Swarm Intelligent Systems

How social insects provide solutions to complex problems

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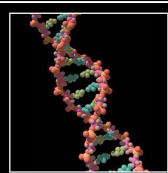
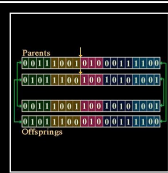
2nd ISCV Thematic Workshop:
Biologically-Inspired Computing
Valparaiso Complex Systems Institute, Chile
December 3-7, 2007

Biological systems: a source of inspiration

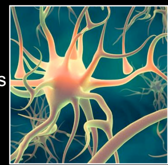
DNA dynamics & population genetics

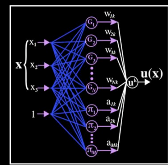




Genetic algorithms

Nervous systems





Artificial neural networks

Social insects

Artificial swarm intelligence

Swarm Intelligence is growing fast

(1999) (2001) (2004) (2005)

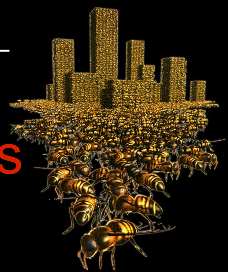
(2006) (2006) (2006) (2006)

From natural to artificial swarm intelligence

- Social insect colonies are decentralized problem-solving systems
- Social insects are flexible and robust systems
- Many of the daily problems solved by a colony have counterparts in engineering and computer science
- Models of social insects behaviors are a rich source of inspiration to design adaptive decentralized artificial systems that self-organize to solve problems

Bonabeau & Theraulaz, *Scientific American* (2000)

A categorization of collective behaviors in social insects



A categorization of collective behaviors

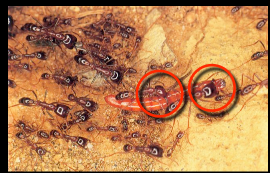
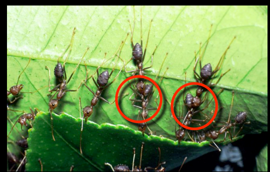
Coordination

- Coordination is the appropriate organization in space and time of the tasks required to solve a specific problem
- Coordination leads to specific spatio-temporal distributions of individuals, of their activities and/or of the results of their activities in order to reach a given goal

(Garnier, S. *et al.*, *Swarm Intell.*, 2007)

A categorization of collective behaviors

Cooperation

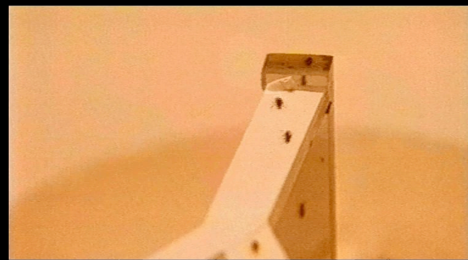




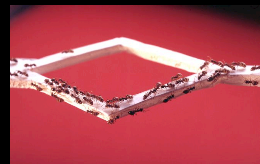
- Cooperation occurs when individuals achieve together a task that could not be done by a single one
- The individuals must combine their efforts in order to successfully solve a problem that goes beyond their individual abilities

(Garnier, S. *et al.*, *Swarm Intell.*, 2007)

A categorization of collective behaviors

Deliberation





- Deliberation occurs when a colony or a group of individuals faces several opportunities and collectively chooses at least one of these opportunities

(Garnier, S. *et al.*, *Swarm Intell.*, 2007)

A categorization of collective behaviors

Collaboration

Tending brood

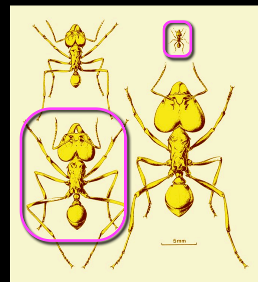
Foraging

- Collaboration occurs when different activities are simultaneously performed by groups of specialized individuals
- This specialization can rely on a pure behavioral differentiation or on a morphological one and can also be influenced by the age of the individuals

(Garnier, S. *et al.*, *Swarm Intell.*, 2007)

A categorization of collective behaviors

Collaboration



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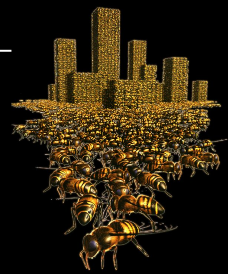
(Garnier, S. *et al.*, *Swarm Intell.*, 2007)

The organization of collective behaviors

Nest construction in the weaver ant (*Oecophylla longinoda*)

- In social insects most of the collective behaviors can be understood as a combination of at least two of the four functions of organization

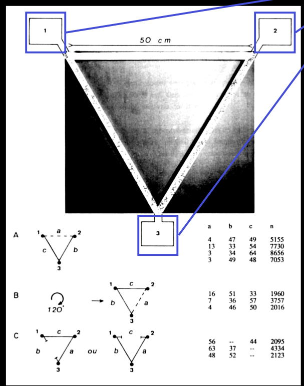
Ant colony optimization



Natural optimization: the case of inter-nest traffic

Triangular network

Nests

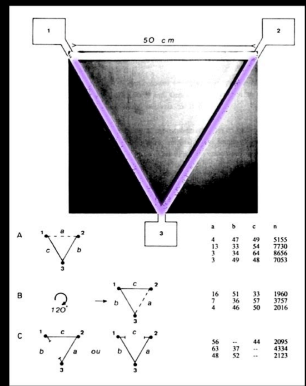


Linepithema humile
(Argentine ant)

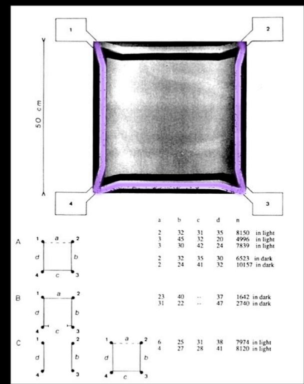
Aron, S. *et al.*, *Biological Motion* (1991)

Natural optimization: the case of inter-nest traffic

Triangular network



Square network

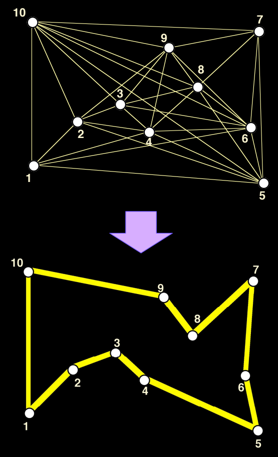


Aron, S. *et al.*, *Biological Motion* (1991)

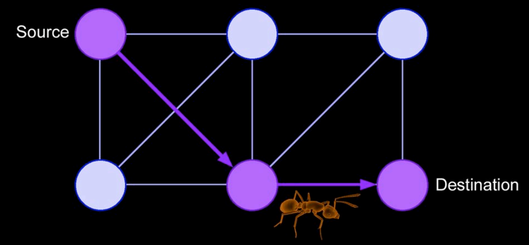
Natural optimization: the case of inter-nest traffic

- The resulting traffic of ants is such that all nests are connected by set of paths that form a minimal spanning tree: ants do not use redundant bridges
- These results are similar to the Traveling Salesman Problem (TSP): given N cities, and a distance function d_{ij} between cities (i and j), find a tour that:

  (1) Goes through every city one and only once
  (2) Minimizes the total distance



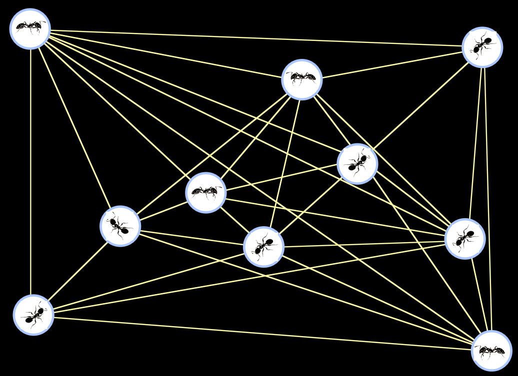
Artificial ants and the shortest path problem



- Using virtual pheromones to direct a colony of artificial ants in the search of the shortest path solutions on graphs
- Portions of good solutions that contribute to the quality of these solutions, are reinforced with virtual pheromone (stigmergic variable)
- Negative feedback is implemented through pheromone evaporation

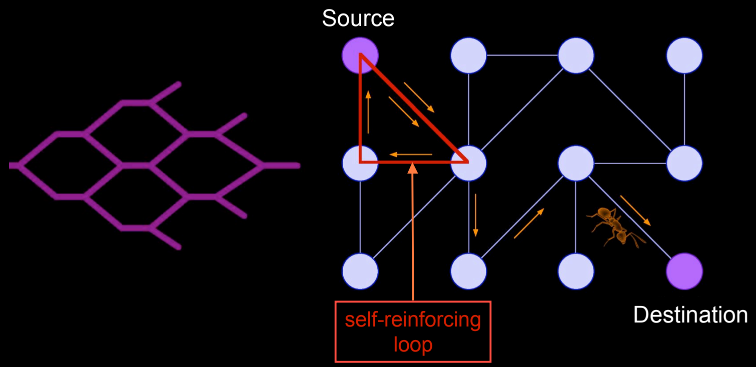
Colorni, A., Dorigo, M. & Maniezzo, V., *ECAL*, (1991)

Ant system solution for the TSP



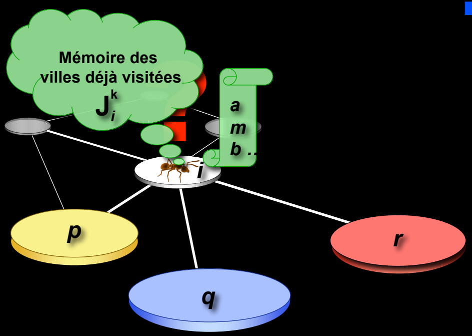
- In Ant System, ants are launched at cities and build solutions to the TSP by traversing the graph until they complete a tour

Real ant behavior cannot be used as it is



- The extension of the real ant behavior (forward/backward trail deposit) to artificial ants moving on a graph doesn't work: problem of self-reinforcing loops

Parameters involved in the decision of ants

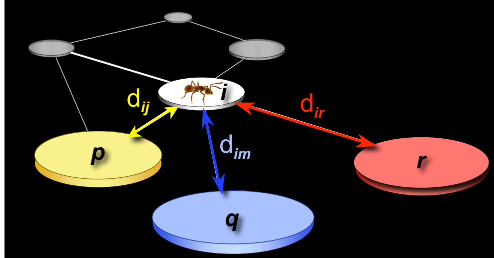


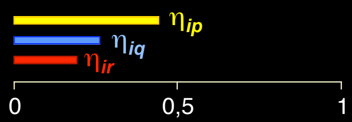
- For each ant the transition from city *i* to city *j* at iteration t depends on:

  (1) Has the city been visited? Each ant *k* maintains a tabu list in memory that defines the set J_i^k cities still to be visited when at city *i*

Dorigo, M. & Maniezzo, V., Colorni, A., *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* (1996)

Parameters involved in the decision of ants





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  (2) The visibility $\eta_{ij} = 1/d_{ij}$ that is inversely proportional to the distance between the two cities

Dorigo, M. & Maniezzo, V., Colorni, A., *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* (1996)

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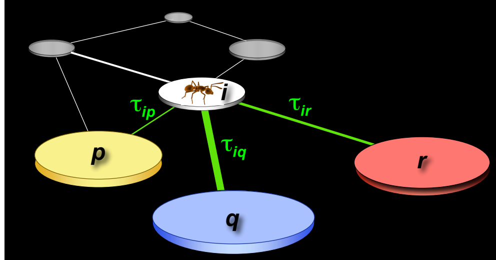

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  (2) The visibility $\eta_{ij} = 1/d_{ij}$ that is inversely proportional to the distance between the two cities

  (3) The amount of virtual pheromone on trail (*i,j*) = $\tau_{ij}(t)$

Dorigo, M. & Maniezzo, V., Colorni, A., *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* (1996)

Probabilistic decision rule

- The probability for ant k to go from city *i* to city *j* while in its t^th tour is:

Global information (pheromone)

Local information (visibility)

$$p_{ij}^k(t) = \frac{\boxed{[\tau_{ij}(t)]^\alpha} \boxed{[\eta_{ij}]^\beta}}{\sum_{l \in J_i^k} [\tau_{il}(t)]^\alpha [\eta_{il}]^\beta} \quad \text{if city j has not been visited}$$

$$p_{ij}^k(t) = 0 \quad \text{if city j has been visited}$$

- α and β are parameters that control trades-off global (pheromone) vs local information (distance)

Dorigo, M. & Maniezzo, V., Colorni, A., *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* (1996)

Update of pheromone trails

- After the completion of a tour each ant k lays a quantity $\Delta\tau_{ij}^{k}$ of pheromone on each edge (*i*,*j*) that it has used
- The amount of pheromone deposited on the links is inversely proportional to the overall length of the tour: the amount $\Delta\tau_{ij}^{k}$ is equal to Q/L_k^t

  L_k^t: the total length of the t^{th} tour of ant k

  Q : an adjustable constant

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$$

- Pheromone evaporates:

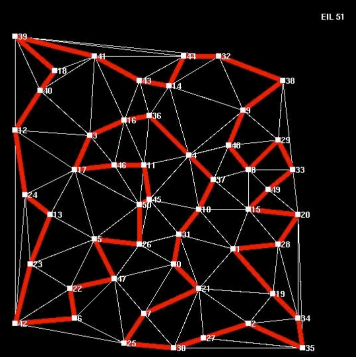
$$\tau_{ij}(t+1) = (1-\boxed{\rho})\,\tau_{ij}(t)$$

Pheromone evaporation rate

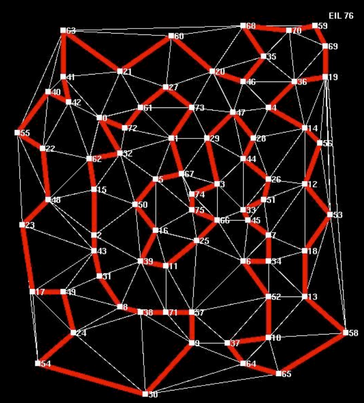
Dorigo, M. & Maniezzo, V., Colorni, A., *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics* (1996)

Simulation results

50-city problem



75-city problem



Comparison of Ant Colony System with other optimization algorithms

Problem	Ant Colony System (Dorigo & Gambardella,1997)		Genetic Algorithms (Whitley *et coll.*, 1989)		Simulated annealing (Lin *et coll.*, 1993)	
	Best tour length	Number of iterations	Best tour length	Number of iterations	Best tour length	Number of iterations
Eil50 (50-city)	425	1830	428	25000	443	68512
Eil75 (75-city)	535	3480	545	80000	580	173250
KroA100 (100-city)	21282	4820	21761	103000	N / A	N / A

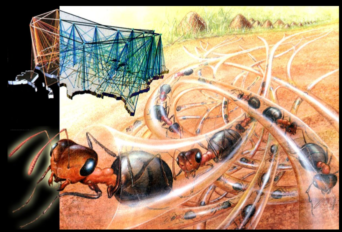
Other applications of ant colony algorithms to combinatorial optimization problems

Problem type	Problem name	Main references
Routing	Traveling salesman	Dorigo, Maniezzo, & Colorni (1991a,b, 1996) Dorigo (1992) Gambardella & Dorigo (1995) Dorigo & Gambardella (1997a,b) Stützle & Hoos (1997, 2000) Bullnheimer, Hartl, & Strauss (1999c) Cordón, de Viana, Herrera, & Morena (2000)
	Vehicle routing	Bullnheimer, Hartl, & Strauss (1999a,b) Gambardella, Taillard, & Agazzi (1999) Reimann, Stummer, & Doerner (2002)
	Sequential ordering	Gambardella & Dorigo (1997, 2000)
Assignment	Quadratic assignment	Maniezzo, Colorni, & Dorigo (1994) Stützle (1997b) Maniezzo & Colorni (1999) Maniezzo (1999) Stützle & Hoos (2000)
	Graph coloring	Costa & Hertz (1997)
	Generalized assignment	Lourenço & Serra (1998, 2002)
	Frequency assignment	Maniezzo & Carbonaro (2000)
	University course timetabling	Socha, Knowles, & Sampels (2002) Socha, Sampels, & Manfrin (2003)
Scheduling	Job shop	Colorni, Dorigo, Maniezzo, & Trubian (1994)
	Open shop	Pfahringer (1996)
	Flow shop	Stützle (1998a)
	Total tardiness	Bauer, Bullnheimer, Hartl, & Strauss (2000)
	Total weighted tardiness	den Besten, Stützle, & Dorigo (2000) Merkle & Middendorf (2000, 2003a) Gagné, Price, & Gravel (2002)
	Project scheduling	Merkle, Middendorf, & Schmeck (2000a, 2002)
	Group shop	Blum (2002a, 2003a)

Dorigo, M. & Stützle, T.
Ant Colony Optimization
(2004)

Dynamic optimization: routing in telecommunications networks by ant-like agents

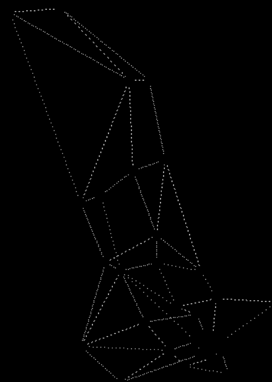
- Routing is a mechanism that allows phone calls to be transmitted from a source to a destination through a sequence of intermediate nodes
- Each node keeps a routing table telling phone calls where to go next depending on their destination
- In real networks conditions are constantly changing: routing algorithms have to maximize the network performance while minimizing the number of call failures
- Ant-based routing uses antlike agents that continuously build and adapt routing tables to local changes to maximize network performance



Schoonderwoerd *et al.*, *Adaptive Behavior* (1996)

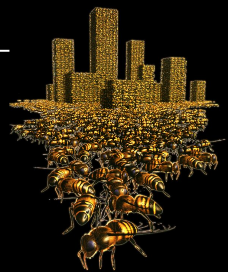
Basic ant-based control idea

- An ant move towards its destination node by following the pheromone table left by ants for which its destination was their source … and the calls are routed to their destination in the same way
- The pheromone evaporates at regular intervals: busy routes will not be reinforced
- The process allows calls to be rerouted towards better parts of the network and enables congested areas to recover rapidly from the overload



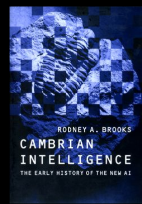
Schoonderwoerd *et al.*, *Adaptive Behavior* (1996)

Swarm robotics



Distributed control in swarm-based robotics

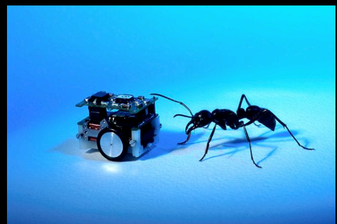
- Traditional approach to build autonomous robots based on AI techniques are unable to deliver real-time peformance in a dynamic world
- With a subsumption architecture a mobile robot is able to navigate in complex and unpredictable environment without any explicit representation of this environment



Brooks, R.A., *IEEE Journal of Robotics and Automation* (1986)

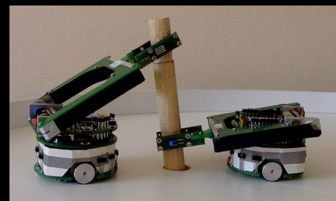
Distributed control in swarm-based robotics

- A group of simple robots may be more efficient than a single sophisticated robot
- A group of simple robots is cheaper and much more reliable than a powerfull complex robot



Distributed control in swarm-based robotics

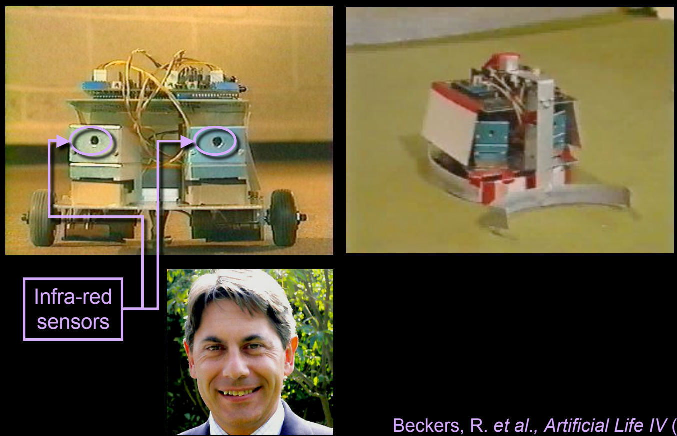
- A group of simple robots may be more efficient than a single sophisticated robot
- A group of simple robots is cheaper and much more reliable than a powerfull complex robot
- Using a group of simple robots brings new problems (scalability, lack of global knowledge, poor communication abilities)
- Swarm-based robotics relies on stigmergic communication (environment is used as communication channel)
- These coordination mechanisms enable a group of robot to operate under a wide range of group sizes



Distributed clustering by a group of robots

An instance of stigmergic communication

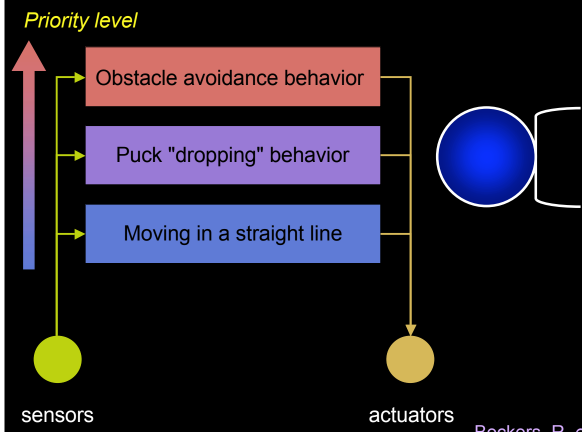
Individual behavior



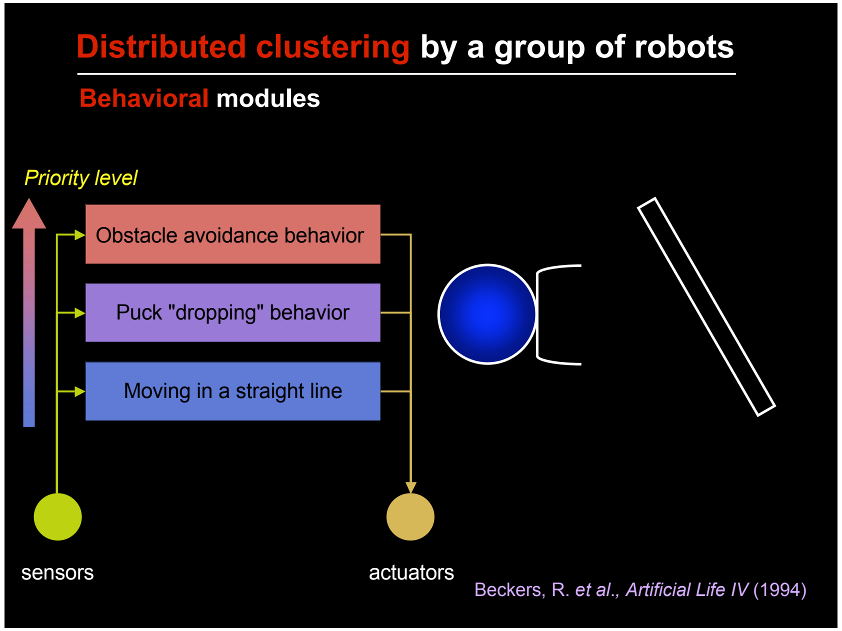
Beckers, R. *et al.*, *Artificial Life IV* (1994)

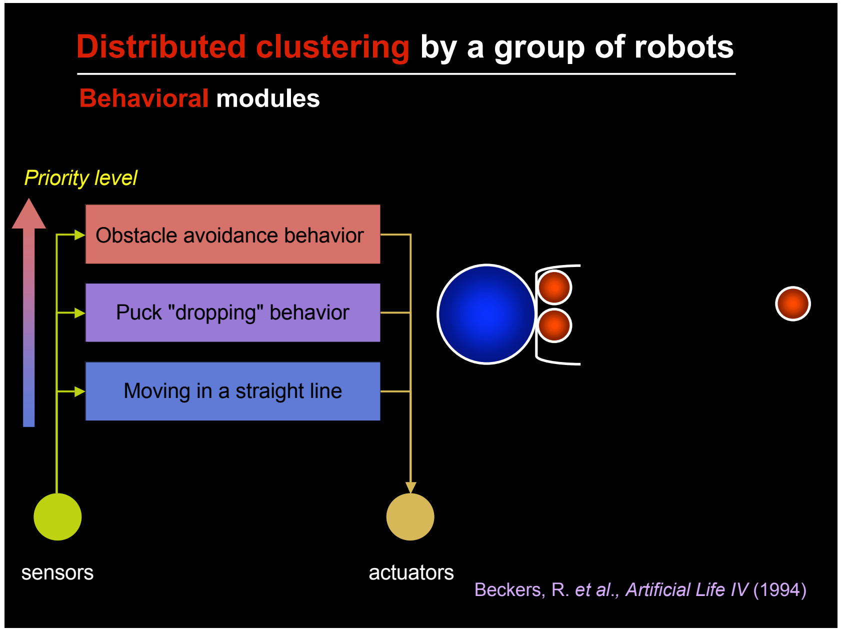
Distributed clustering by a group of robots

Behavioral modules



Beckers, R. *et al.*, *Artificial Life IV* (1994)


Distributed clustering by a group of robots
Behavioral modules
Priority level
Obstacle avoidance behavior
Puck "dropping" behavior
Moving in a straight line
sensors
actuators
Beckers, R. et al., Artificial Life IV (1994)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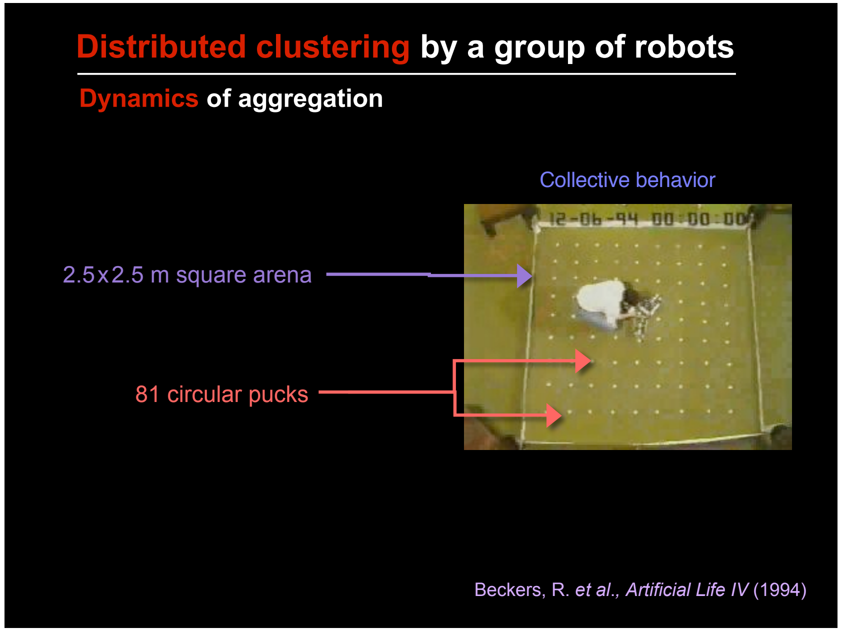
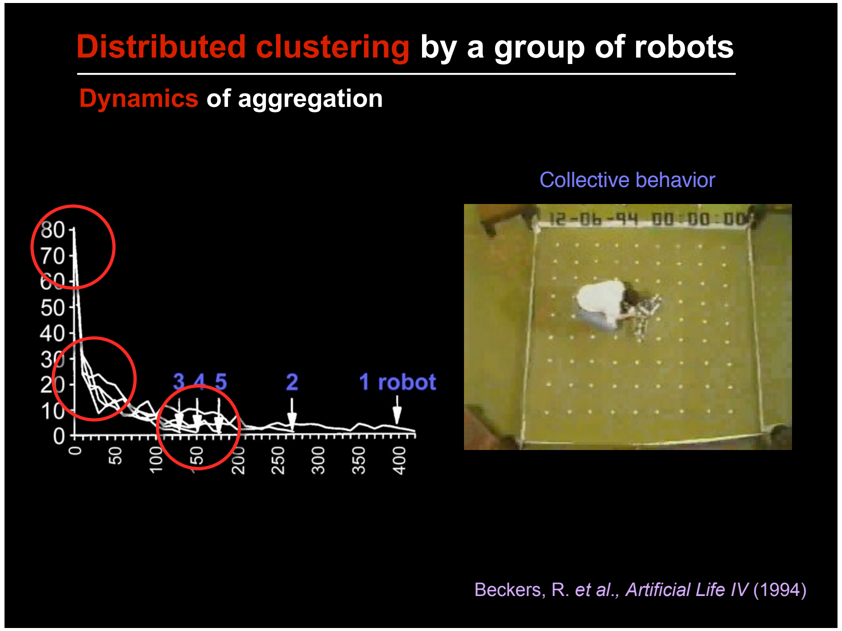
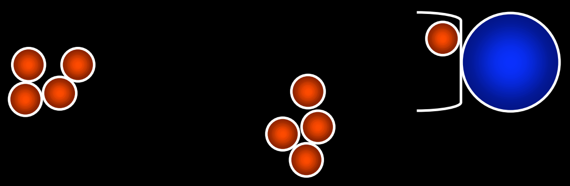

Distributed clustering by a group of robots
Dynamics of aggregation
Collective behavior
2.5x2.5 m square arena
81 circular pucks
Beckers, R. et al., Artificial Life IV (1994)


Distributed clustering by a group of robots
Dynamics of aggregation
Collective behavior
80
70
60
50
40
30
20
10
0
0
50
100
150
200
250
300
350
400
3 4 5
2
1 robot
Beckers, R. et al., Artificial Life IV (1994)

Distributed clustering by a group of robots

Dynamics of aggregation

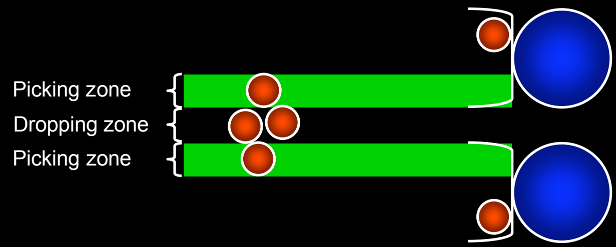


- Pucks can be removed from a pile only if the robot collides it almost tangentially

Beckers, R. *et al.*, *Artificial Life IV* (1994)

Distributed clustering by a group of robots

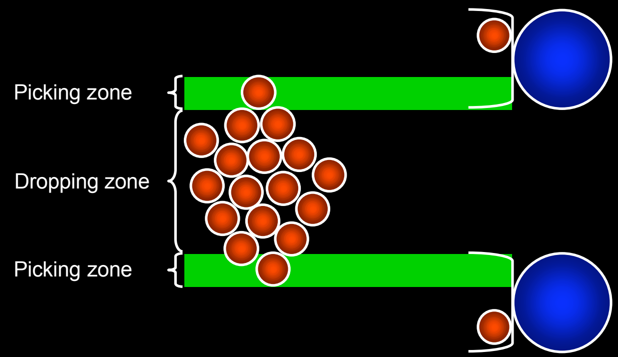
Dynamics of aggregation



Beckers, R. *et al.*, *Artificial Life IV* (1994)

Distributed clustering by a group of robots

Dynamics of aggregation



Beckers, R. *et al.*, *Artificial Life IV* (1994)

Distributed clustering by a group of robots

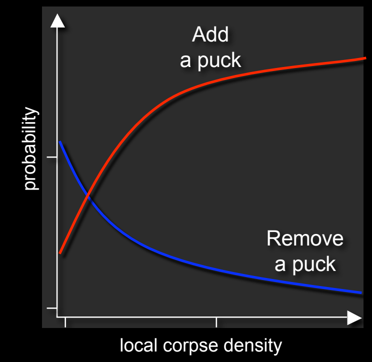
Dynamics of aggregation

- The probability to remove a puck from a pile decreases with pile size

$$\frac{\text{Picking zone}}{(\text{Picking zone} + \text{Dropping zone})}$$

- The probability to add a puck to a pile increases with pile size

$$\frac{\text{Dropping zone}}{(\text{Picking zone} + \text{Dropping zone})}$$



Beckers, R. *et al.*, *Artificial Life IV* (1994)

Distributed clustering by a group of robots

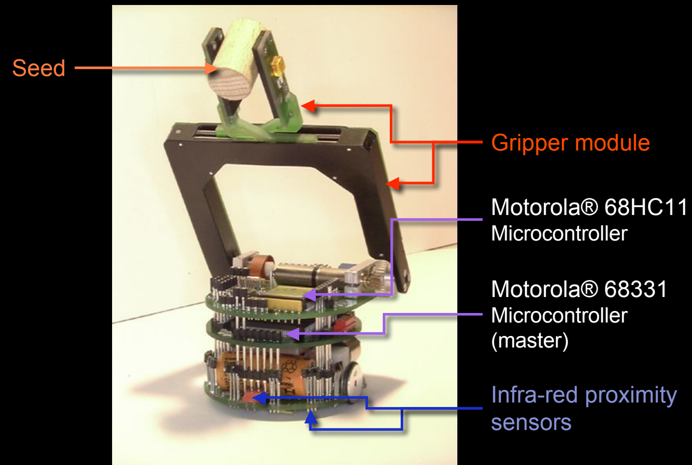
From coordination to cooperation

- Robots are autonomous
- No explicit communication among robots
- Control architecture is mainly reactive and based on simple behaviors

Martinoli., A. *et al.*, *Robotics and Autonomous Systems* (1999)

Distributed clustering by a group of robots

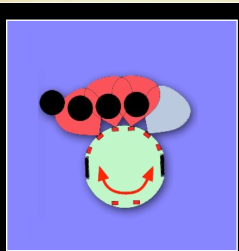
Main features of the Khepera robot



Distributed clustering by a group of robots

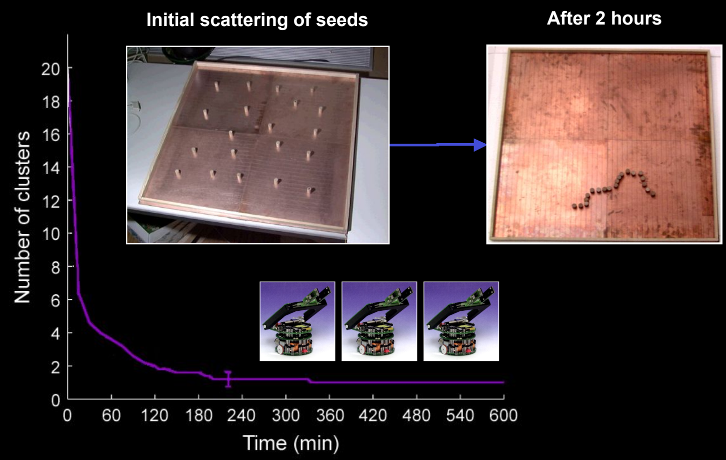
Robot discriminating behavior

- The robot discriminating behavior is based on a wobble movement in front of the found object
- If the number saturated sensors is > 2, the object is considered as an obstacle and the robot avoids it
- If the number saturated sensors ≤ 2 the object is considered as a seed that can be picked up or in front of which another seed can be deposited



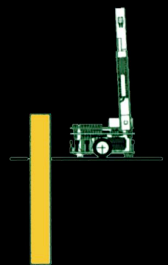
Distributed clustering by a group of robots

Experimental results with 3 robots



Cooperative stick pulling

Sequence of cooperation between robots



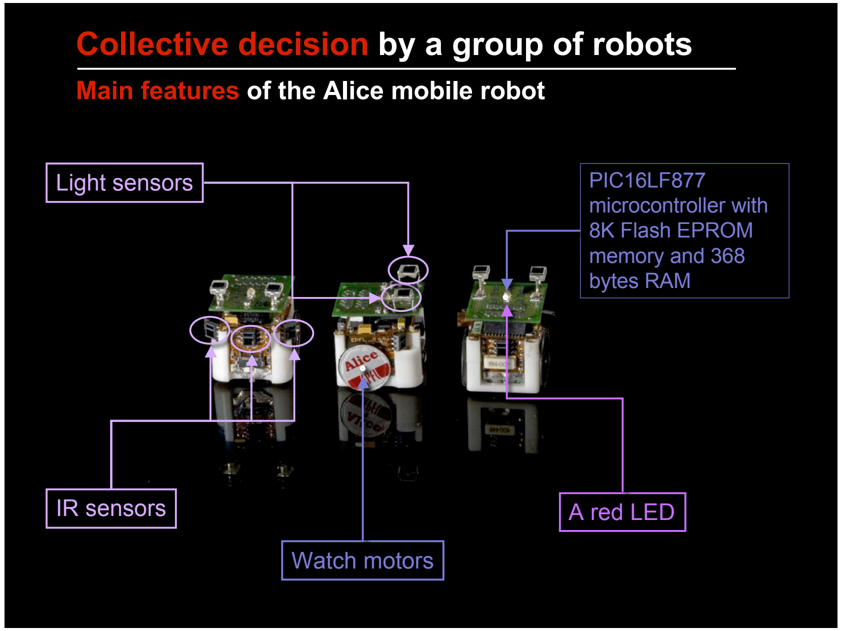
Robot A detects the stick

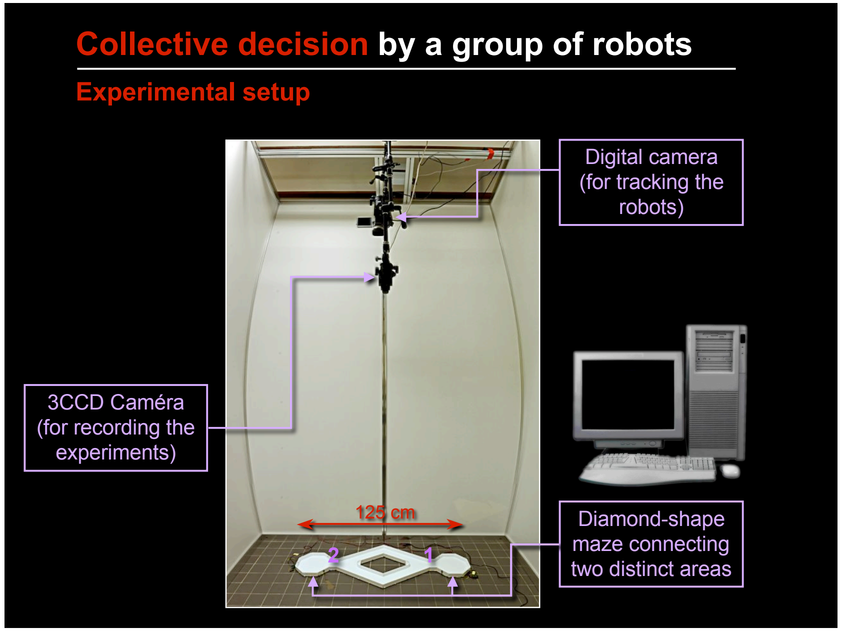
Ijspeert, A.J. *et al.*, *Autonomous Robots* (2001)

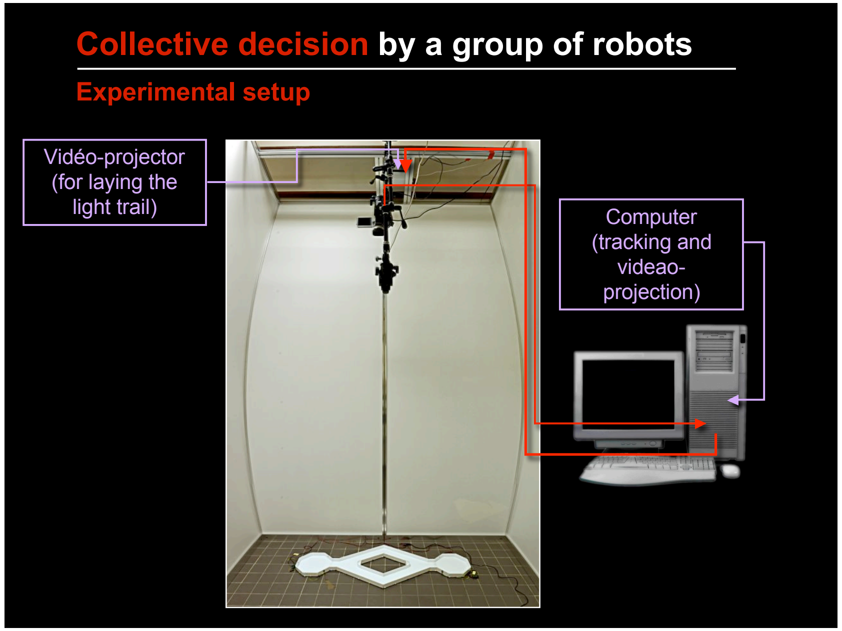
Collective decision by a group of robots

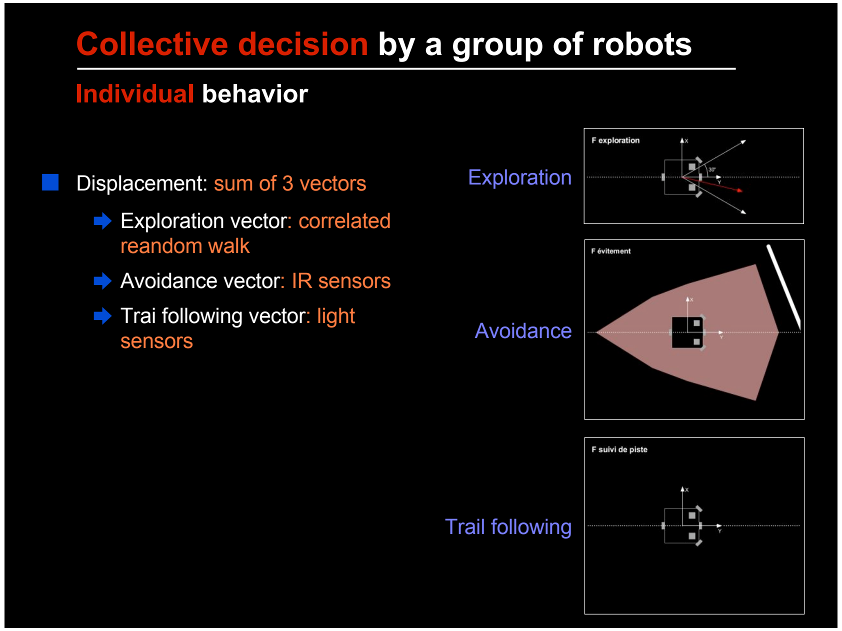
Stigmergic communication based on light trails

Garnier, S. *et al.*, *IEEE SIS* (2007)


Collective decision by a group of robots
Main features of the Alice mobile robot
Light sensors
PIC16LF877 microcontroller with 8K Flash EPROM memory and 368 bytes RAM
IR sensors
Watch motors
A red LED


Collective decision by a group of robots
Experimental setup
Digital camera (for tracking the robots)
3CCD Caméra (for recording the experiments)
125 cm
2
1
Diamond-shape maze connecting two distinct areas

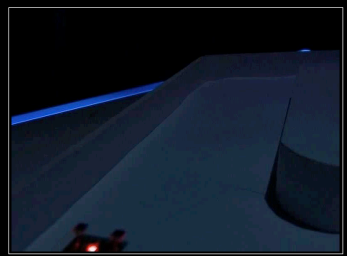

Collective decision by a group of robots
Experimental setup
Vidéo-projector (for laying the light trail)
Computer (tracking and videao-projection)


Collective decision by a group of robots
Individual behavior
Displacement: sum of 3 vectors
Exploration vector: correlated reandom walk
Avoidance vector: IR sensors
Trai following vector: light sensors
Exploration
F exploration
Avoidance
F évitement
Trail following
F suivi de piste

Collective decision by a group of robots

Individual behavior

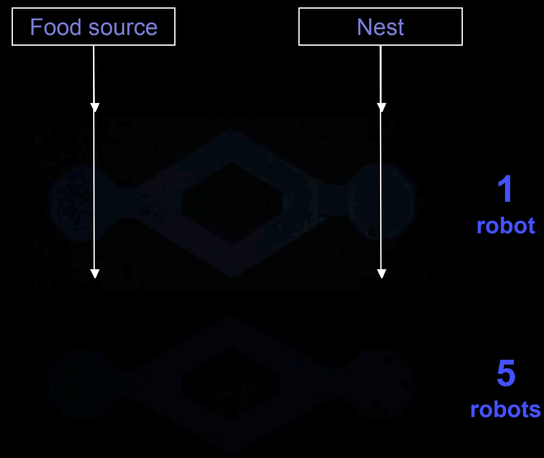
- Displacement: sum of 3 vectors
  - Exploration vector: correlated random walk
  - Avoidance vector: IR sensors
  - Trai following vector: light sensors
- Trail laying behavior:
  - A robot begins to lay a light trail when it leaves the food source area
  - A robot stops trail laying only when it enters the nest area or comes back to the food source



Trail laying

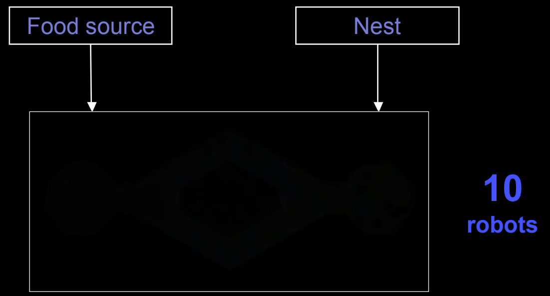
Collective decision by a group of robots

Collective path selection



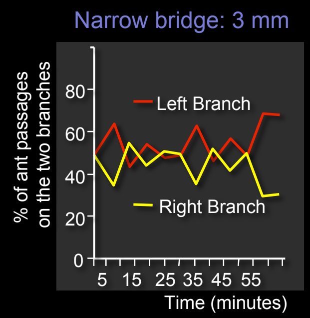
Collective decision by a group of robots

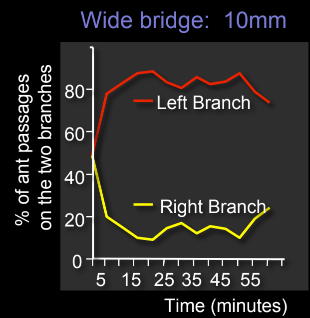
Traffic organization under crowd conditions



Collective decision by a group of robots

Traffic organization under crowd conditions



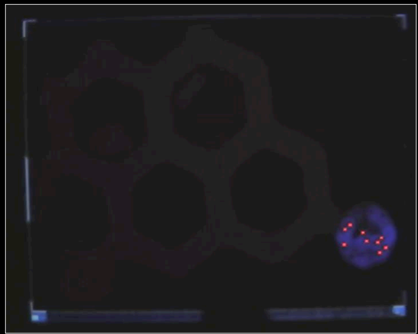


Dussutour, A. *et al.*, *Nature* (2004)

Collective decision by a group of robots

Shortest path selection

10 robots

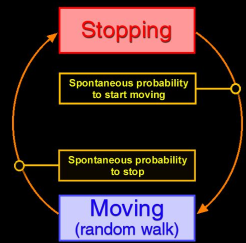


Collective decision
based on self-organized aggregation

Behavioral model

- In cockroaches, aggregation relies on a self-amplification process of the individual resting behavior
- In the presence of two or more dark shelters in an arena, all the cockroaches aggregate under only one of these shelters
- Collective choice relies on a modulation of the individual resting period under a dark shelter by the number of nestmates present under this shelter

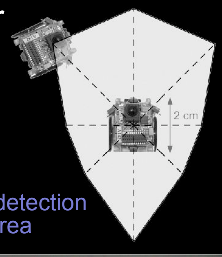
Individual behavior



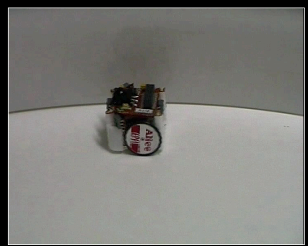
Collective decision in groups of robots
based on self-organized aggregation

Implementation of cockroaches behavior

- Displacement and local aggregation rules of cockroaches have been implemented in micro-robots
- Robots can make an estimation of the local density of nearby robots and compute the probability to stop or to start moving



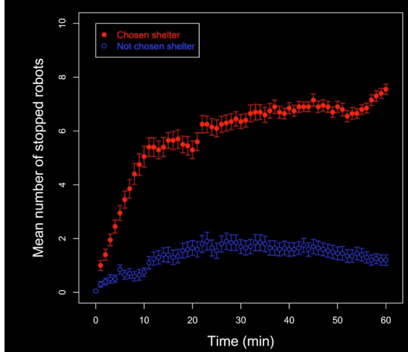
Local detection area

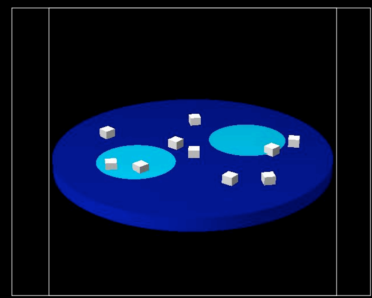


Garnier, S. *et al.*, *Lectures Notes in Computer Science* (2007)

Collective decision in groups of robots
based on self-organized aggregation

Experimental results with identical shelters



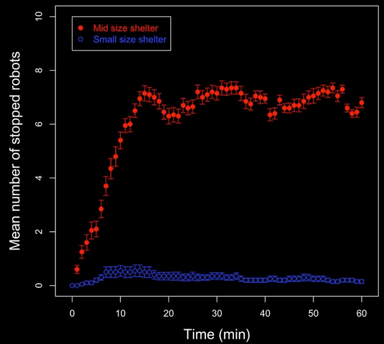


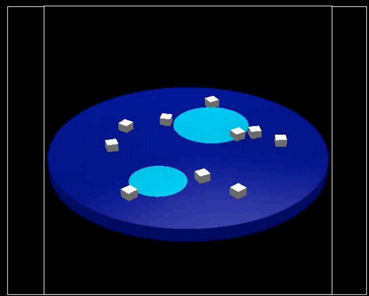
Real time : 1 hour

- Robots can only stop under the shelters (IR intensity drops): aggregation process can only occur under the shelters
- The self-enhanced aggregation process allows the robots to collectively choose a “rest site” among two aggregation places

Collective decision in groups of robots
based on self-organized aggregation

Experimental results with shelters of different sizes





Real time : 1 hour

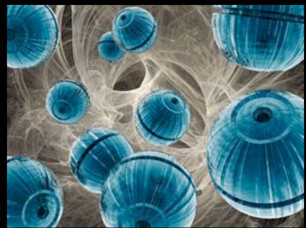
- A difference of size or darkness between the two shelters may bias the seeding process and unbalance the final choice
- The robots are thus able to collectively sense a difference between the aggregation places

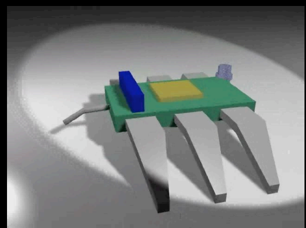
Swarm robotics: the best has yet to come

- Most of the works are robotic implementations of the mechanisms found in social insects and transpositions of the natural situations in an artificial context
- The decentralized logic of social insects can be successfully used by groups of simple robots to coordinate their activities
- New questions are open regarding the problem of scalability in natural and artificial systems

Swarm robotics: the best has yet to come

- One promising field of application of swarm algorithms is nano-robotics
- The European I-SWARM project aims to take a leap forward in robotics by building a real micro-robot swarm, i.e. a thousand micro manufactured autonomous robots ($2 \times 2 \times 1$ mm³) designed for the collective execution of different tasks in the small world

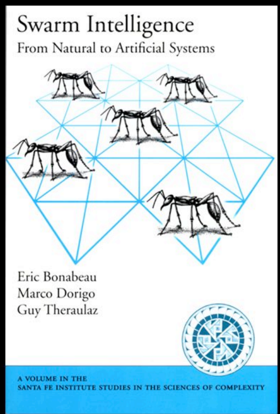




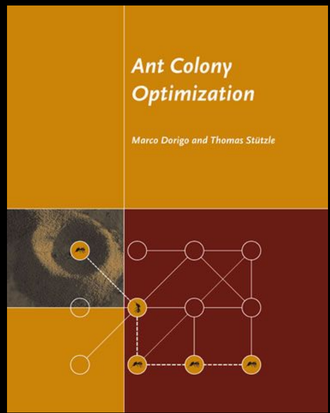
Conclusions and perspectives

- Swarm intelligent systems possess a number of interesting properties (flexibility, robustness, decentralized control and self-organization)
- Swarm intelligent systems are well suited to cope with complex and dynamic environments
- Still some issues need to be addressed: most of the existing algorithms have been adapted from existing models of collective behaviors in social insects
- The question is now: how should we "program" a swarm of agents so that it performs a given task ?

To learn more about Swarm intelligence and Ant colony optimization

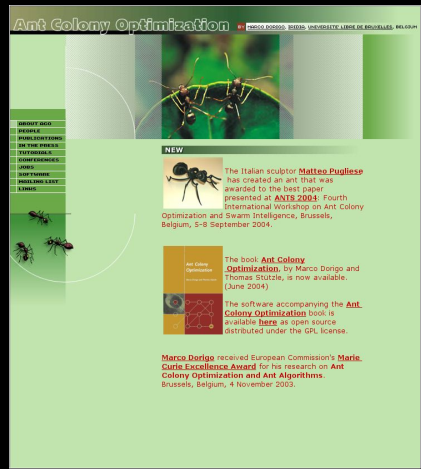


(Bonabeau, Dorigo & Theraulaz, 1999)
Oxford University Press

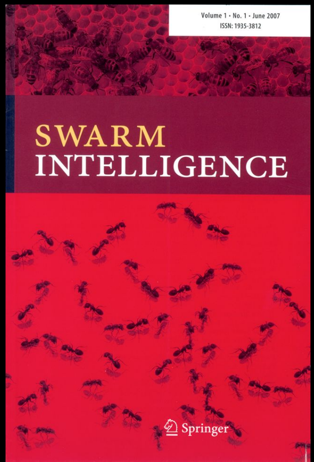


(Dorigo & Stützle, 2004)
MIT Press

On the web:
http://www.aco-metaheuristic.org/



New Journal !



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