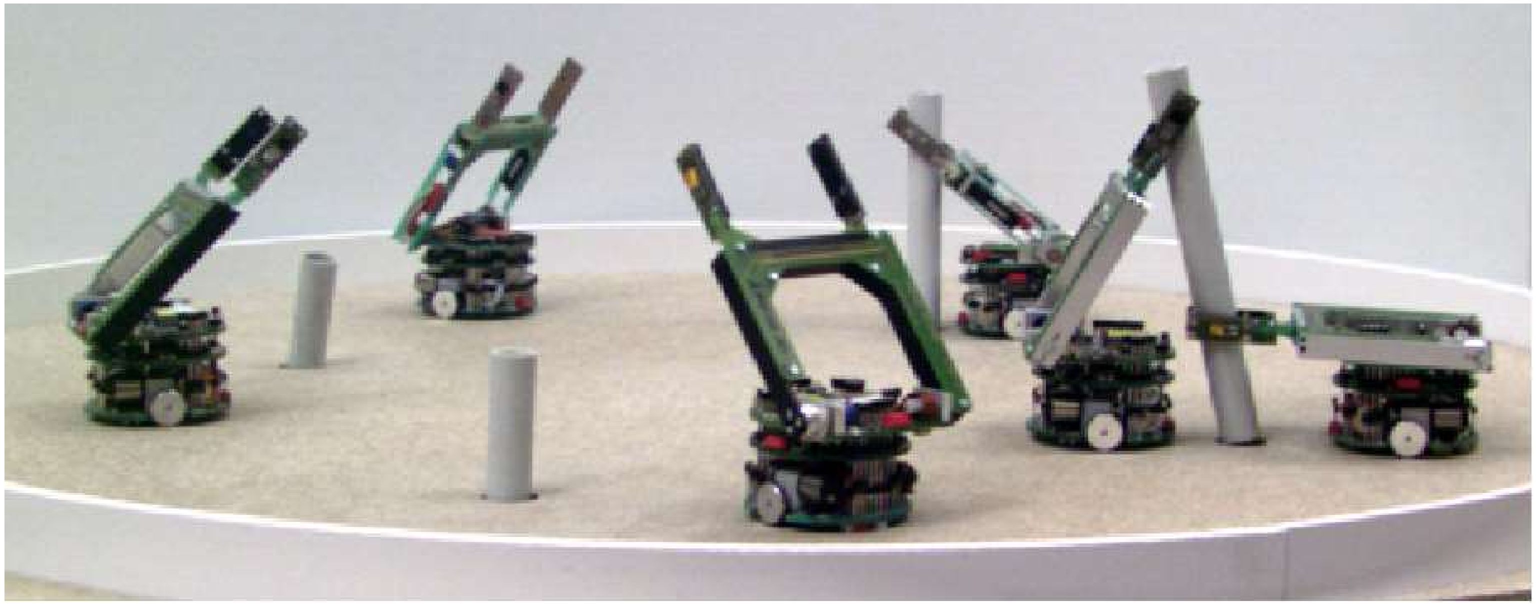
Cooperative transport (2/2)



Cooperative manipulation (1/3)

Desert ants cooperate to pull out of the ground long sticks (too long for a single ant). This behavior can be reproduced with a group of robots as study case.

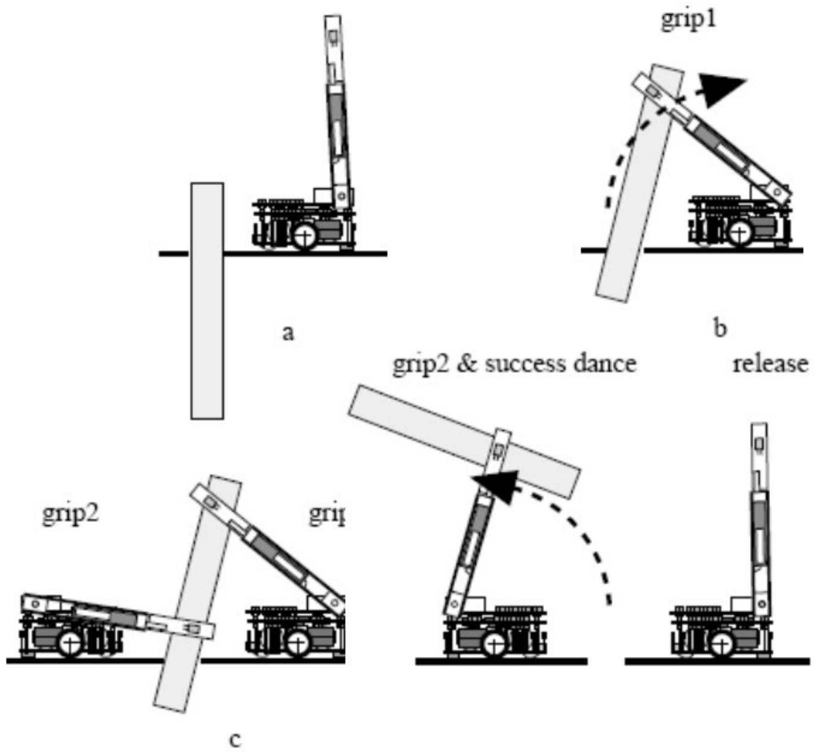
optimization problem: How long to wait for a teammate?



Cooperative manip. (2/3): gripping & waiting

waiting too long: deadlocks

waiting too short: many unfinished grips



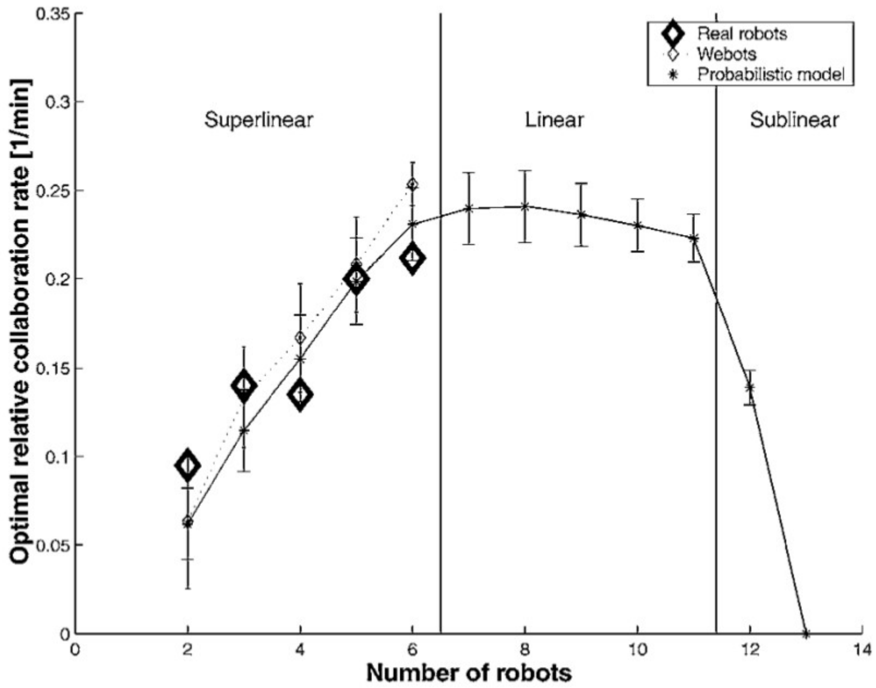
Cooperative manip. (3/3): super-linear performance

relative collaboration rate per robot

⇒ the number of a robot's collaborations over time

with 4 robots about
3 times more collaborations per robot than with 2 robots;
summed over the whole swarm about 6 times more collaborations

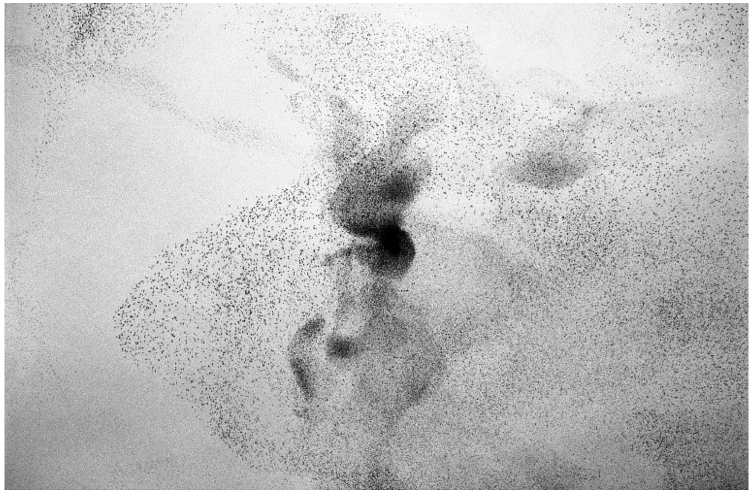
(Ijspeert et al., 2001)

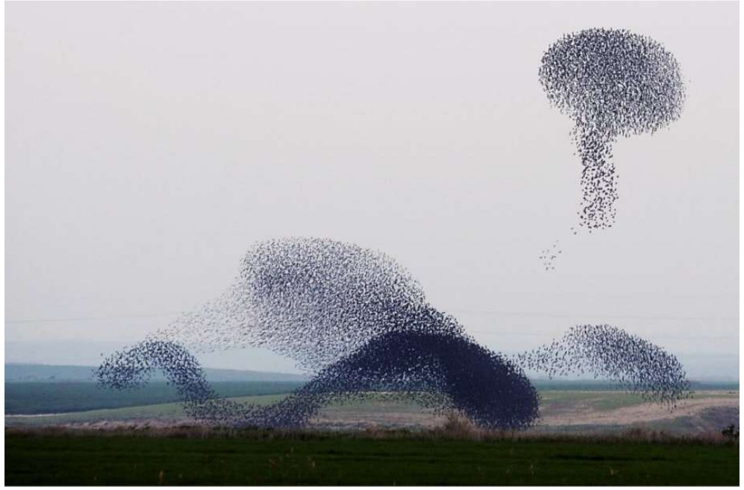


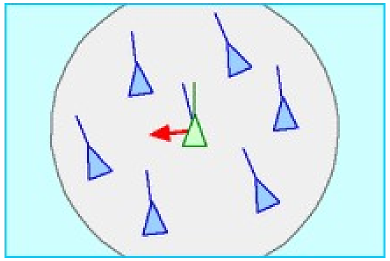
Flocking / shoaling / herding (1/4)

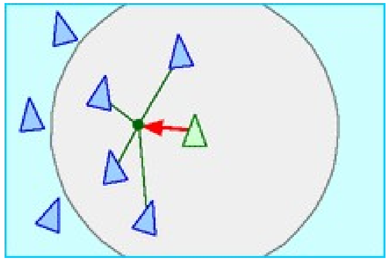
Task: stay together, move in the same direction, avoid collisions

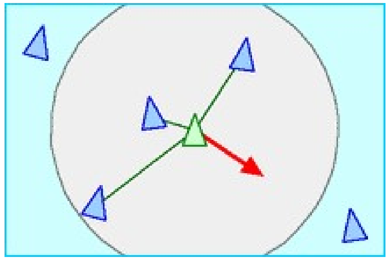
examples from biology: starlings, herring, buffalos



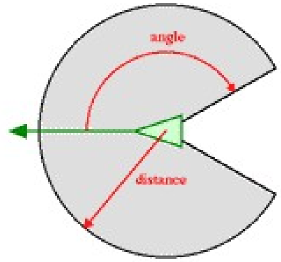


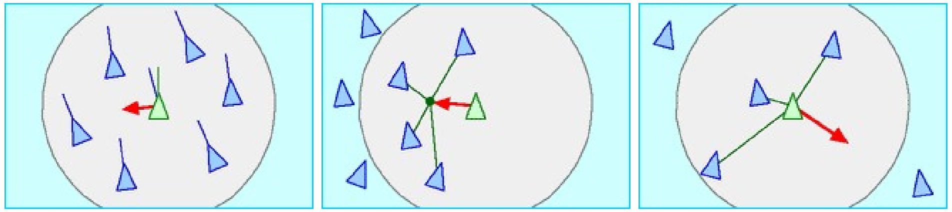






Flocking / shoaling / herding (2/4)



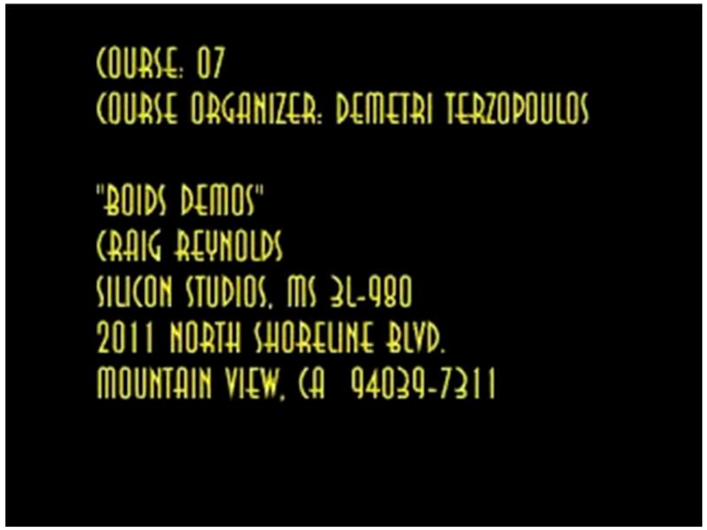


generation of flocking behavior by

3 simple rules:

- alignment: adapt direction to that of neighbors
- cohesion: stay close to neighbors
- separation: if too close increase distance to avoid collisions

+ ignoring flockmates in the back

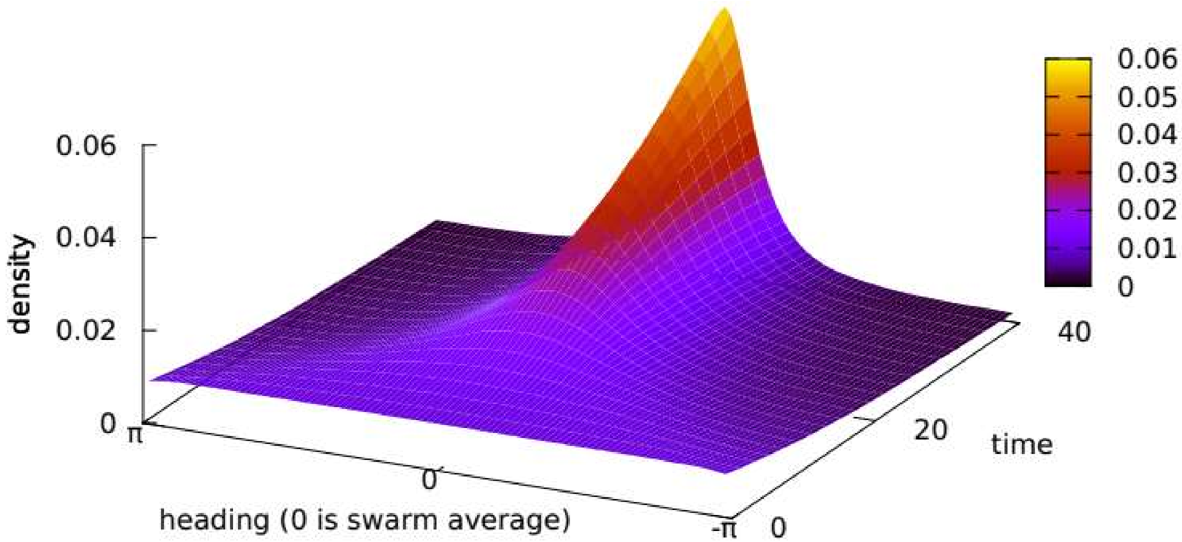


Reynolds (1987)
recent results: in natural systems dependence on network topology instead of distance (Ballerini et al., 2008)

Flocking / shoaling / herding (3/4)

example **measurements** in a simulation of flocking (part 1):
distribution of **agent headings** over time
relative to the average heading over all headings of the swarm

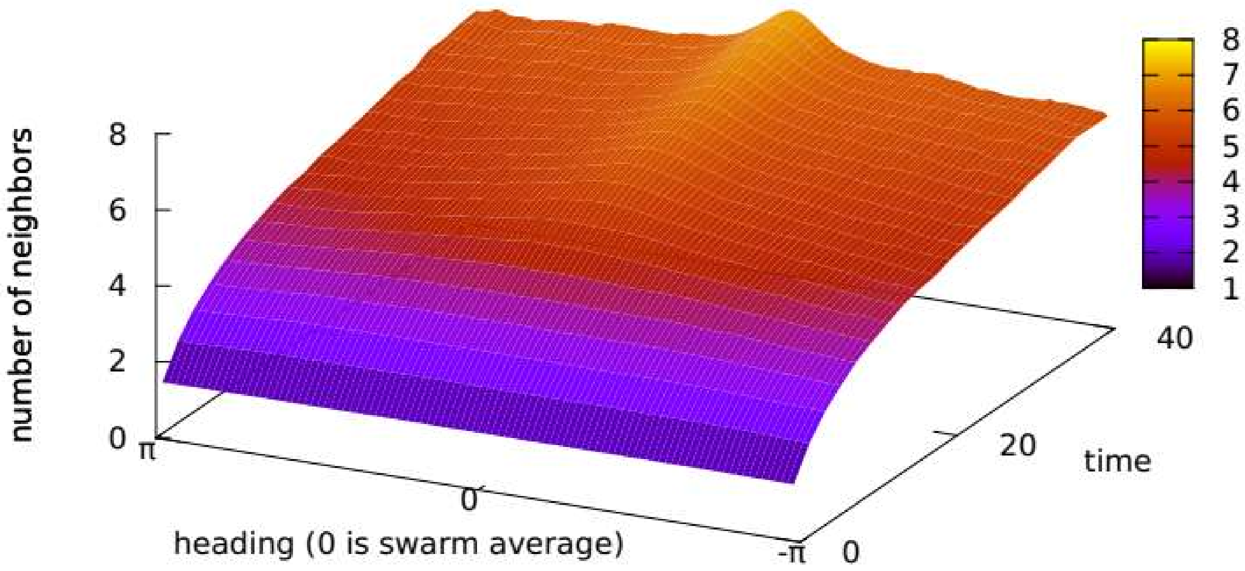
→ Effective aggregation



Flocking / shoaling / herding (4/4)

example **measurements** in a simulation of flocking (part 2):
number of neighbors per agent over time
relative to the average heading over all headings of the swarm

→ Effective aggregation



Foraging

task:

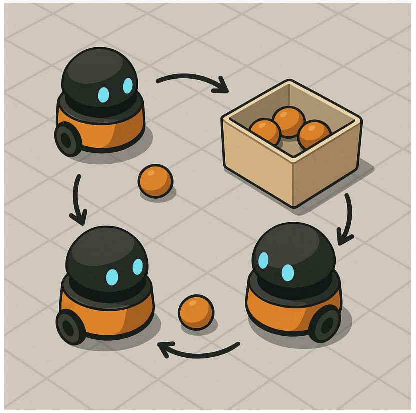
collect items,

find food source (any target area), exploit it (e.g., establish trail)

subtasks:

exploration, navigation, recruitment, (collective) transport

biological examples: ants, wasps (building material)



Foraging – overview

Exploration: random walk or special strategy, e.g., when to explore, risk management etc.

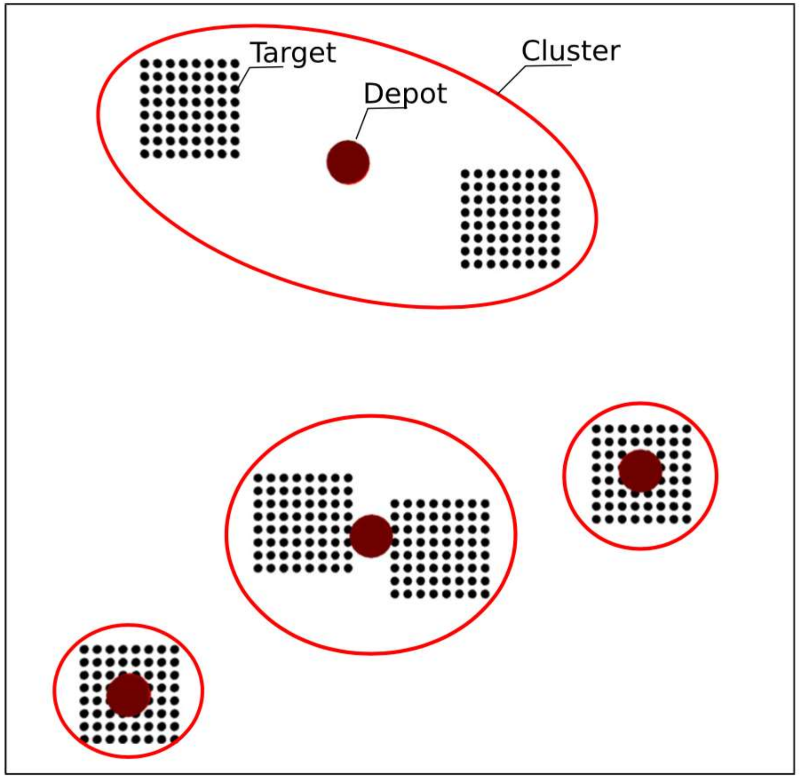
Navigation: GPS(?), light beacon, pheromones, landmarks, etc.

Recruitment: attract other robots to rich food sources (e.g., social cues)

(Collective) transport strategy: pushing only, grasping, caging (forming a closure with robots to trap the object)

according to survey paper by Tuci et al. (2018)

Foraging – multiple (dynamic) depots



(Lu et al., 2018)

Central place foraging: does not scale as more and more robots will try to enter the 'nest'

Multiple place foraging: more depots are added with increasing swarm size

Multiple place foraging with **dynamic depots**: depots can be strategically placed offline before runtime and/or depots can move at runtime

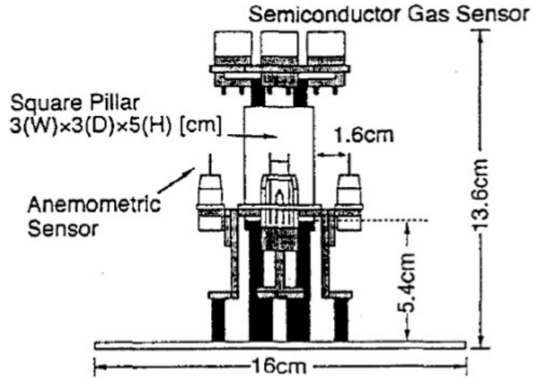
Foraging – example recruitment by social cue

Minecraft and ‘fireworks’ as (honest) social signal/cue of foraging
(project with Ralf Kurvers and Pawel Romanczuk, SCIoI Berlin)

Foraging – stigmergy in robotics

idea to implement stigmergy: real liquids/gases instead of virtual pheromones

→ massive technical challenges with pheromones

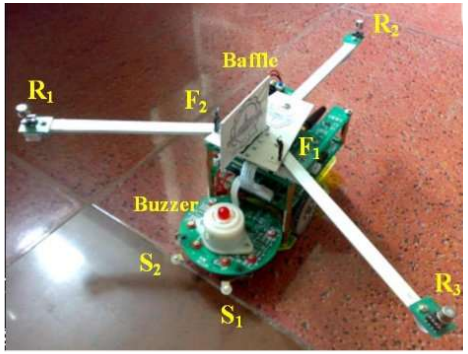


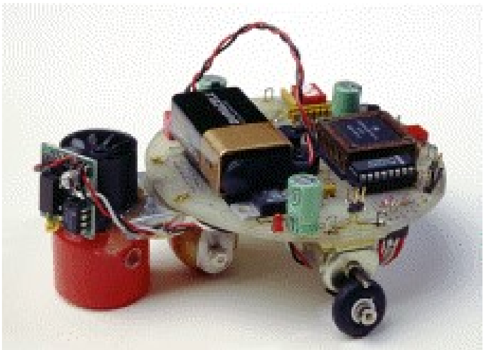
chemical sensing is difficult

due to limits in sensors and

complex dynamics

of air flow (e.g., turbulences)





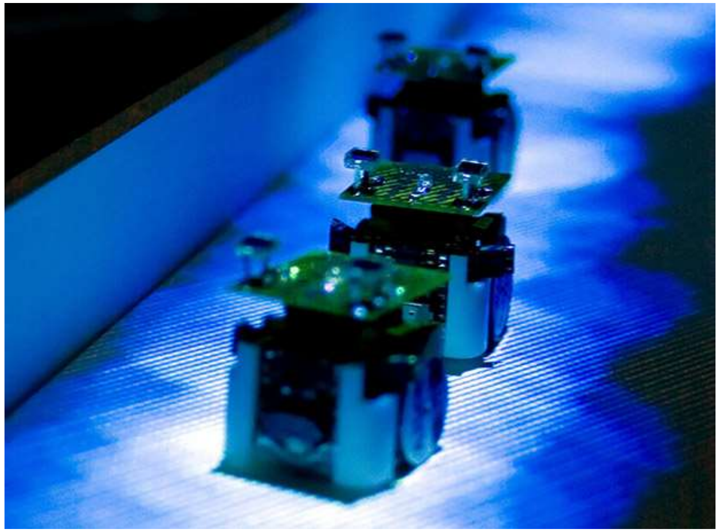
Foraging – robots form paths

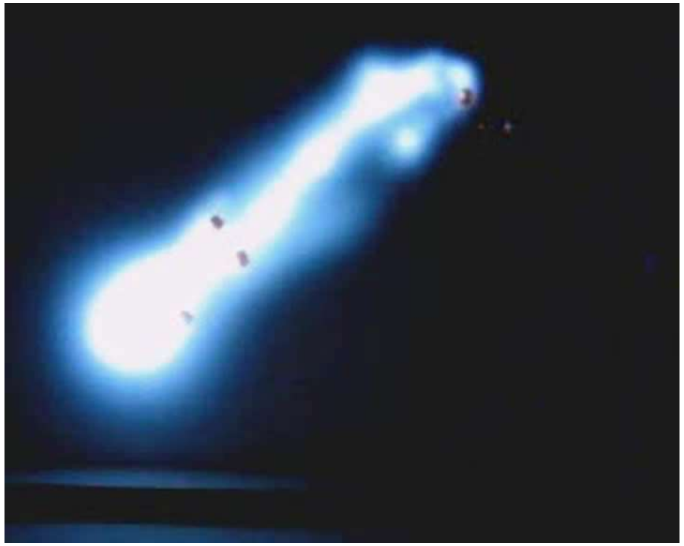
instead of pheromones: robots mark path by forming a chain

Foraging – emulating pheromones (1/3)

Optical simulation of pheromones, option 1: projection

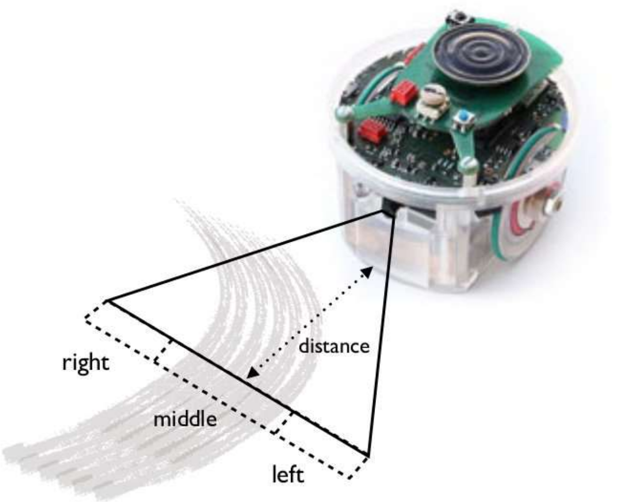
video projector simulates pheromone trails with differences in brightness, robots are tracked and signal pheromone deposit with LED (tracking is a central element!)

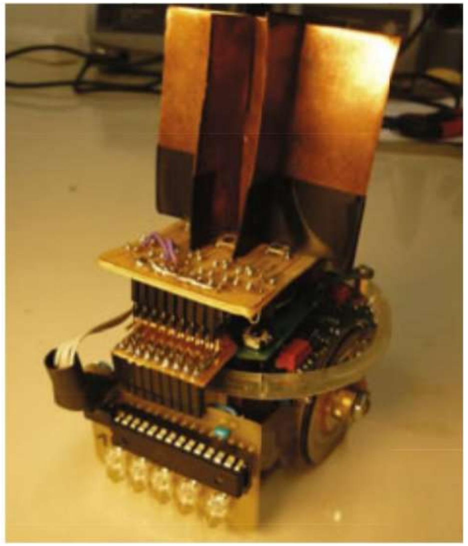




Foraging – emulating pheromones (2/3)

optical simulation of pheromones, option 2: ultraviolet light + glow paint (phosphorescence)





Foraging – emulating pheromones (3/3)

https://www.youtube.com/watch?v=i3ht90IX9XY

Division of labor and task partitioning

division of labor: work is organized, not everyone is doing the same tasks, and consequently the work needs to be usefully distributed among the workers

task partitioning is the problem of defining smaller pieces of work (tasks)

Task allocation

Task allocation is the problem of assigning tasks to the robots, hopefully in an efficient way.

If the task allocation is dynamic, then a strategy for task switching is required:

(a) monitor current supply & demand,

(b) determine if task switch would be efficient,

and (c) if so, do it.

Classroom Activity

Materials:

- A large sheet (physical or virtual whiteboard) representing the environment.
- Colored dots or markers representing tasks (each with a type or difficulty level).
- Tokens representing robots (can be done via cards, coins, or software like Google Jamboard/Miro for online).
- Optional: Timer and score sheet.

Instructions:

- Each group simulates a team of robots operating in an environment with multiple scattered tasks.

Define Task Environment (Instructor provides)

- E.g., 15 tasks of different types (red = high priority, green = low priority).
- 5 robots per team, each with a unique ability (e.g., speed, task type compatibility).
- Design a Task Allocation Method

Each group must:

- Choose or invent a task allocation mechanism (e.g., market-based, threshold-based, auction, role assignment, first-come-first-served, stigmergy).
- Write down how tasks will be assigned, resolved, and re-allocated in case of failure or conflict.

Groups report:

- chosen method
- How it performed under simulated conditions
- Strengths, weaknesses, and potential improvements

Discussion Points (Instructor-led):

- Which methods scaled better with more tasks/robots?
- How did groups balance fairness, efficiency, and robustness?
- What mechanisms supported reallocation under failure?
- How do these strategies relate to biological systems?

Multi-robot task allocation – taxonomy

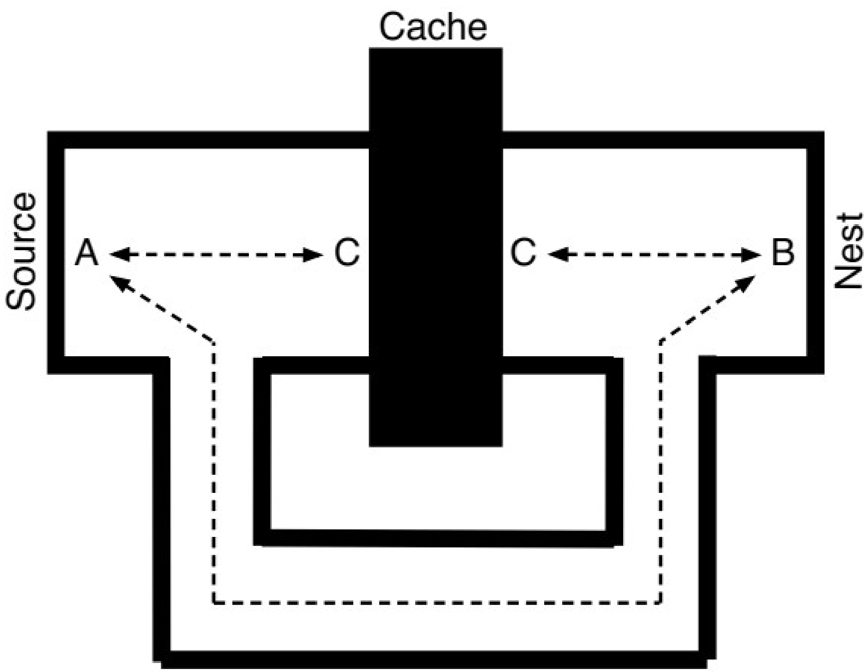
Single-task robots (ST) vs. multi-task robots (MT)
ST: each robot is capable of executing at most one task at a time
MT: some robots can execute multiple tasks simultaneously

single-robot tasks (SR) vs. multi-robot tasks (MR)
SR: each task requires exactly one robot to achieve it
MR: some tasks can require multiple robots

instantaneous assignment (IA) vs. time-extended assignment (TA)
IA: instantaneous allocation of tasks to robots, with no planning for future allocations
TA: information is available, such as the set of all tasks that will need to be assigned, or a model of how tasks are expected to arrive over time

Gerkey and Mataric (2004)

Task alloc. as multi-armed bandit problem (1/2)



Pini et al. (2012): a robot can decide against task partitioning and transport objects from A to B directly, or a robot can decide to go for task partitioning and transport objects only from A to C or from C to B; when to do what?

Task alloc. as multi-armed bandit problem (2/2)

Multi-Armed Bandit (MAB) for Task Selection

- K levers, each with unknown reward distribution R_i
- Goal: Choose which lever to play
- Challenge: Exploration–Exploitation tradeoff

Robot Task Allocation

- Each robot selects between Task B and Task C
- Measures cost $\hat{t}_{\mathrm{j}}$: estimated time to complete task j ∈ {B, C}

Decision Rule (UCB1 Policy)

Go to B if:

$$\hat{t}_B - \gamma \sqrt{\frac{2\ln(n_B + n_C)}{n_B}} < \hat{t}_C - \gamma \sqrt{\frac{2\ln(n_B + n_C)}{n_C}}$$

n_B num. of times went to B, n_C num. of times went to C

γ to tune degree of exploration

References

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