Collective Robotics
Part 3: Scenarios

Prof. Dr. Javad Ghofrani

Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

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

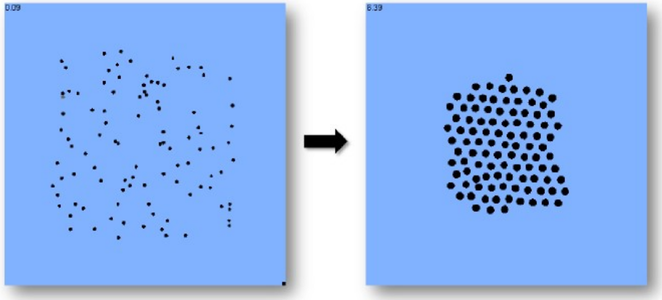
Task: robots position themselves close to each other by aggregating in one spot
⇒ minimization of distances between robots

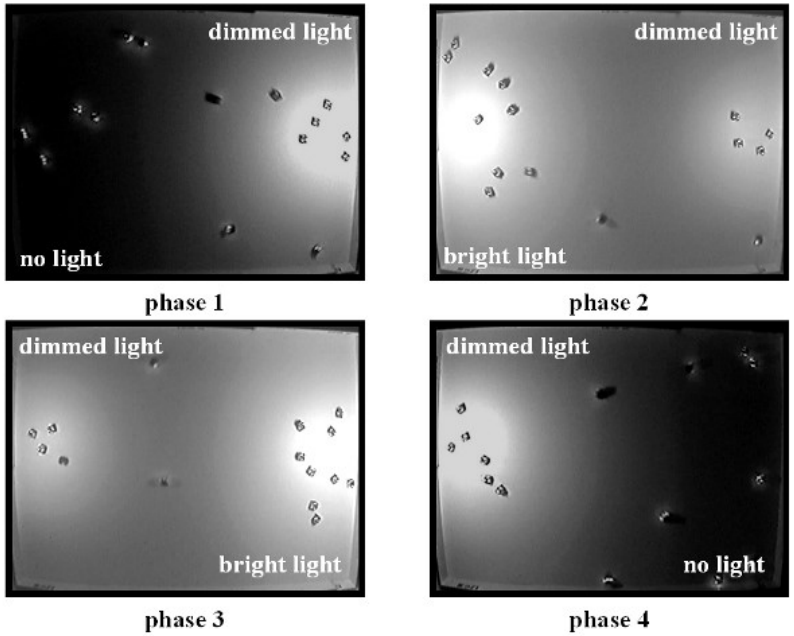
position of aggregation spot can be unspecified
⇒ robot swarm self-organizes to find a consensus position
(cf. decision making)

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?

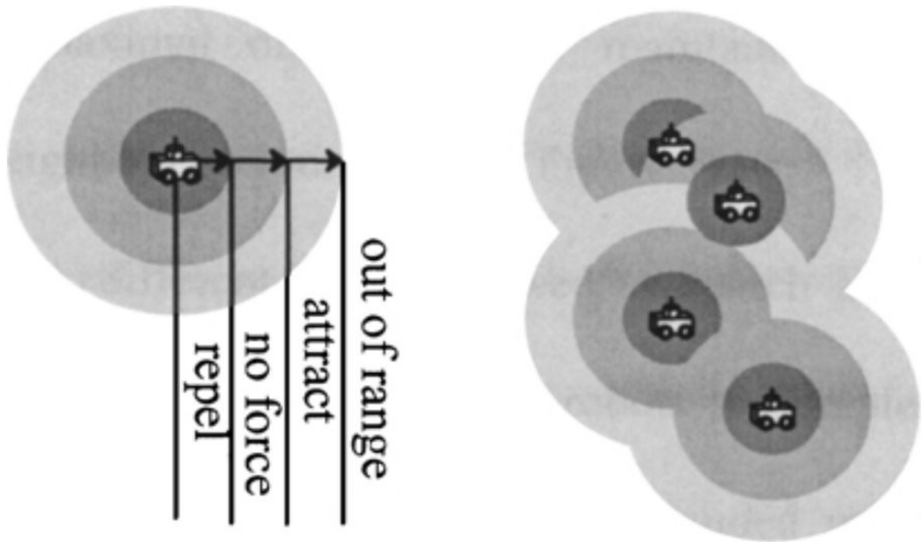
⇒ will be discussed later in detail

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



Aggregation – approach from control theory

Idea:

Use control-theoretic formalism to guide swarm agents toward aggregation.

Each robot's behavior is derived from minimizing a global cost function.

Outcome:

Robots follow a distributed control law based on local differences.

All agents converge to a common point or cluster.

Cost Function (Distance-Based):

$\varepsilon(x) = (1/2)\ \Sigma_i\ \Sigma_{j \in \mathcal{N}_i} \|x_i - x_j\|^2$

Gradient Descent Flow:

$\partial\varepsilon(x)/\partial x_i = \Sigma_{j \in \mathcal{N}_i} (x_i - x_j)$

Equation of Motion (Consensus Dynamics):

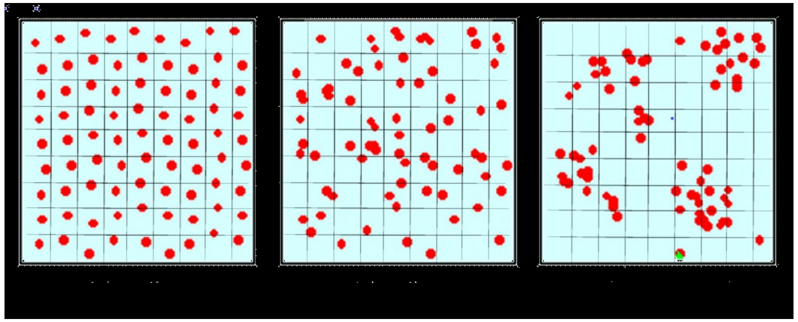
$\dot{x}_i = -\ \Sigma_{j \in \mathcal{N}_i} (x_i - x_j)$

Dispersion – overview

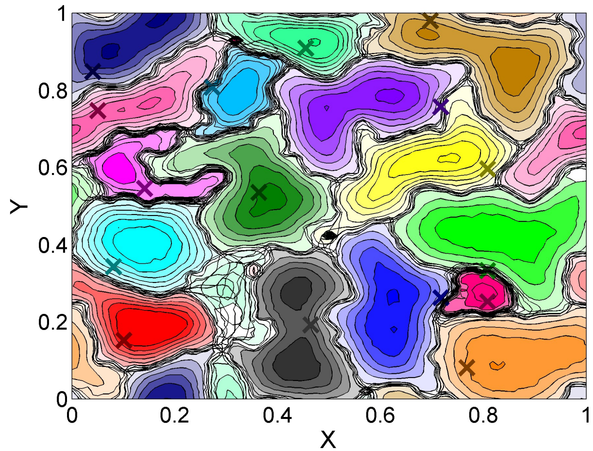
Task: robots position themselves as far as possible from each other while staying in contact

⇒ maximization of distances between robots

examples of biological systems: territory selection

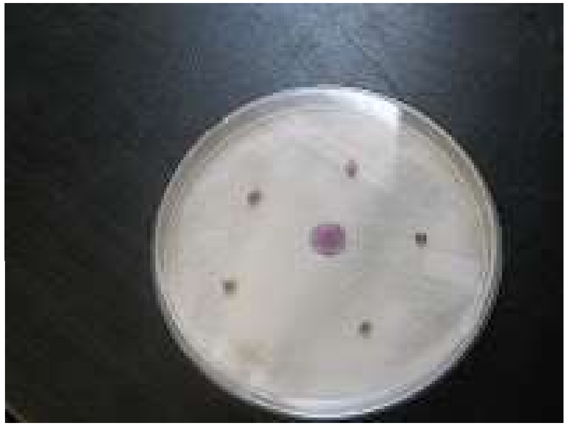


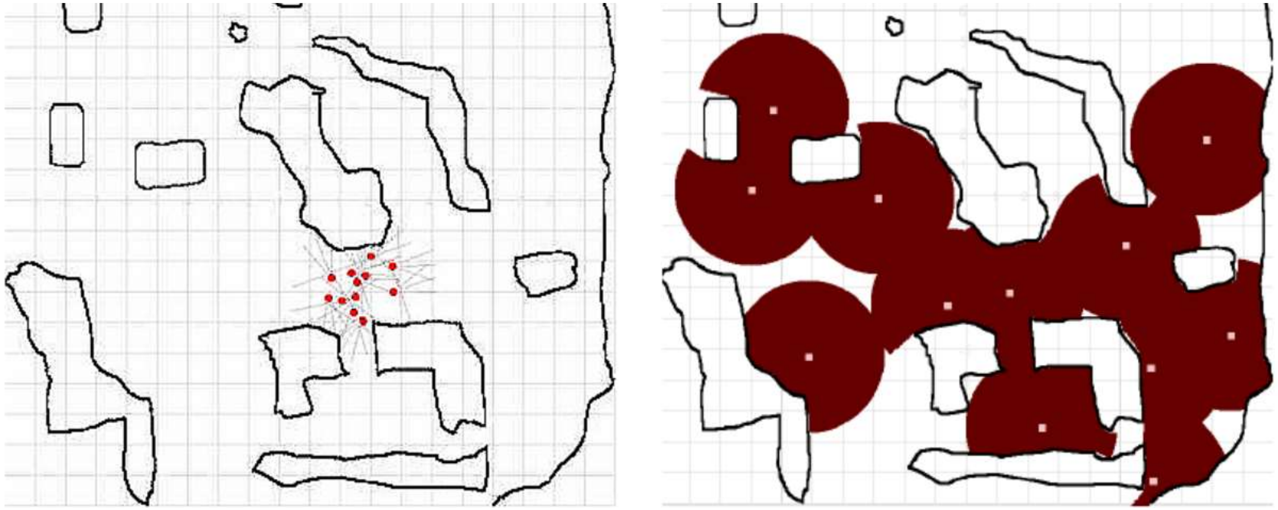
types of dispersion: uniform, random, clustered



Dispersion (2/3)

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

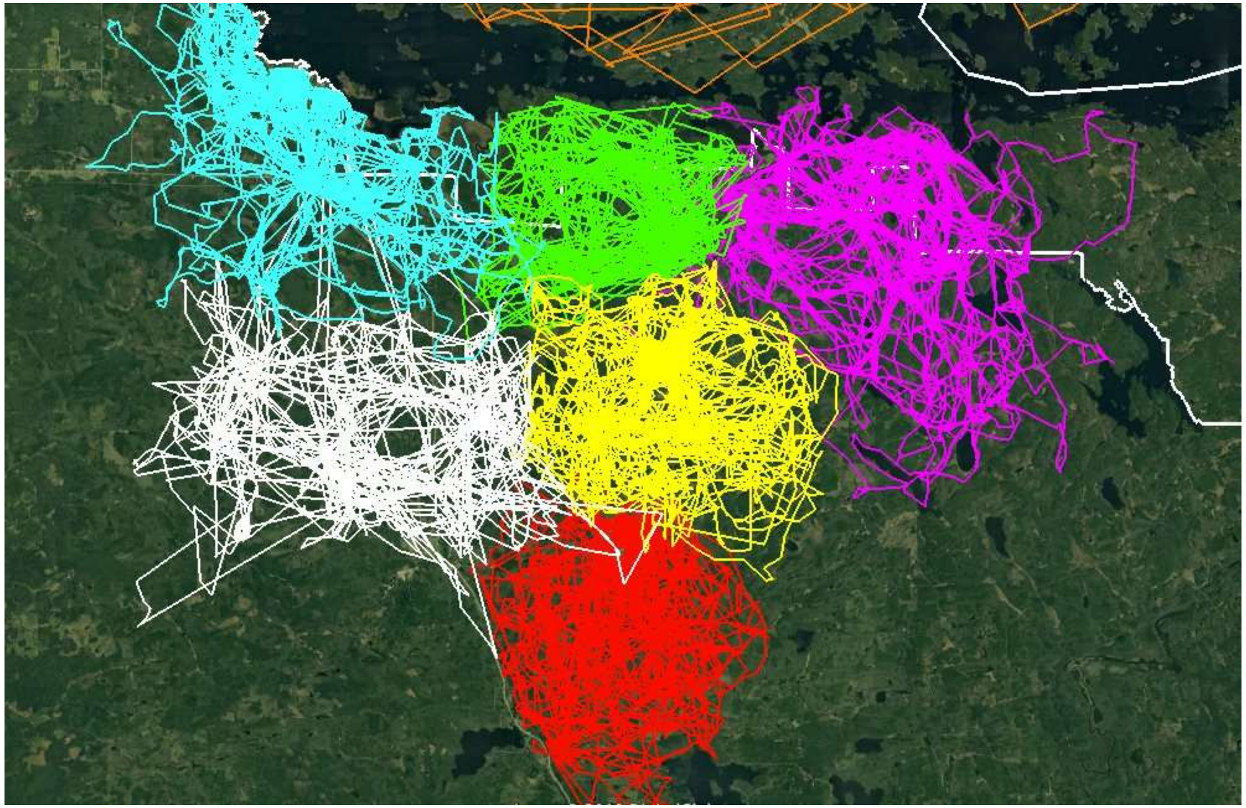




dispersion of robot swarm using wireless intensity signals
(Luke Ludwig , Maria Gini, 2006)

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 – approach from control theory (1/2)

also dispersion is simple enough for control theory,

let's require a prescribed inter-robot distance δ

as cost for all relevant robot pairs (i, j) we define:

$$\varepsilon_{ij}(\|x_i - x_j\|) = \frac{1}{2}(\|x_i - x_j\| - \delta)^2$$

We can define again a gradient descent flow

$$\frac{\partial \varepsilon_{ij}(x)}{\partial x_i} = w_{ij}(\|x_i - x_j\|)(x_i - x_j)$$

this time defined in a generic way for any task-specific weight $\boldsymbol{W_{ij}}$

Dispersion – approach from control theory (2/2)

based on eq. 4 we then get as weight:

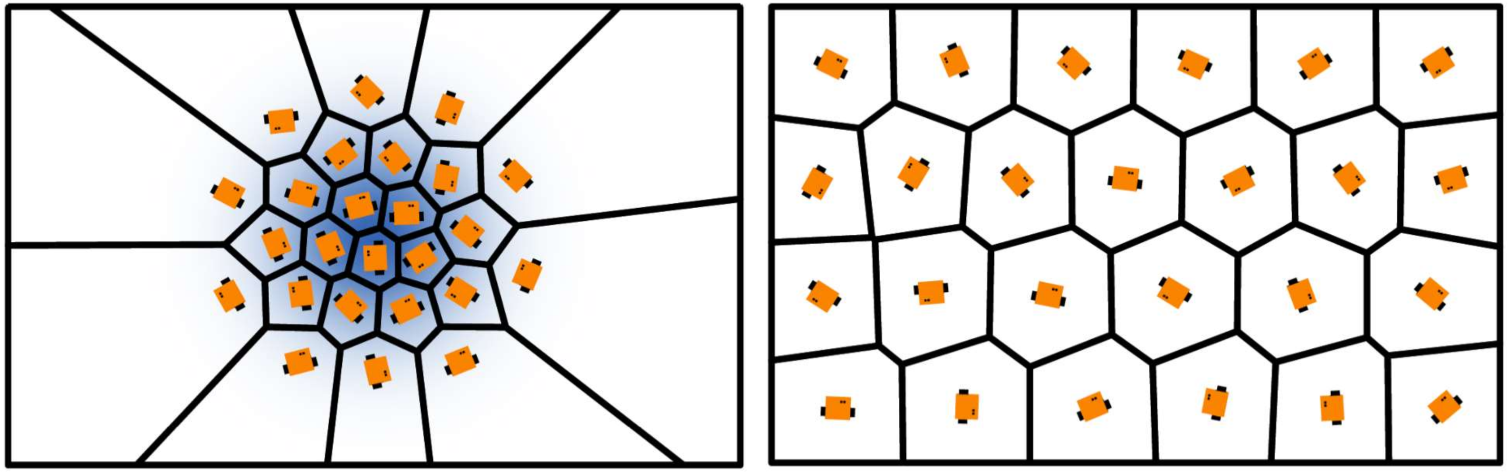
$$w_{ij} = \frac{\|x_i - x_j\| - \delta}{\|x_i - x_j\|}, \tag{6}$$

as motion equation we get:

$$\dot{x}_i = -\frac{\partial \varepsilon}{\partial x_i} = -\sum_{j \in \mathcal{N}_i} w_{ij}(\|x_i - x_j\|)(x_i - x_j) \tag{7}$$

any issues due to limited **swarm connectivity** are not considered and would potentially break the formalism

Dispersion – with equal shares of resource



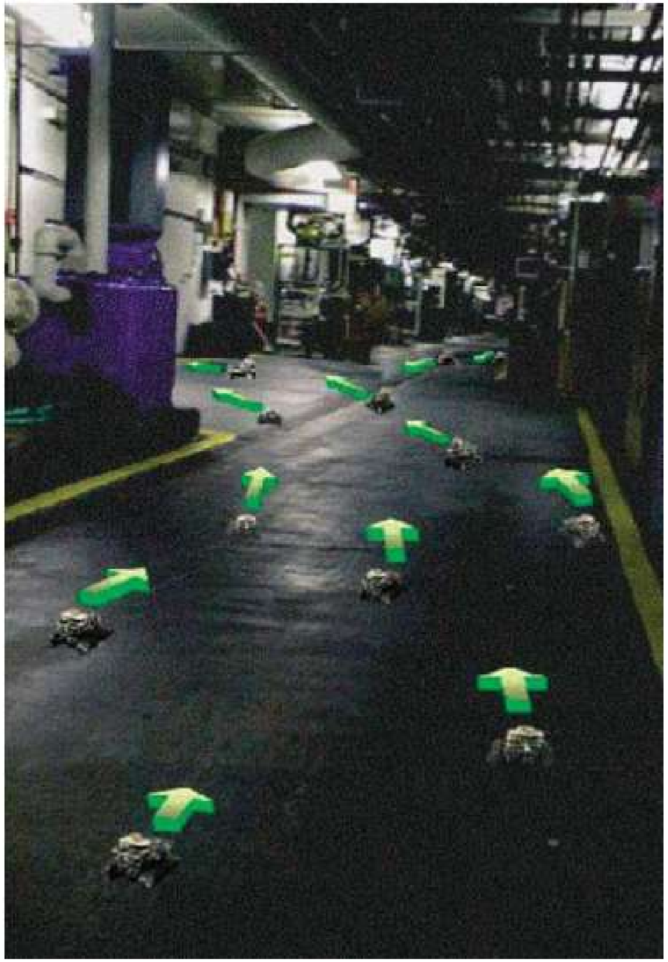
Centroidal Voronoi tessellation

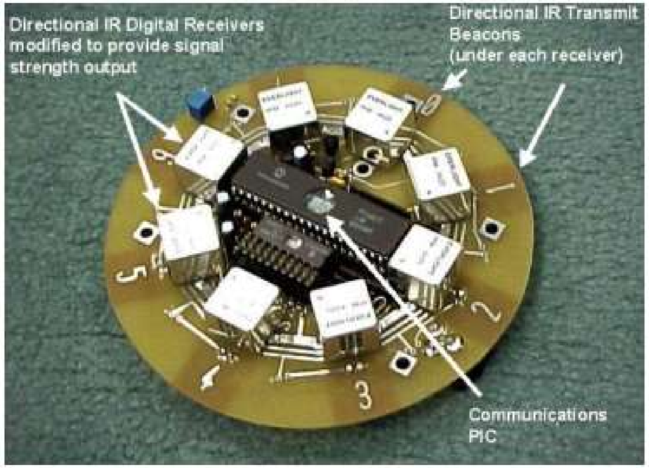
left: in a gradient (spatially centered Gaussian density function) such that each Voronoi cell contains the same amount

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

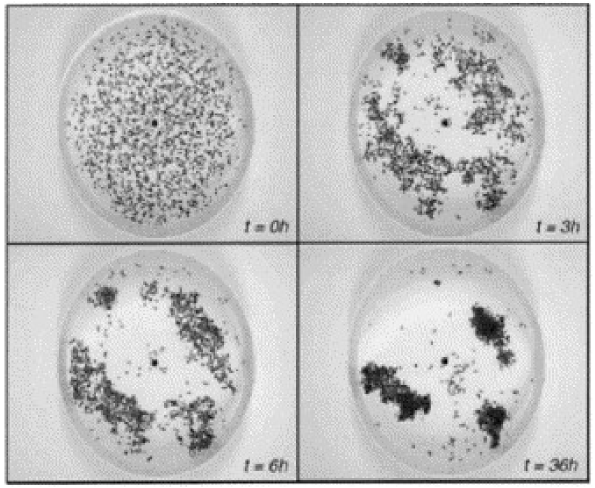
Task: robots position objects close to each other by clustering them in one spot ⇒ minimization of distances between objects

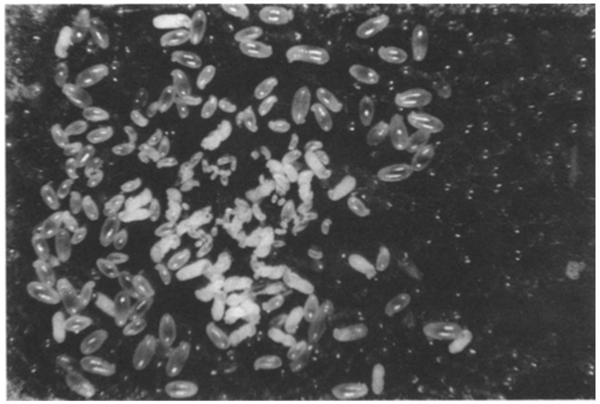
ants cluster. . .

. . . 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

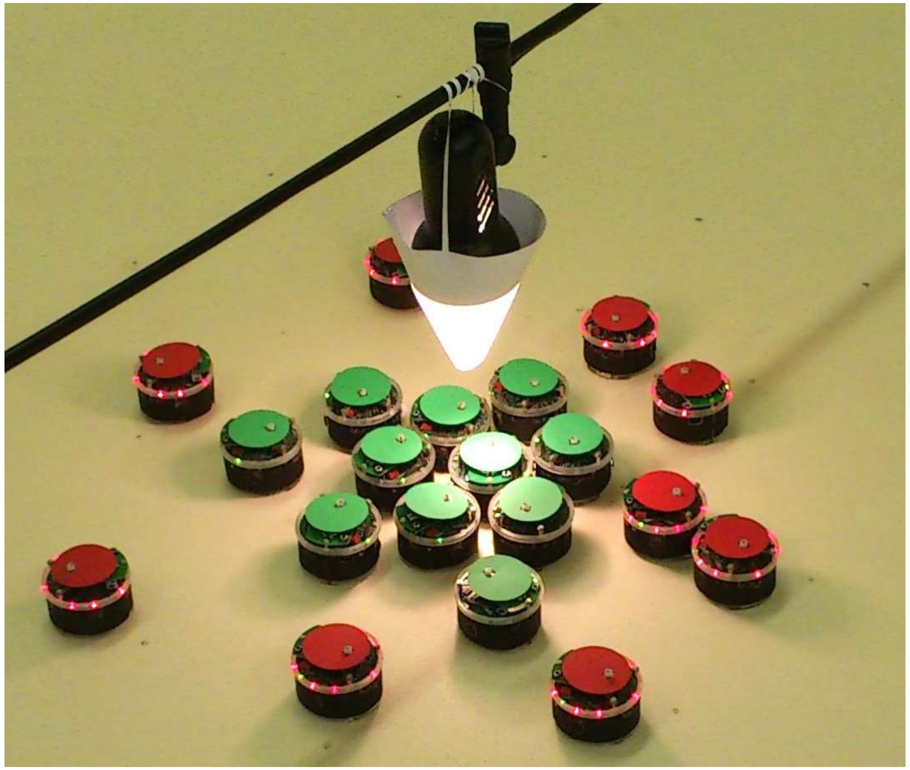
simple behavioral model of clustering:

- 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

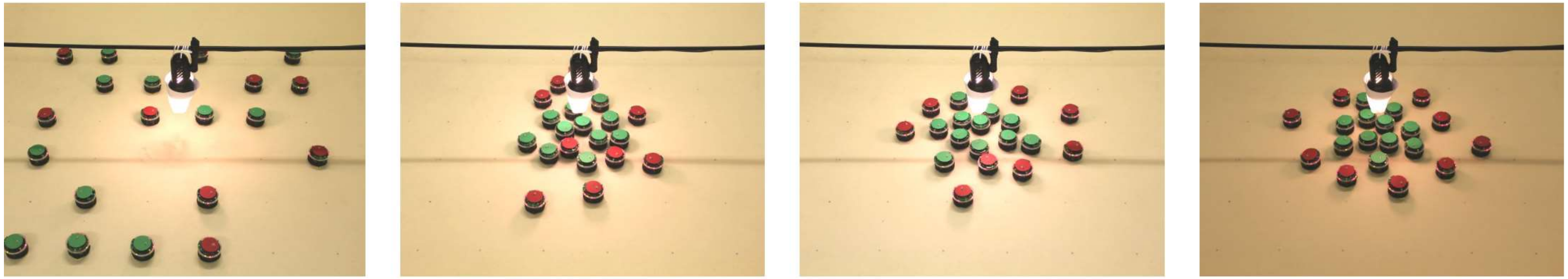
Floreano and Mattiussi (2008)

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)